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Asset Pricing and Artificial Neural Networks: A Case of Pakistan's Equity Market

by

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To Holy Prophet Muhammad Sallallahu Alaihi Wasallam and My Teachers, Family, Friends and Those Strive for a Cause

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1. Jan, M. N., & Ayub, U. (2019). Do the FAMA and FRENCH Five-Factor model forecast well using ANN?. *Journal of Business Economics and Management*, 20(1), 168-191.

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Abstract

The job of forecasting the stock market returns in the emerging markets is challenging due to some peculiar characteristics of these markets. For years, conventional forecasting methods have been developed, but they have succeeded partially or have failed entirely to deal with the nonlinear and complex nature of stock returns. Artificial Neural Networks approach is a relatively new and promising field of the prediction of stock returns.

Neural networks approach is a mathematical model, flexible enough to accommodate both linear and non-linear aspect of stock returns and act like human brains to simulate the behavior of the stock prices. The literature review reveals that there are a large number of studies trying to forecast the stock market returns using conventional statistical techniques. However, there is a dearth of literature on the use of machine learning techniques in the area of asset pricing. The study is an attempt to fill this gap by addressing the major issue of using the asset pricing models for prediction of portfolio returns in the presence of Artificial Neural Networks.

We investigate the forecasting ability of single factor CAPM, Fama and French three factor and five factor model by using Artificial Neural Networks. This study employs the monthly returns of all the companies listed on Pakistan Stock Exchange for the period 2000-2015. Data on market capitalization, book-to-market ratio, total assets and operating profit is used to construct factors used in multi-factor models. The factors of Size, value, investment, and profitability are constructed by following the industry standards. Thirty Portfolios are constructed by beta; resulting into high, medium and low beta portfolios based on monthly returns. These factors are used as inputs and outputs in the neural network system.

We construct an artificial neural networks system to predict portfolio returns in two stages; in stage one, the study identifies the best-fit combination of training, testing, and validation along with the number of neurons for the three asset pricing models for a full sample from 2000 to 2015. In stage two, the study uses this best combination to forecast the model under 48-month rolling window analysis and

evaluate its ability to forecast the stock returns in an emerging market. In-sample and out-sample comparisons, regression and goodness of fit test and actual and predicted values of the stock returns of the ANN model are conducted.

A comprehensive methodology of the neural networks is applied to achieve the primary purpose of forecasting. The methodology includes the initial architecture consists of three layers, i.e., an input layer, hidden layer, and an output layer. The hidden layer utilizes 1-50 neurons for processing. The study uses varying parameters for an effective Artificial Neural Networks system. The study also employs rolling windows to calculate and compare forecasting error among competing asset pricing models by using 16 data combinations. The Artificial Neural Networks take the values of monthly returns of the first 48 months as a training set and predict the 49th value for the monthly returns. Mean Squared Error measures the performance of the Artificial Neural Networks.

The significant findings of the study are: firstly, CAPM-based networks models have predicted 48%, while the Fama and French three factors and five factors models based networks returned 94% and 98% respectively of the time periods accurately. Secondly, the number of the optimum number of neurons does not follow some mathematical rule instead it is based on the presentiment of the researcher to apply an exhaustive search for the number of optimum neurons. Thirdly the performance of the CAPM-based networks is the best at the 75-10-15 dataset and 16 neurons.

The Fama and French three factors model generate the best results at 60-20-20 dataset and 27 neurons and the Fama and French five factors model return the best results at 28 neurons and 75-20-05 dataset. The magnification of the performance with the increase in the number of neurons is a useful heuristic for the future researchers. The fourth significant finding is that the difference of errors between the testing and training data set is minimum and the networks are not suffering from the over-fitting phenomenon.

The fifth finding is that the predicted value of high beta portfolios is better than the low beta and mid beta portfolios. This finding reinforces the investment principle that the market compensates the high-risk portfolios more than other classes. The

Fama and French five factors model show more promising results as compared to the other two models. The best results are converging at 75-20-05 Dataset at 28 neurons, and the success rate of accurate prediction is 98%. This implies that the addition of the investment and profitability factors demonstrate good predictive power in this market. Our findings reinforce the investment principle that the markets compensate the high-risk portfolios more than the other classes. The proposed prediction methodology will significantly improve the return on investment against the buy and holds strategy.The proposed model achieves a significant improvement in the return on investment, and the investors can magnify their profitability.

Our methodology using ANN models,although, have accurately predicted the returns, it remains open to more experimentation. At this point, given the 'black box' nature of the ANN, it is difficult to offer any explanation beyond the well-known ability of the ANN to capture 'hidden' relationships between inputs and outputs. Future researchers should focus on clustering, classification, hybridization of other nonlinear techniques with a neural network system. The portfolio selection can also be optimized using particle swarm optimization and other artificial intelligence techniques. We hope that future research in the fields of both asset pricing and artificial intelligence would be able to offer an opportunity for interdisciplinary research and present more challenges to the established investment theories.

Key words: Asset Pricing, Capital Asset Pricing Model, Forecasting, Fama and French Five Factor Model, Fama and French Three Factor Model, Artificial Neural Networks, Equity Market, Pakistan

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Abbreviations

ANN	Artificial Neural Networks
BR	Bayesian Regularization
BP	Back Propagation
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
EMA	Exponential Moving Averages
FF3F	Fama and French three factor Model
FF5F	Fama and French five factor Model
FFNN	Feedforward Neural Networks
FSO	Fast Stochastic Oscillator
GA	Genetic Algorithm
KSE-100	Karachi Stock Exchange Index-100
LM	Levenberg Marquardt
MLP	Multilayer Perceptron
MSE	Mean Squared Error
MACD	Moving Averages Convergence Divergence
MKT.CAP	Market Capitalization
PSX	Pakistan Stock Exchange
PNN	Probabilistic Neural Networks
RBF	Radial Basis Function
RSI	Relative Strength Index
SMA	Simple Moving Averages

Chapter 1

Asset Pricing And Artificial Neural Networks

1.1 Introduction

The stock market spurs the economic development of a country thus playing a pivotal role in shaping the economies and the growth of important economic indicators (Bonfiglioli, 2008; Levine et al., 2003; Rajan and Zingales, 2003). The magnitude of investments in stock markets worldwide shows that the stock markets mobilize massive investments from all quarters of the society and many emerging economies develop a strong foundation for economic development through the stock markets (Bekaert et al., 2005; Levine, 2008).

However, the analysis of the actual returns of the investors both in emerging and developed markets reveals that their average return on investment is low as compared to the market (Malkiel, 2011). This rate of return in the bearish markets is even lower than the market. The reasons behind this non-synchronization in returns are beyond the understanding of typical investors, and according to (Fama and French, 2010) the returns of some of the investors are above the market in those same markets and situations.

Some authors attribute the responsibility of variable returns to the panic and irrational decision making of the investors while investing in risky assets. Other investments experts highlight well-established reasons for this difference in investment returns. These reasons include; the lack of the use of the nonlinear mathematical and statistical techniques for forecasting, classification, clustering, and pattern recognition of stock returns and portfolio formation, the wide gap between the academic researchers and floor traders and the inability of the researchers to test their models in the actual environment of the markets.

Forecasting the returns and directional changes of the stock markets is a challenging but lucrative task for the policymakers, corporate researchers, academicians and floor traders. This challenge becomes complex because the returns of financial assets are affected by economic, fundamental, and technical factors. Furthermore, the financial markets demonstrate non-linearity and exponential movements: making any prediction about the stock markets a difficult task.

The peculiar characteristics of the volatile emerging markets pose added complexity to the challenge of prediction due to some peculiar reasons. Carvalhal and Ribeiro (2008) and Harvey (1995) outline the highly volatile macro and micro economic indicators of the emerging markets to be a hindrance in forecasting the stock market's return and portfolio formation process. The investors, researchers, and academicians have recently focused their research orientation to these markets due to the presence of higher returns as compared to the developed markets, the weak integration of these markets with other developed markets and effective portfolio diversification.

These reasons provide a significant rationale for exploring the opportunity of forecasting the stock returns in the emerging stock market of Pakistan. This market has attracted many institutional and individual investors in recent past from the global markets and their presence is the reason of focus of the renowned international analyst groups. Pakistan's equity market is classified as the major market by Bloomberg (2015) and Pakistan Stock Exchange is declared the fifth best performing market in the world ranking. A recent report by the Indian edition of Quartz (2016) reveals that PSX has beaten the major Asian equity markets in terms of volume and actual returns and Bloomberg (2016) report declares Pakistan as the "tiger" of Asia, reaffirming KSE-100 as one of the best in the world. All these reports and indicators assign substantial importance to Pakistan's Equity Market.

In such an emerging market like Pakistan's Equity Market, Forecasting the stock returns and direction of the market is a passion of the researchers and traders in anticipating excess returns on their investments. These stakeholders of the stock markets are always in search of latest forecasting techniques having the capability to present an accurate and robust prediction of the stock markets. The forecasting techniques are introduced by researchers from many diversified disciplines and can be categorized as traditional techniques and artificial neural networks.

The traditional techniques include structural econometric models and auto-regressive models. These models possess simplicity in their application; at the same time suffer from certain drawbacks. Firstly, these models require a pre-specification of the data set and secondly, these models assume that the nature of the underlying data is linear. The forecasting success rate of these models is only 64 %. These limitations of the autoregressive and structural models cast a question mark on their actual application in the stock markets run time in the presence of more innovative technologies.

The technology of artificial neural networks imposes no such limitations and offers a meaningful replacement for predicting the stock markets behavior and returns. The Artificial neural networks can revitalize the pricing of risky assets and investment theory and enable the investors to organize their investments more profitably and expect above-average returns (Gunn and MacDonald, 2006). The asset pricing models have played a vital role in enhancing the portfolio returns and it is widely believed that these models have the enormous capability of explaining the investors' returns. The subject of asset pricing is a central theme of the investment and portfolio decision making (Malkiel, 2003).

The Capital asset pricing model is the pioneering asset pricing model developed by four different authors independently, these authors include (Lintner, 1969; Mossin, 1966; Sharpe, 1964; Treynor, 1961). These authors provide a foundation for the asset pricing in a quantitative form, and almost all the researchers in finance recognize their work. CAPM draws its underlying assumptions from the modern portfolio theory with additional assumption of unlimited borrowing, lending and permission for short sales (Sharpe, 1964).The model is a cornerstone of pricing risky assets in financial economics. According to Fama and French (2004), the CAPM is not only strong theoretically, but the mathematical derivation is also very appealing when the stock expected rate of return and risk are calculated.

The model is tested by many researchers in its early years to validate its application in different markets and situations. Studies like (Beaver et al., 1970; Galai and Masulis, 1976; Hamada, 1972), report favorable results for CAPM. Some early studies like Black (1972) did not entirely reject the theory of CAPM but suggest certain changes, thus introducing his zero- beta CAPM. Renowned studies in asset pricing like Fama and MacBeth (1973) and Blume and Friend (1973) suggest the adoption of CAPM in asset pricing.

Some renowned authors including (Ball, 1978; Banz, 1981; Basu, 1977; Fama and French, 1992; Reinganum, 1981; Ross, 1977; Stattman, 1980) find the CAPM to be invalid. A number of studies point out significant anomalies in CAPM. The first anomaly of size identified by (Banz, 1981) and confirmed by studies of (Basu, 1983). The second major anomaly of value effect identified by Stattman (1980). He argues that the dependence of asset returns based on a single factor is a debatable and questionable argument. These anomalies are incorporated in CAPM by Fama and French (1992) resulting in Fama and French three factors Model.

Fama and French (2015) add two additional factors identified by (Novy-Marx, 2013; Aharoni et al., 2013). These factors capture the impact of profitability and investments in the investment returns. The new model is called the Fama and French five factors model and the model is being applied recently by many authors both in the developed and developing markets and the results are encouraging. Our study focuses on the application of single factor CAPM, three factors Fama and French model and five factors Fama and French models in Pakistan's equity market to predict the stock returns and test their success or failure in this emerging market using artificial neural networks. The present study, however, is not investigating the validity or invalidity of these models in the sample market.

1.2 Background, Motivation, and Statement of the Problem

The corporate and academic researchers help the major stakeholders of stock markets in finding innovative models which can explain the mechanics of the equity markets. The functioning of these models requires many financial, technical and state variables. A lot of researchers have identified and tested these variables in estimating the behavior of the stock markets. Besides the search for appropriate factors, the invention of innovative forecasting and regressive techniques in other disciplines is providing an impetus for the finance researchers' community to modify their previous limitation of data processing. The computational power of the recent years is an added advantage for these researchers.

The phenomenon of forecasting has its problems and challenges regardless of the investment theory or the mathematical techniques. Firstly, some forecasting studies are unable to ascertain the future results, and the element of uncertainty is a major limitation of such research. Secondly, the researchers sometimes select the variables for which no past data is available or the association between the selected variable is not justified by finance theory, and finally, the forecasting methodology has the potential to succeed or fail a particular prediction study.

The research of the last two decades in the application of artificial neural networks in almost all the branches of finance has given new hope to the forecasting of stock returns. A diversified group of researchers with a finance background and other disciplines, i.e., Computer Sciences, and Engineering have developed some models to define the relationship between financial variables. The recent years have seen a sharp surge in this area and the literature search easily highlights at least 20 articles in a year on innovative methods of forecasting (Tkáč and Verner, 2016).

The majority of the investigations in artificial neural networks are related to the financial markets of the developed world; for example, (Vortelinos, 2017; Wang and Wang, 2015). The application of ANN in the emerging financial markets is limited and studies like Azadeh et al. (2010), Carvalhal and Ribeiro (2008) and Dixit et al. (2013) are related to different emerging economies. The use of ANN in Pakistan Equity Market is taken up by (Haider and Nishat, 2009; Iqbal et al., 2013; Danial et al., 2008; Fatima and Hussain, 2008).

These studies mainly concentrate on the stock market index only, using the price based technical variables, and they recommend looking at other aspects of ANN and investments theory in this emerging market. The discussion as mentioned above advocates the application of neural networks system to capture the relationship between the economic, financial and state variables in the equity market of Pakistan.

1.2.1 Motivation

The finance researchers influence the society through their modeling and play a decisive role in the well-being of the community by educating and equipping the stock markets players with the state of the art technologies and investment theories. In the words of Malkiel (2011) "The attempt to predict the future course of commodity prices accurately and thus the appropriate time to buy or sell stock must rank as one of the investors' most persistent endeavors."

I have adopted this philosophy of the investment as major force behind my motivation for the present study. I am attempting to implement the technology of artificial neural networks to forecast the future stock returns and assess the direction of the stocks by using the traditional financial factors of the various asset pricing models. My motivation is further increased when I look at the success or failure of these models in an emerging market like Pakistan.

1.2.2 Problem Statement

The discussion mentioned above has provided a solid ground for research opportunity along with problems. I take into consideration the problem of forecasting faced by major stakeholders in stock markets. The forecasting studies suggest that the stock returns are partially predictable by various order lags of past returns and some primary valuation gauges. They use various linear, nonlinear statistical and mathematical tools of forecasting. However, the application of the established finance theories along with neural network technology is rare in the literature. The present study is an attempt to investigate the forecasting performance of ANN using various asset pricing models. The study attempts to state this problem in these words"Can the artificial neural networks be implemented to forecast the stock returns by using the composite factors of established asset pricing models and generate economic significance for the investors."

1.3 Research Questions

The present thesis makes a significant contribution to the subject of asset pricing by addressing the following questions. The answers to these questions are expected to solve the major concern of investors in overcoming the uncertainty of the Equity markets in the emerging markets.

Research Question 1

Can the employment of the composite factors of asset pricing models improve the forecasting accuracy of portfolio returns by using the Artificial Neural Networks? The resultant errors in the actual and simulated returns will determine forecasting accuracy level of the model?

Research Question 2

Which asset pricing model under what ANN parameters ensure the maximum forecasting capability?

Research Question 3

Is there any redundancy in the established and known factors (size, value, investment, profitability) while forecasting the portfolio returns?

Research Question 4

Is the application of ANN in asset pricing models a successful exercise?

1.4 Objectives of the Study

The following objectives have been decided for the present study:

Research Objective 1 To generate a one month ahead forecast of the portfolio returns and assess its accuracy level by using the Artificial Neural networks.

Research Objective 2 To analyze and compare the performance of multi factor and single factor model regarding forecasting accuracy in the presence of nonlinear methods.

Research Objective 3 To demonstrate that the forecasting performance of ANN enhances in the presence of established attribution factors of various asset pricing models and this strategy outperform the buy and hold strategy.

Research Objective 4 To pave the way for intra-disciplinary research with a background in finance and analytical capability in engineering, Computer Science, and Mathematics.

1.5 Justification and Significance of the Study

The present study is applying the three asset pricing models in an emerging market with a state of the art technology of ANN. The technique, although, has been implemented by many authors; the scope of the majority of these studies is limited. We aim to investigate the asset pricing and ANN from broad horizons including the number of theories and the parameters of the Artificial Neural Networks. This study has significance due to the following reasons.

1.5.1 Pioneering Study

The explanation and prediction of the behavior of KSE-100 have attracted the attention of researchers in recent years due to many reasons, including the substantial financial support of the Central Bank and the Government of Pakistan. The analysis of these studies reveals the use of traditional econometric tools for estimating and predicting the stock index or Firm's returns. Our research will enable the investors to take advantage of this state of the art technology and design more profitable strategy in this market. Similarly, the application of the composite asset pricing based factors along with neural networks will open a new venue for further research and investigation.

1.5.2 Choice of Inputs

The review of the literature suggests the concentration of technical or fundamental financial variables only for prediction of the stock exchange index or individual stock using ANN in the developed and emerging markets. we employs the financial variables of the established asset pricing models in a nonlinear processing tool, assigning significance to the present study. Most of the prediction studies based ANN and asset pricing are related to the developed markets, and limited research is available on the application of ANN and asset pricing in an emerging market like Pakistan. The present investigation examines the stock returns of an emerging economy and predicts the returns of individual stocks and portfolio selection through asset pricing models and ANN.

1.6 Contribution of the Study

The present study is an endeavor to benefit from the massive computational power of the current times and applies a pure engineering and computer science based tools and contribute to the existing body of knowledge in many ways. Firstly the study has vast testing horizons regarding the network testing parameters, time span, input-output selection, investment theory, and designing of various programs. The application of well-known investment methods in forecasting the stock returns and paving the way for robust investment strategies in an emerging market is a significant contribution to the existing body of knowledge.

Secondly the present study is the assessment of the success or failure of the asset pricing models in this market. Thirdly the study provides broad guidelines on the prediction of time series of stock returns and makes a productive contribution to the theory of investments. Fourthly we utilize various programming and application tools instead of commonly use softwares to arrive at the desired objectives. These programs include MatLab (2015), Neurointelligence, MS-Excel, Endnote, Preplit, and Grammarly.

1.7 Limitations of the Research

This study is limited in scope to the forecasting aspect of ANN and asset pricing models. Other aspects like classification and clustering of stocks on the basis of various features, formation of portfolios on the basis of ANN and hybridization of ANN with regression techniques requires future research. Another important limitation is the lake of literature support on the subject. The literature review on the ANN and asset pricing phenomenon is rare. Even a major search for a literature review is not fruitful to fetch any literature on the concerned subject. Other limitations of the study include ....

1.8 Outline of the Study

The remaining chapters are organized as follows. Chapter two on literature review provides the foundation for most of the research. The previous studies have provided the building blocks regarding its contents, the selection of financial variables, and the concern of investors, methodology, and interpretation of results. The literature review describes major theories of investments, forecasting studies, and comments on the lake of research endeavors by finance experts in the area of artificial neural networks. Chapter three describes the actual design of the study including the hypothesis of the study, description of the data, the formation of the inputs and outputs for the forecasting, and the structure of the MATLAB program and other applications.

Chapter 4 presents the results of ANN regarding prediction of the time series of portfolio returns, the actual vs. predicted. The performance of ANN with broad testing parameters, the relationship of various input variables to the target outputs, in the sample and out sample comparisons and the justification of the results from the literature review are presented in this chapter. Chapter 5 compiles the conclusions, restates the thesis hypotheses and discusses them regarding the analysis of data. Conclusions are extracted, and the thesis findings are put into perspective. Finally, the next steps for further research are elaborated.

Chapter 2

Literature Review

2.1 Literature Review

Forecasting the stock returns has always been an exciting and arguable issue among the finance researchers and the asset pricing theorists. Although (Yang et al., 2010) considers the forecasting studies merely a data snooping exercise, the vast repository of prediction studies provide a solid background for estimating future returns in stock markets. The wide variation in stock returns can be predicted accurately with the help of financial and economic variables. The findings of some important papers [1] provide meaningful evidence for the success of forecasting endeavors.

The financial modeling in forecasting is a subject of research concentration in recent years. All these studies[2] point out some essential characteristics of predicting the risk and returns relationship and the forecasting models in stock markets. Firstly, the stock returns are predictable by some financial variables. Secondly, a linear relationship exists between the stock returns and the variables and thirdly linear forecasting models are a better and convenient fit for the stock markets. On the other hand, some studies[3] find that the actual behavior of the stock markets

[1]Keim & Stambaugh, 1986; Fama & French, 1988; Campbell & Shiller, 1998; and Ferson & Harvey, 1991, 1993

[2]Keim & Stambaugh, 1986; Fama & French, 1988; Campbell & Shiller, 1998; and Ferson & Harvey, 1991, 1993

[3]Eakins, Stansell & Buck (2003); Cao, Leggio & Schniederjans (2005); and Cao, Parry & Leggio (2009

is nonlinear and it moves exponentially in some economies.

It is commonly believed that before the forecasting models are formally introduced to the general public, the authors use them to generate higher returns on investment in the testing stage. These models incorporate the variables, having a proven predictive ability of future events with the limitation of constant change in their predictive power.The one-time best-declared forecasting model would not always ensure the best results; instead, the model requires modifications all the times to look for profitability.

Pesaran and Timmermann (1995)provide indirect evidence of this changing mode of the forecasting models and predictor variables. They suggest that the performance of the models can be everlasting if these are adjusted over time, and the experimentation on the financial variables continue. This philosophy is embedded in the thinking of the finance research community and is the principal motivation for the continuous refinement of the investment theory.The presence of many asset pricing models and forecasting techniques is the result of this quest on the part of the researchers.

The asset pricing theory enables us to forecast the and returns of the financial securities (Dimson and Mussavian, 1999). The basic theory of asset pricing is based on the Capital asset pricing model (CAPM) which suggests that the excess stock returns are related to the systematic risk of the market. The market risk is reflected in the variation of market returns which is the function of the macroeconomic factors. The validity and invalidity of the model have been tested in many developed and emerging markets with varying results.

The continuous testing and validation of the model have resulted in many variants of the basic model. The Fama-French three factors and five factors CAPM are the results of this consistent endeavor on the part of researchers, and today these are known as the established models for investigating the variation and forecasting of the returns in stock markets. All these models have utilized the traditional linear regression techniques; the nonlinear nature of stock market data requires an investigation into the application of nonlinear techniques in the asset pricing theory.

The experience shows that the floor traders enjoy autonomy in investment decision making and they often ignore the advice of Researchers of the investment firms and educational institutions. The decision making of these floor traders is the function of their judgment and overreaction of the investors. The gap in the thinking of various stakeholders of the financial markets is explained by (Sargent et al., 1993). According to his studies, the financial modeling in the stock markets is, in fact, the modeling of the thinking of the investors and most of the time, this thinking is not rational. Even the availability of all the public and private information does not make all the decision making to be balanced, and they have to learn the changing factors of an investment situation on the spot.

This gap in thinking, action of the stakeholders and the non-linear nature of stock markets require the adoption of the approximation models in asset pricing models that can accurately capture the trends in the stock markets. The artificial neural networks demonstrate these features. This technology captures not only the nonlinear nature of stock market data but also behaves like humans in decision-making. The principles of artificial neural networks draw its foundation from the thinking capability of the human beings for approximating the decision making of the stakeholders in a particular situation.

This chapter provides a literature review of the forecasting performance, models development, and empirical testing of various asset pricing models. The literature review on artificial neural networks is related to the coverage of stock market prediction using different financial variables including the factors of asset pricing models. Section 2.1 discusses the subject of forecasting in the presence of the highly predictive Financial Variables and Asset Pricing models. The section further explains the Linear and Nonlinear Forecasting Techniques, in sample and out sample prediction, Basic Theory of asset pricing models, various anomalies and the predictive performance of asset pricing models. Section 2.2 elaborates the details of the artificial neural network. Section 2.3 elaborates the forecasting performance of ANN as compared to the traditional regression models and its application in the financial markets worldwide, 2.4 presents the hypothesis of the study and finally section 2.5 concludes the chapter.

2.2 Forecasting, Financial Variables, and Asset Pricing

The empirical research of the last few decades has identified a substantial number of financial variables, demonstrating a high degree of predictability for the stock returns. For example, short-term interest rates (Fama and Schwert, 1977; Ferson and Harvey, 1991), yield spreads (Campbell, 1987; Fama and French, 1989; Keim and Stambaugh, 1986), and stock market volatility (French et al., 1987). Other studies[4] expand the list and identify book-to-market ratio and price - earnings ratio as essential variables, ascertaining the predictive ability of financial models.

Many authors investigate the relationship between the excess returns and the fundamental variables in the long and short-term. A strong predictive relationship between Company specific variables and excess returns, in the long run, is found by (Cochrane, 1991; Fama and French, 1988; Harvey, 2001), while Ang and Bekaert (2006) see only short-term predictability for excess returns using fundamental analysis. The use of historical averages in forecasting stock returns is investigated by Goyal and Santa-Clara (2003). His findings suggest that the application of historical returns generates better results while Rapach et al. (2010) recommends a combination of forecasts which can reduce the volatility of the stocks.

The use of price-based or technical variables in the prediction studies shows firm reservation about the use of these variables in forecasting studies. Pesaran and Timmermann (2007) suggests that these variables should be employed with caution. This discussion provides the evidence that forecasting of the stock returns by random financial variables lacks the generalization ability and the use of established composite financial factors of various renowned asset pricing models possess wide acceptability in finance sphere.

The application of asset pricing models in estimating the future returns of stocks and portfolios is taken up by many renowned studies. Campbell and Cochrane (2000); Campbell and Viceira (1999); Cochrane (1991); Goyal and Santa-Clara

[4] Kothari and Shanken (1997) or Ponti and Schall (1998)), (Lamont (1998) or Campbell and Shiller (1988a) Goyal and Santa,(2003)

(2003) propose the application of dynamic and conditional versions of the asset pricing models.

2.2.1 Linear vs. Nonlinear Forecasting Techniques

Researchers from multiple disciplines have developed different Linear and nonlinear techniques over the years to conduct forecasting. The linear methods include moving averages, linear regression models with a time and exponential smoothing models being the most popular ones. The nonlinear techniques include Autoregressive moving averages (ARMA), autoregressive integrated moving averages, generalized autoregressive conditional heteroskedasticity (GARCH) and Artificial Neural Networks (ANN).

The use of linear predictive models in most of the empirical finance research is simple, but the related econometric problems of forecasting accuracy are numerous. These models suffer from an inherent limitation to capture the impact of the nonlinear nature of the stock market data. According to Ang and Bekaert (2006) and Campbell (1991) the forecasting capability of the linear models suffers from various limitations. Campbell and Shiller (1988) note that the actual relationship between predictor variables and long-term stock returns is nonlinear, and the use of linear regression might produce bearish results.

Stambaugh (1999) notes that many fundamental, technical and state variables exhibit natural predictive power and high persistence and the regression of these variables produce spurious results. This study cast severe reservations on the use of linear processing techniques in evaluating the data of financial markets. Ferson et al. (2003) also confirm the notion of spurious results from predictive variables. Another problem with the linear predictive models, in the long run, is the use of overlapping data which causes the error terms to be strongly correlated. Ang and Bekaert (2006) state that fundamental variables in the presence of structural regression model don't produce significant forecasting results in the long run.

The findings of Amihud and Hurvich (2004); Chiquoine and Hjalmarsson (2009); Jansson and Moreira (2006), validate the point that the use of linear regression in the prediction studies comprehend less accurate forecasting. Recent failures and turbulence in Stock markets consolidates that nonlinear relationship exists in the stock markets which can be captured with nonlinear techniques. Similarly the exponential growth of some stock markets make the nonlinear models to be a natural choice for prediction studies.

Brock et al. (1992) provide evidence of successful application of nonlinear processing technique in the study of financial and economic data sets. According to Brock (1993), "There appear to be nonlinearities in stock returns and Treasury bill rates. There may be a low-dimensional (deterministic) chaotic process. But the results are also consistent with many other (stochastic) dependent processes that are not chaotic". Keim and Stambaugh (1986) employ a nonlinear technique to study the relationship between these variables for forecasting asset prices.

An influential study by Brooks and Persand (2003) points out the inability of linear models to explain the behavior of stock markets. McMillan (2005) finds that the world financial markets are behaving in a nonlinear fashion, and the application of nonlinear technique will capture this turbulent phenomenon very accurately. Furthermore, the extreme changes in the stock markets, worldwide, support the implementation of nonlinear processing technologies in the asset pricing models (Froot and Obstfeld, 1991; Summers, 1986).

Forecasting the asset returns with the help of fundamental external indicators by (Froot and Obstfeld, 1991), using nonlinear models is a step towards the use of nonlinear forecasting model. The findings of this paper confirm that the nonlinear models can explain the characteristics of the stock returns over a period. This discussion validates the point that the challenge for all the forecasting models is an ongoing debate.

2.2.2 In Sample and Out Sample Prediction

The poor performance of the linear prediction models on in sample and out sample data set is probed by many studies including (Butler et al., 2005; Campbell and Thompson, 2007; Goyal and Santa-Clara, 2003). These studies find that the linear predictive models generate poor out sample performance and are of little use for the practical purpose. Rapach and Wohar (2006), on the other hand, investigate the predictability of return with a bootstrapping technique and find that forecasting ability of specific financial variables on in sample and out sample data is significant.

Some studies, for instance, Fama and French (1988) find a successful out sample performance of the prediction model based on fundamental analysis, while Bossaerts and Hillion (1999) find that even the best prediction models demonstrate poor out sample performance. Goyal and Santa-Clara (2003) investigate the in sample and out sample performance of the conventional regression models and conclude that the historical average return almost always generates better forecasts. However, Campbell and Thompson (2007) show that most of the variables used by Goyal and Santa-Clara (2003) perform better on out sample than the forecast produced with the historical average return if weak restrictions on the signs of coefficients and return estimates are imposed. All these studies depict a mixed picture of the predictive performance of the linear techniques on out sample data. The use of nonlinear technologies like artificial neural networks has excellent predictive capability both on in sample and out sample data sets and are expected to generate encouraging results for prediction (Krollner, 2011).

2.2.3 Basic Theory of CAPM

The basic model of forecasting the stock return is the Capital asset pricing model (CAPM) which suggests that the excess stock returns are related to the systematic risk of the market. This model is based on the pioneering work of (Markowitz, 1952) and he postulates that "in trying to achieve a small variance, it is not enough to invest in different securities. It is necessary to avoid investing in stocks with high covariances among themselves". This strategy generates an optimal relationship between the risk and return (Markowitz, 1952, 1959, 1991).

The typical psychology of investors is to include a stock to a portfolio by its absolute risk; the Markowitz model considers this inclusion by its contribution to the total risk of the portfolio (Dimson and Mussavian, 1999). The Markowitz model provides a mathematical basis for the prediction of returns in the presence of a given level of risk of a portfolio if the constituent securities have minimum covariance among them. The Markowitz efficient frontier is the result of this combination of risk and return, and all the portfolios lying on this frontier provide the highest predicted returns for a given level of risk.

The main contribution of the Markowitz model is to provide an empirical basis for the investors' expectations. The model becomes a basis for further extensive research, and the first significant contribution is initiated by (Tobin, 1958). The Tobin's model shows the allocation of wealth by investors in various classes of assets. According to his framework: 'breaking down the portfolio selection problem into stages at different levels of aggregation-allocation first among, and then within, asset categories.' The theorem states that an optimal portfolio based on the risk-return trade-off always exists, and the one which is held by all investors as a result of the distribution of the investor's wealth among the conventional portfolio and risk-free assets is defined by the behavior of investors towards risk (Limkriangkrai, 2007).

These models provide valuable guidelines for understanding the preferences of investors for selecting the risk level for investment. Both these models give a quantification of the theory of investment strategies. One major limitation of Markowitz model is the requirement of extensive computation for an individual investor to arrive at his optimal portfolio. The computational power available at that time makes the model infeasible, and the general and institutional investors are unable to construct their portfolio investment decisions with the help of this model (Limkriangkrai, 2007).

This difficulty in estimating the portfolio selection model and the fact that the returns of the individual securities can be predicted with the broad movements of the market, Sharpe (1963) extends the model to overcome the estimation difficulty and reduces the number of parameters to estimate. The Sharpe (1963, 1966) analysis assumes a linear relationship between security returns and broad market returns. The model can predict the security returns by the mean and variance of the stocks. The computation is also based on less vigorous estimations as against the portfolio optimization model and estimates only three parameters for individual securities. In this way, the Sharpe's model makes the job of risk measurement and portfolio optimization more meaningful and manageable (Dimson and Mussavian, 1999).

This model is based on the mean-variance relationship of portfolio selection of (Markowitz, 1952) and the equilibrium model of Tobin (1958) to determine the asset prices (Buiter, 2003). The model provides a thorough base for the 1) analysis of the portfolio and 2) examination of the relationship between market returns and security returns, During the same period, two other researchers' Lintner (1969) and Mossin (1966) also develop their asset pricing models. The model developed by the three authors is known as Capital asset pricing model (CAPM). In most straightforward words, the CAPM describes the way in which the prices of assets can be estimated in the financial markets and shows the relationship between expected return and risk. The model is based on several simplifying assumptions[5] . These assumptions seem to be unrealistic but like any other theory, these can be relaxed, and its impact can be empirically determined.

The first assumption about the capital market perfection implies firstly that all the investments are infinitely divisible which suggests that an investor can invest in any fractional proportion of shares or portfolio. This interpretation makes the investment alternative as continuous curves rather than a discrete curve. Secondly, the number of investors in the capital markets is large, and no single investor can influence the market. In other words, all the investors are price takers. Thirdly, there are no taxes or the transaction costs in buying or selling the assets which mean that these expenses do not influence the buying and selling decision of the investors. Finally, the assumption of unlimited borrowing and short selling plays an important role (Dimson and Mussavian, 1999).

[5]Firstly, the assumption of homogeneous expectations of the investors and the liquidity aspect of the separation theorem makes the model to forecasts that a rational investor will hold a market portfolio which mainly contains all the individual assets. The market portfolio itself is assumed to be optimal in that it touches the efficient frontier at the tangency point which ultimately provides a maximum ratio for a risk-return relationship. Secondly, when the investor's portfolio is composed of a sufficiently large number of assets available in the market, the firm's specific risk or unsystematic risk is fully diversified or minimized (Krause, 2001). The proposition implies that the decision to include a share in a portfolio is not based on its risk rather its contribution to the total risk.

The second critical assumption is that investors can borrow or lend any sum of money at the risk-free rate; the CAPM assumes that investors have access to risk-free borrowing and lending rates. Thirdly, investors exhibit their risk-averse psychology as they plan for a single period utility maximization. The last assumption is related to the similar expectations of investors. Based on these assumptions, the model has some fundamental propositions about the portfolio formation process of investors and the behavior of investors (Krause, 2001).

The market risk or the systematic risk, which is measured by the beta in CAPM is uniform for all the firms and thus cannot be diversified. Systematic risk is the only source of worry, and the market compensates the investors for bearing this risk. All other parameters are known in the model, and this risk factor is priced for investors. The mathematical form of the model envisages a positive and linear relationship between stock returns and its sensitivity to the market risk premium.

2.2.4 Initial Testing and Alternative Testing Methodologies of CAPM

The initial validity testing of CAPM is encouraging and provides support for the practical application of CAPM in investment setting. Sharpe and Cooper (1972) conducts the initial testing of CAPM on the data of New York Stock Exchange for the period 1931-1967. The stock beta is calculated for the individual stock, and ten equally weighted portfolios are formed. The Portfolios are rebalanced each year by calculating the stock beta each year, and the annual portfolio's returns are regressed on the corresponding betas. The findings suggest that the beta explains the cross-section of returns with 95% confidence. The study identifies a contradiction of the model that the intercept term is higher than the risk-free rate.

Another contradictory result is found by Miller and Scholes (1972)(1972) when they conduct a test of CAPM on NYSE stocks over the period 1954-1963. The study estimates the slope of market risk premium to be 4.2% as compared to the expected gradient of 16.5%. The estimated intercept term comes out to be 12.7% while the expected intercept term is zero and document that the estimated slope of the market premium is only 0.042, which is considerably smaller than the expected 0.165. Furthermore, they find that the estimated intercept term is 0.127, which is expected to be zero. The model's intercept term is approximately 5.54%, while the actual risk-free rate during that period is below 2%. From the investor's point of view, these findings suggest that low risk (low beta) stocks generate abnormal returns (positive alpha) while high risk (high beta) stocks exhibit losses (negative alpha). These suggestions are in contradiction with the predictions of CAPM.

The introduction of a two-step regression by Black (1972) is a significant contribution to the asset pricing theory. This pioneering study applies the two-pass methodology in testing the CAPM. They criticize the previous studies on the ground that all these tests of the model are conducted through a cross-sectional analysis and ignore the time series analysis. The research suggests that the model is unable to capture the stock returns accurately. The intercept term is significantly different from zero, and the slope of beta is also distinct from the market returns. This problem is due to the bias present in the selection of stocks when beta categorizes securities. The two-pass methodology first estimates the time series of returns and then these returns are regressed on the betas to arrive at the results.

The same two-stage regression method is executed in another significant test conducted by (Fama and Schwert, 1977) with specific changes. This investigation calculates the betas for the previous period and attempts to predict the portfolio returns. According to this work, the CAPM has three aspects of testing, i.e. (1) a linear relationship exists between the expected returns and systematic risk of security. (2) The systematic risk of security can be measured with beta only which means that beta is a complete measure of risk. (3) The investors, in general, are risk averse so their high risk-taking should be compensated with high returns.

The study suggests that the t-statistics of the coefficients are relatively small and insignificant. The relationship between beta and expected returns is linear, and the signs are randomly negative and positive. These results are consistent with the major prediction of CAPM.

2.2.5 Suitability of CAPM for Prediction Studies

The CAPM is derived in an ex-ante form, which implies that its results are based on the future expected rates of returns of the individual securities and market itself. Derivation of this kind creates difficulty to generate the ex-ante data, and the researchers resort to the use of the ex-post data. The replacement of ex-post data instead of ex-ante is in clear violation of the fundamental principle of the model. This problem is solved by Muth (1961) and according to him the expected returns, in the long run, converges to the past (realized) observations. Simin (2008) and Javid and Ahmed (2008) have investigated the predictive performance of single factor and multifactor CAPM in conditional and unconditional form.

Simin (2008) points out a significant limitation of the testing of CAPM. The study compares the predictive performance of the conditional and unconditional version of the asset pricing models. His findings suggest that the regression takes the already tailored values of the model to assess the expected returns of an asset. His findings suggest that the conditional asset pricing models show a significant improvement in predictability. The findings of Javid and Ahmed (2008) show that the forecasting power of multi factor CAPM is better than the conditional CAPM or consumption CAPM.

The practitioners in financial also prefer CAPM and its variants most of the time as compared to other models in estimating the cost of equity. Graham and Harvey (2001) report that 73.5% of respondents of a survey (392 CFOs), always use the CAPM when estimating the cost of equity capital. The remaining participants either use the historical averages or the multi-factor models.

2.2.6 Performance of CAPM in the Developed and Emerging Markets

Most of the research work related to CAPM is based on US stock markets in the initial years of its composition while other developed markets have undertaken this task in later years. Modigliani and Pogue (1973) is the first study which investigates the testing of CAPM in 8 major stock exchanges of the European countries including France, Italy, UK, Germany, Switzerland, Netherland, Belgium, and Sweden, using the same intervals and time periods of the US study. The findings suggest that the European results, on the whole, are consistent with the hypothesis of CAPM and the securities returns on the average are explained and predicted by systematic risk. The results of the portfolio are also compatible with the model in the case of France, Italy, and the United Kingdom; however, The German results are inconsistent with any reasonable expectations.

Other studies find mixed results for CAPM, for example, (Sauer and Murphy, 1992) find that CAPM is a better indicator of capital asset pricing and finds the validity of CAPM in German and Italian equity markets. Yonezawa and Hin (1992) see that CAPM is invalid in Tokyo stock exchange. Bhatnagar and Ramlogan (2012) and Nikolaos (2008), find an insignificant relationship in stock returns and market variations over the period of study in London stock exchange. These studies conclude that systematic risk is not the significant factor in explaining stock returns at the London stock market. The results of CAPM in Belgian stock market are also unfavorable (Hawawini and Michel, 1982).

The case of emerging markets has always posed particular challenges to the finance researchers due to some characteristics, and here it is pertinent to mention those features. According to Harvey (1995), first, these markets have low correlations with the developed financial markets and the addition of these markets to the portfolios significantly diversifies the investment risk. Second these markets are not entirely integrated with the world's capital markets, and exposure to the common risk factors as identified by asset pricing models is insignificant. Third, the asset returns in these markets are more predictable by local information rather than global variables and finally, the time variation of the risk exposure in these markets is not constant as is the case in developed economies.

In the words of Harvey (2001), "Emerging markets provide a formidable challenge to current asset pricing theory. The reason that emerging markets do not follow the standard asset pricing conventions is due to the lack of complete market integration of in global context. Füss (2002) has documented additional peculiar characteristics of the emerging markets and according to his findings these markets have a monopolistic nature and the market making activities are occupied by a few big players with loose corporate control.

The emerging markets are small, and the stock turnover is thin which makes it more vulnerable to panic situations. The political stability is low with high dependence on foreign debts and the loose controls on foreign exchange flow; the economies always suffer from a chaotic situation. The investor covers his risk exposure mainly by investing in a few stocks causing non-synchronous trading in the market (Füss, 2002). The performance of CAPM in the emerging markets seems to verify the philosophical conclusion of these studies, and the application of CAPM for predictive or explanatory purposes in these markets present a different picture as compared to the developed markets.

It is worth noting that most of the emerging markets have introduced comprehensive programs of financial sector liberalization and integration resulting in more efficiency in these markets in the last two decades. According to some authors, the broad-based liberalization agenda have converted these markets into a ripe ground for international investment, and some of the market inefficiencies have disappeared from these markets with the passage of time. The testing of established economic and financial models is now generating results in line with the developed markets. The recent studies of the emerging markets document varying results as compared to the past results. It seems that the emerging markets have reduced some of their deficiencies as pointed out by (Füss, 2002; Harvey, 1995). The related studies are discussed to understand the integration of these markets in global markets.

Claessens et al. (1995) rigorously investigate the case of emerging markets including Pakistan. He selects a group of 19 emerging markets to assess the behavior of average stock returns in the presence of the CAPM parameters. The average stock returns of most of the emerging markets uniformly respond to risk factors, but the sign of the coefficients are positive as against the developed markets. This study finds the case of Pakistan equity market to be different with a significant negative beta risk premium. Similarly, Clare et al. (1998) report document a positive and significant association between the market risk premium and the stock returns in the equity markets of Singapore, Malaysia, and Hong Kong.

The findings of Yalwar (1988) support the applicability of CAPM in the Indian stock market, while some studies find CAPM to be insufficient in predicting stock returns (Gupta and Sehgal, 1993; Obaidullah, 1994; Sehgal, 1997). Similarly, Estrada (2000) concludes that stock returns and betas in emerging markets do not seem to be related, while Mollah and Mobarek (2009) suggest that the overall market movements do not influence the share returns in the Botswana Stock Exchange. Ward and Muller (2012) find that CAPM is inappropriate in Dhaka Stock Exchange.

Pakistan's Equity Markets has gone through various phases of development after the massive liberalization and integration programs of the successive Governments since 1990's. The market presents a typical picture of an emerging market where the risk returns relationship is different from the developed markets, and the stock returns show high autocorrelation. However, the market recently is presenting the characteristics of a disciplined market, attracting the investments from all corners of the world (Munir et al., 2013).

The empirical research on the applicability of CAPM in Pakistan Stock Exchange is dated back to early 90's, and many researchers have attempted to test the stock return predictability using CAPM. The findings of these studies are mixed as some studies document the risk returns behavior of stocks to be predictable as per the conclusion of CAPM. Other studies provide no evidence for the risk-return trade-off in Pakistan Stock Exchange; for example, (Akbar et al., 2010; Hanif, 2010; Iqbal and Brooks, 2007; Javid, 2009; Javid and Ahmed, 2008)[6] , find no validity of CAPM in Pakistan Stock Exchange, while the findings of Ahmed and Rosser Jr (1995), Farid et al. (1995) and Jawaid et al. (2011) provide partial support for CAPM in Pakistan Stock Exchange.

The studies mentioned above, worldwide, have not only tested the applicability of CAPM for explanation and prediction of the average stock returns but also

[6]Hanif and Bhatti, 2010 , Zubairi and Farooq, 2011; Masood et al., 2012; Qamar and Shah, 2013; Shah and Asalya, 2013; Rizwan et al.,2013; Shamim et al., 2014; and Akbar & Nguyen, 2015), (Khilji, 1993,1994)

identified reasons for the success or failure of the CAPM. The researchers are always in search of other patterns in asset pricing, which have a better explanatory and predictive ability for the average stock returns. The patterns which are not included in the asset pricing models are considered as anomalies search for such anomalies[7] .

2.2.7 Anomalies and the Alternative Asset Pricing Models

Some prominent studies have identified situations wherein certain aspects of the firm's performance are left unattended. The prevailing mindset of the researchers, believing in the prediction of CAPM is that the market return emulates all other technical or fundamental risk factors, while others have undertaken the task of empirically verifying the existence of certain anomalies, having more explanatory and predictive capability for stock returns. These anomalies are identified and empirically validated by some major studies. The anomalies are discussed here to get a good grasp of the resultant asset pricing models.

2.2.8 Size Anomaly

The first anomaly is related to the firm size and is based on the conventional notion of investment theory that the stocks of large size firms have little growth prospects as compared to small firms. The first test of this notion is taken up by (Banz, 1981). This study documents the size effect in NYSE stocks from 1936 through 1977. The experiments divide the sample firms into size quintiles, and the average returns of different quintiles are calculated. The small size companies placed in the smallest size portfolios consistently earn higher risk-adjusted returns on an annual basis as compared to the firm's put in the largest quintiles.

Other studies also point out similar findings regarding the size effect. Heston et al. (1999) searches size premium in many European markets and suggests that size

[7]The anomalies in asset pricing refer to the empirical findings which are not following the established concepts of asset-pricing. These anomalies indicate the presence of inefficient markets and inappropriateness of the model (Schwert,2003)

effect is positive for eleven markets but statistically significant for four countries only. The stock markets of Australia Spain, Japan, and the UK also report positive and considerable size effects while France, Netherlands, etc. have positive and insignificant size effects. Griffin (2002) finds a positive and significant size effect in Japan and Canada. The presence of size effect in the emerging markets is investigated by (Heston et al., 1999). The findings suggest that the markets of Argentina, Malaysia, Mexico, and Zimbabwe demonstrate a positive and significant effect on the size anomaly. This study covers Pakistan Stock Exchange also and finds a negative and insignificant size effect. A recent study by (Shepeleva, 2013), investigates the presence of size premium in nine Emerging markets. The findings document the presence of size premium in these markets.

2.2.9 Value Effect

Another vital investment phenomenon is the presence of value stocks in the market. This concept is documented as the book-to-market anomaly and suggests that the firms with high B / M ratio earn high average returns as compared to the firms with a low ratio. The value effect is first documented by (Stattman, 1980). This study suggests that the stock market returns are not the function of market risk premium only; other factors like company's size and book-to-market also play a significant role in explaining and predicting the stock returns.

Many authors studied the value effect in the international markets, recording varying results for these markets; for example, (Fama and French, 1988) investigates the presence of value effect in many European markets and document a positive and significant impact in Belgium, Canada, France Singapore, and Australia. Heston et al. (1999) find a positive and significant size effect for Brazil, Chile, Greece, Korea, Malaysia, and Zimbabwe, but the negative and insignificant effect for Pakistan. While Griffin (2002) find the size effect in Canada only.

Other noteworthy studies[8] , for the size and value premium find mixed results.

[8] Chan, Hamao, & Lakonishok, 1991; Halliwell, Heaney, & Sawicki, 1999; Mukherji, Dhatt, & Kim, 1997; Roll & Ross, 1994

All these anomalies are defined for the US market[9] . Later on, the presence of size and value effect are investigated in other developed and developing markets by many authors. Van Dijk (2011) finds the presence of size effects across the globe and rejects the notion that the size effect is disappearing from the prediction and explanation of stock returns.

The recent investigation of Fama and French (2010) finds a strong presence of size and book-to-market effects in 23 developed markets. The presence of size effect is taken up by Cakici et al. (2013). The study confirms the presence of size patterns and momentum effects in 18 emerging markets and along with integration with US stock markets. The findings suggest the existence of uniform size effects across the small and large capitalization firms.

Many notable Pakistani authors document the size and value premiums in Pakistan Stock Exchange. Mirza (2008) outline the size and value premium to explain and predict the average stock returns in Pakistan Equity market. Hassan and Javed (2011) report the presence of size and value premium in PSX, and the results conclude that the Size factor is significant and related to portfolio returns at 95% confidence interval. Book to market factor is also found significant and positively related to portfolio returns. Ali et al. (2011) and Khan et al. (2011) determine the size and value premiums and find it positive and significant in determining the stock returns in Pakistan Stock Exchange.

The anomalies identified by various authors are jointly tested by (Fama and French, 1992)[10] to assess their explanatory and predictive capacity for the stock returns. This study employs the NYSE, AMEX, and NASDAQ stock over a period of 1962-1989. The variables of market beta, firm's leverage, B / M ratio, size, and E / P ratios are taken as predictor variables to explain the cross-sectional stock returns of all the non-financial firms. Fama and French employ an innovative way of sorting the stocks into distinct portfolios. The size of the firms first classifies the stocks and then beta estimates apply the second sort.

[9]Davis et al.; 2000, Aleati et al; 2000 Connor and Senghal; 2001, Drew and Veeraraghavan;2002,2003. Kargin; 2002 and Griffin et al.; 2003)

[10]The (Fama and French; 1992) is a step towards the three factors model. The results of this study provide a quantitative foundation for portfolio formation and investment evaluation in the long run. The results provide guidelines for pension and mutual funds management

The sorting of stocks results in the formation of 100 distinct portfolios, and following the Fama and Schwert (1977) two-pass regression, the portfolio returns are regressed on the specified explanatory variables. Each explanatory variable is first studied individually, and then various combinations are applied to estimate the behavior of portfolio returns towards these combinations. The study finds that the market beta is a less significant predictor variable even in an individual setting. The impact of other significant variables, i.e., E / P and leverage disappear when the size and B / M factors are added to the model. These results suggest that besides the market premium, size and book to market factors can explain the major portion of portfolio returns, and this is a contradiction of the prediction of CAPM.

2.2.10 Fama and French Three-Factor Model

Fama and French (1992) investigate the impact of market, size, and Book-to-market ratios on the average returns of stocks by using the Black (1972) method of regression. The stocks from NYSE, AMEX, and NASDAQ are used along with the corporate and treasury bonds for 1963-1991. An innovative approach to portfolio formation is applied, wherein; size and book-to-market ratio sort the portfolios. A long position is taken in the portfolios consisting of the 30% smallest size stocks having the highest book-to-market ratio, and a short trading position is taken in the portfolios having the largest 30% of the firms with the lowest book-to-market ratio.

The term structure of interest rates and default risk premium, represented by their respective factors are taken to explain the behavior of bonds. The factors describing the size and value effects are the innovative factors constructed for this study are named as HML and SMB factors. The stocks sorted by size and value results into 25 portfolios while the government bonds are sorted into two portfolios. The corporate bonds are classified into quintiles based on Moody's rating of the corporate bonds, and the returns of the stocks and bonds are regressed against their explanatory variables.

The model has experimented various combinations of the variables, and the testing confirms the previous findings that both the size and B / M ratios have significant predictive power. A vital contradiction to the earlier study is also identified regarding the significance of market beta. It is found that the impact of this variable is not subsumed by the size and value factors as noted in the previous study. The factors related to the bonds returns are found to be relevant for bonds only, and when these two factors are removed from the model, the results generate an intercept term which is not different from zero.

These findings suggest that the variables have full explanatory power for the stock returns and points towards a strong predictive power for future returns. The results propose a formal modification to the already existing asset pricing models and the new model is now known as Fama and French three factors model. The explanation of the factors of the FF3C model is provided by (Fama and French, 1992, 1995). The SMB factors (a proxy for Size effect) represent the relative distress element of the firm. The weaker stocks, having a consistent track record of weak sales and low profitability will have high book-to-market ratio resulting in the steep slope for HML. The three-factor model exhibits a high R square with 90% value.

Like any other theoretical or empirical financial model, the Fama and French three factors model has been criticized by many authors, and many of them consider the model as a data snooping exercise while others declare the model to be an empirical study and believe that the primary model is still the CAPM. They point out that the inclusion of other markets, i.e., human capital, real estate, etc. in the market risk premium of CAPM will automatically make the three factors model redundant. This poses a formidable challenge to the model, and some authors have documented their criticism in their research work for example (Daniel and Titman, 1997; Lakonishok et al., 1994). The authors of FF3C model answer these criticisms and contend[11] that that the model is of considerable practical use when portfolios are constructed on their methodology.

[11]Criticism of the three factors model is that it an empirical model rather than a theoretical model. Most of the factors identified by the model disappear if the dataset is modified. The criticisms are answered by the (Fama and French, 1998).

A recent investigation of the Tokyo stock exchange concludes that the method of portfolio construction proposed by the model is too complicated. More easily understandable approaches can be followed to magnify the stock returns. This academic debate results in more valuable asset pricing models and the empirical research based on this model is vast in almost all the stock markets of the world. Here it is pertinent to mention that empirical research.

The three-factor CAPM is recently applied by Hu (2007) to estimate the portfolio returns a step ahead. The study employs some structural financial variables such as term premium, default risk premium, and dividends yield to predict the returns. The results demonstrate that the Fama-French three-factor model with factor premiums estimated from structural variables is more reliable than the standard practice in forecasting the returns. Pettengill et al. (2012) test the predictive ability of the three factors model and the findings suggest that the FF3C model can predict the stock returns variation accurately along a risk-return continuum.

2.2.11 Additional Anomalies and Fama and French Five-Factor Model

Typical psychology of the investors is their adverse reaction to the capital investment decision of the firms because they think that the long-term investment decisions of the firms will suppress their expected dividends and ultimately their future stock returns would be small. Due to this thinking on the part of investors, the capital investment decisions of the firms have significant implications for the investors. Some authors have investigated this aspect of the capital asset pricing, and they come out with the conclusion that the future abnormal returns have a negative relationship with the capital investment (Titman et al., 2004). These findings have identified a critical anomaly which is now called the investment anomaly.

The investment anomaly is investigated by many authors. Titman et al. (2004) find that the continuous expansion of the firms sends negative signals about the near future returns ability of the stocks resulting in a negative relationship between these indicators. The author calls it as empire building by the manager thus creating a negative implication for the near future on the stock returns. Cooper et al. (2008) interpret the capital investment as the asset growth, and his findings suggest that the market reaction to the asset growth is negative initially, but these sentiments are corrected afterward. Recently, Aharoni et al. (2013) document a weaker but statistically reliable relation between investment and average return.

Another major criticism regarding the three factors model is the absence of the impact of profitability of the firm from the model. Regardless of the size or other factors, profitability has the potential to predict and explain the stock returns. Some notable studies have identified profitability as a key element in stock performance estimation. These studies[12] suggest that profitability and investments explain the variation in average returns. This factor is first investigated by (Haugen and Baker, 1996), and he finds that Profitability has a positive predictive ability for the stock returns. Similarly, Cohen et al. (2002) document a positive relationship between positive cash flow news and high stock returns for the institutional investors.

The three factors model ignores these factors, but the recently introduced five factors model emulated all these factors and recognized as the major factors in the asset pricing theory. The Fama and French (2015) relate the impact of investment and profitability on the average stock returns. The methodology of the research confirms the relationship between the asset returns and the factors of book-to-market equity ratio, profitability and investments. The study employs the dividend discount model to investigate the relationship of these variables to average stock returns. With a little manipulation of the dividend discount model, two additional factors are formed to represent investments and profitability. These factors are added to the three-factor model.

The factor of profitability is defined as the operating profit minus interest expense divided by book equity, and investment factor is the change in total assets divided by total assets. The study covers 606 months of data from July 1963 to December

[12](Cohen et al.; 2003, Fairfield et al. 2003; Titman et al.; 2004; and Fama and French; 2006, 2008)

2013, including an additional 21 years of new data a. At each end of June, stocks are grouped by size using NYSE market-cap breakpoints. Also, the other factors (i.e., value, operating profit, etc.) are segregated into their respective categories and ranked from low to high. The authors calculate the monthly excess returns of the factor portfolios over the one-month Treasury bill rate. Finally, it measures the standard deviations, t-statistics, correlations, regression intercepts, coefficients, and slopes of the portfolios.

The significant finding of the Fama and French (2015) is that the five-factor model outperforms the three factors model in explaining the stock returns. The model is useful in explaining the cross-sectional variations of the expected return. The explanatory power of the five factors model is more than 80%. Despite the five-factor model failing the Gibbons et al. (1989) statistical test, it does produce good results because the unexplained average returns for individual portfolios are nearly all close to zero.

Various combinations of the composite factors are applied to study the behavior of the cross-sectional returns of the stocks. This exercise is conducted to investigate the most influential factors in the five factors CAPM. It is found that the exclusion of the value factor does not affect the performance of the model. The model declares this factor as redundant in the presence of investment and profitability factors. This is an important conclusion about the HML factor because all the previous studies assign substantial importance to the value factor.

Recent research highlights the strengths and weaknesses of the model, and interestingly we find research work on the FF5C model both in the developed and emerging markets. Cakici et al. (2013) investigate the application of the five factors model in 23 developed markets world. The study uses the firm-level data from the developed markets of Europe, Asia-Pacific, Japan and North America. The portfolios are constructed by size- Book- to- market, size-gross profit, and size-investment portfolios. The study identifies with five main conclusions; first, the returns on the size and size-GP portfolios of these markets and the US are found to be the same, second, the value effect is weakly significant in North America while high in other regions. The profitability effect is statistically significant for

Europe but not for North America while the investment factor is insignificant for Japan and the Asia Pacific.

The third finding is surprising, and it cast doubt on the Fama and French five factors model to be the best model worldwide. The fourth result rejects the conclusion of (Fama and French, 2015) that some factors become redundant in the five-factor model; this study finds all the five factors to be important in predicting and explaining the stock returns. And finally, the research suggests the asset pricing models in other parts of the world should be based on indigenous factor rather than global factors.

Martinsa and Eid Jr (2015) apply the five factors model in the emerging market of Brazil and find the model to be the best fit for this market, while the size and value factors perform poorly, signifying typical characteristics of an emerging market. Nguyen et al. (2015) undertake the application of the five factors model in Vietnam stock market and find it more appropriate than other variants of asset pricing models. The impact of value factor is not affected by the inclusion of investment factors.

The problems of the five factors model pose additional challenges to the researchers. The big concern is the perception of the investment community[13] . Particularly when the value factor is becoming redundant and replaced by profitability and investment factors, it becomes a four-factor model. Somewhat surprising is that small-cap stocks still seem to be elusive to their model. This reservation is addressed by some new studies and its application for predicting and explaining the stock returns has been undertaken.

The literature mentioned above on asset pricing models has relied on the use of linear regression techniques with some modifications, suggesting a high opinion of this processing method. The application of the nonlinear technology in stock market forecasting or asset pricing theory, although, is not entirely an innovative idea and studies; for example (Akarim and Akkoc, 2013; Qi, 1999; Yang et al.,

[13]Some leading portfolio Managers describe the five factors model to 1) fill the literature gap only 2) addition of more factors complicates the portfolio formation process 3) the new model still ignored momentum. (Pim van Vliet, Portfolio Manager Conservative Equities, David Blitz, Head of Quantitative Equity Research and Matthias Hanauer, Quantitative Researcher)

2010) have applied nonlinear techniques in financial markets. These investigations have mainly relied on the use of technical, fundamental or state variables and model-driven nonlinear methods; very few papers have hybridized the asset pricing models with nonlinear techniques.

2.2.12 Linear vs. Nonlinear Techniques in Asset Pricing Models

The results of the asset pricing models, presented in the literature review so far, are based on the linear regression techniques although the forecasting accuracy of linear models is only 64%. The application and supporting studies of nonlinear methods is a recent phenomenon in financial modeling and these techniques have demonstrated 93% accuracy in forecasting stock returns. Desai and Bharati (1998) provide substantial evidence that the predictive power of the economic and financial variables employed in the asset pricing models can be enhanced if the statistical technique of linear regression is replaced by nonlinear methods.

Kanas and Yannopoulos (2001) also find that the nonlinear forecasts are significantly more accurate than linear projections. The suggestions mentioned here the about the nonlinear techniques and the findings of some other renowned studies[14] suggest that the nonlinear techniques outperform the traditional regression. These findings[15] and the recent turbulence in equity markets, derivatives markets, and commodity markets points towards the adoption of sophisticated and nonlinear processing techniques for research in pricing risky assets.

There exist some nonlinear regression techniques, most of them are model specific and require the declaration of parameters; and hence these methods can be classified as model-driven approaches. In comparison, artificial neural networks are a data-driven approach, i.e., pre-specification of the Model is not required.

[14](Sharda & Patil, 1990; Tang, Almeida, & Fishwick, 1991; Tang, & Fishwick, 1993; Ansuj, Camargo, & Radharamanan, 1996; Zhang et al.; 1998; and Hwang, 2001)

[15]Kohzadi et al.;1996, Hann & Steurer;1996, Leung et al.;2000, and Choudhury et al.;2002) also suggest the superior performance of non-linear techniques

2.3 Introduction to Artificial Neural Networks (ANN)

The estimation of the required rates of returns of the investors can be termed as the mathematical representation of the thinking of the investors. The rise and fall of the market prices of the risky assets are interpreted by the investors in different ways, depending upon their behavior towards risk. They demonstrate their reaction in the form of buying and selling decisions of the securities. This response points towards the continuous learning and adjustment of the human beings. This ability is termed as the generalized form of human behavior.

The estimation of the financial modeling is based on this psychology of the investors. The reaction of the stakeholders as a result of changes in private and public information cannot be considered as entirely rational (Sargent et al., 1993). The key players in financial markets, although, have full access to all types of information, they still have to learn the appropriate reaction on the spot. The artificial neural networks are believed to possess this ability to mimic the human psychology and can be employed as a replacement for the rational thinking in the financial markets.

The artificial neural networks are designed on the nervous system of the human beings to process information. The difference in the accuracy and speed is attributed to the availability of billions of neurons to the human beings, while the artificial neural networks rely on the precision of mathematical equations and the speed of the electronic gadgets. The empirical finance is using this epistemology of the artificial neural networks in decision making. The basic foundation of ANN is lying on the assumption that the access to information and time to process that information is limited. These limitations are considered as bounded rationality. According to Patterson (1995), the hypothesis of bounded rationality refers to the mathematical representation of the investor's expectation about their rate of returns.

This discussion takes us to an established philosophy that the stakeholders in the financial markets always learn and adjust to the ground situation on the spot and their decision making is based on the newly available information and errors of the recent past. The salient feature of the artificial neural networks system is that it captures the last moment changes in the financial variables up to a certain level, which can alter the decision making of the investors and other decision makers (Garson, 1998).

The mechanism and algorithm of the artificial neural networks closely resemble the human brains. For example, when the market forces cause a change of 5% or less than that in the required rate of returns of the investors, they may ignore it. If this trend continues and the rates of returns are changing above the threshold level of the investors, they positively frame their reaction and alter their decisions accordingly. The continuous upward or downward trends may result in liquidating their long or short positions.

Here we want to justify a point that the reaction of decision makers is nonlinear and unbalanced in particular situations in financial markets. The ANN has an established ability to define these situations in financial markets and other conditions. In finance, distinguished sphere applications of ANN are (Guresen et al., 2011; Pettengill et al., 2012; Vanstone and Finnie, 2006; Zarandi et al., 2012; Zhang and Wu, 2009)[16] . A brief overview of some important articles is given below.

Callen et al. (1996) uses neural networks and attempt to predict monthly earnings for a sample of 296 firms on the NYSE, and find that the forecast errors are more significant for their neural network compared to linear forecasting techniques. Similarly, Thawornwong and Enke (2004) find the predictive power of ANNs generate higher profit with lower risks than the naïve buy-and-hold approach, conventional linear regression, and the random-walk model. The practical implications of these studies, however, is limited.

A number of recent studies; for instance[17] Carvalhal and Ribeiro (2008); Dunis et al. (2011); Fadlalla and Amani (2014); Jabbari and Fathi (2014); Maknickiene

[16]Refenes, 1995; Gately, 1996 White,1998, (Steiner and Wittkemper, 1997), (Torsun, 1996), (Kim and Chun, 1998), (Kamruzzaman and Sarker, 2003), (Atiya, 2000), (Smith and Gupta, 2000), McNelis and McAdam (2004)), (Medeiros et al. (2006), Wong et al. (2007), Trippi & Turban, 1993; Azoff, 1994).

[17]Kuo and Reitsch (1996); Nam et al.,(1997); Luther (1998)

and Maknickas (2013); Qiu et al. (2016) find that ANN present better and sound forecasting results as opposed to classical techniques. The findings of these studies suggest that the performance of ANN is not only surpassing the traditional methods in prediction studies; the analytical results of ANN are also better than most of the conventional and other nonlinear techniques. Most of these studies have employed the variables on the concept of convenience thus ignoring the established factors used and appreciated by stock market researchers.

It should be noted, however, that implementing neural networks does not necessarily translate into better prediction results always. Some researchers find simple linear forecasting time series models better at predicting their desired goals. Some recent studies, i.e. (Kara et al., 2011; Stansell and Eakins, 2004) find unfavorable results of ANN in forecasting as compared to the traditional techniques. Some authors are of the opinion that life is too short and the learning and application of ANN require years of time investment. Besides these limited studies, majority of the investigations find ANN to be a better replacement of the human wisdom in stock markets.

2.3.1 Artificial Neural Networks-Basic Theory

The mathematical representation of the artificial neural networks is believed to be mimicking the human thinking and decision-making process. The mathematical modeling of the human brain in this way has revolutionized the contemporary decision making and industrial processes. The application in finance, however, has numerous challenges because a thorough understanding of ANN requires a solid background in Physics and Statistical Mechanics, Computer Science, Artificial Intelligence, Control Theory, and Mathematics, etc. This reveals that the application of ANN requires interdisciplinary research ventures to model the financial markets successfully. The vast repository of capital markets research using ANN, originating from researchers of other disciplines, is perhaps pointing towards this interdisciplinary knowledge acquiring (Kasabov, 1996).

The development of ANN modeling has gone through three different stages. These steps are a marked with success and failures at various times. The pioneering work of (McCulloch and Pitts, 1943) is the first stage in which the first mathematical representation of the human thinking process is modeled. In the second stage Rosenblatt (1962) introduces the single perceptron convergence theorem and revitalized the ANN theory but the spirit is slowed down by (Minsky and Papert, 1969)[18]. Their work points out a limitation of the single layer perceptron. Due to this limitation, the field of ANN remains inactive for twenty years. In the third stage, Hopfield and Tank (1985) introduces the energy approach in ANN and Werbos (1988) designs the back propagation approach for a multi-layer perceptron. The multi-layer perceptron experiments by Rumerlhart (1986) make it usable for industrial purpose.

2.3.2 Mathematical Representation of Neurons

The pioneering effort of McCulloch and Pitts (1943) demonstrate that the mathematical model for the working of an artificial neuron is in the form a binary threshold unit. If the sum of the inputs is above a certain level, an output of one is produced. Otherwise, the system returns a value of zero for the output. Mathematically this relationship is represented as follows.

$$y = \theta \left[\sum_{j=1}^{n} w_j x_j - u \right] \tag{2.1}$$

where θ is a single function and w is the associated synapse weight with the j_{th} input.

The negative and positive weights of the inputs appear like excitatory synapses to the model. McCulloch and Pitts (1943) ascertain that when the weights of the inputs are defined accurately, then the computation of the ANN system can

[18] Minsky and Papert(1969) wrote a book on ANN covering perceptron. A heated discussion on the ANN between the early originators of ANN and these authors regarding the controversy in the study of artificial intelligence withered the passion about the ANN research. The later book reviews show that the prediction of the authors was pessimistic which was the result of erroneous claim about the direction of ANN research

generalize without any fear. There is a simple similarity here to a biological neuron: wires and interconnections model axons and dendrites, connection weights represent synapses, including the threshold function, approximates the activity in a soma. However, their design is more simplified on assumptions that they do not follow an exact behavior of biological neurons. The McCulloch-Pitts model is wide-ranging in several ways. The sigmoid function is the most commonly employed in ANN"s. with the desired level of flatness and asymptotic properties; it is a stringently cumulative function. The standard sigmoid function is a logistic function and can be defined as:

$$g(x) = \frac{1}{1 + exp^{-\beta x}} \tag{2.2}$$

where β is the slope parameter.

2.3.3 Network architectures

The architecture of ANN is designed in a way where weights are specified, artificial neurons are nodes, and directed edges (with weights) are connections. These connections are between neuron outputs and inputs layers. Based on the connection pattern, ANN's can be classified into two different categories; Figure 2.2 represent ANN Architecture:

ANN's most familiar family is of feed forward networks in which graphs have no loops. In this family, the neurons are arranged into layers which in turn have unidirectional connections among them. Generally speaking, static feed-forward networks have different connectivity producing different network performances. These have only one set of output values rather than an arrangement of values from a given input. Feedforward networks peculiarity is that they have no memory, meaning, that their response to a particular input is independent of the previous state (Gerstner et al., 1996).

On the other hand, recurrent or feedback networks have loops recurrence. This is due to the feedback connections thus making it vibrant systems. For a given new input pattern, the neuron outputs are measured, and these inputs to each

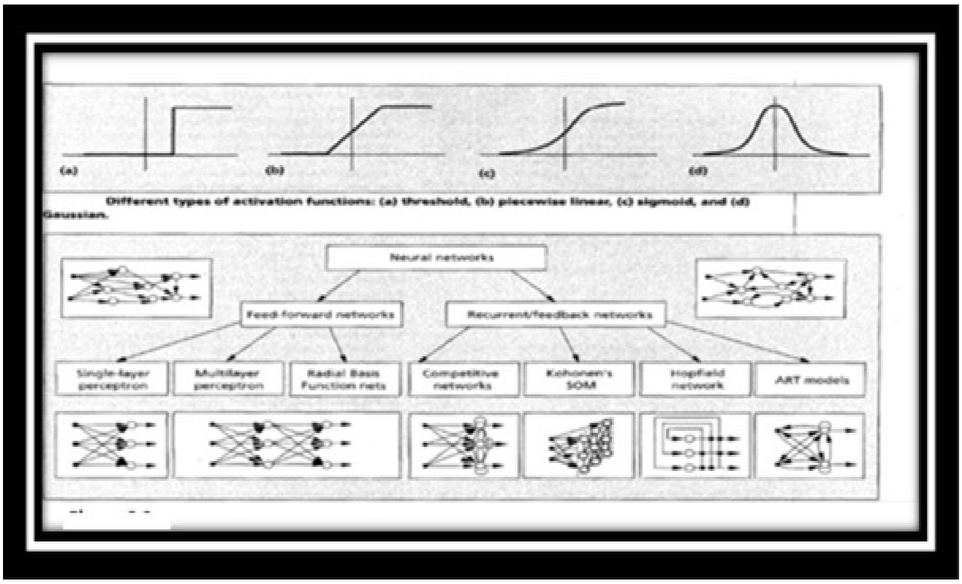

Figure 2.1: ANN Techniques of Training.

neuron are adjusted. This enables the network to enter a new state primarily due to the feedback paths; however, different network designs may require appropriate learning algorithms.

2.3.4 Network Learning

An essential hypothesis of the Neural Network system is that its algorithm has an inbuilt ability to learn from the environment. The learning ability of the ANN can be described as updating its design and the input weights to produce a desirable target of outputs. The learning ability of the weights for the input variables is produced from the training methods and the examples of the Data set. The ANN constructs its rules of learning during the training from the available input data and updates its self to generate the minimum level of errors.

Aforementioned is a unique characteristic of the ANN as compared to other expert system techniques (Kamruzzaman et al., 2006). Neural networks need an environment to operate, and it is dependent on the information available to the network. Due to this characteristic, it is recognized as learning by example system. Three learning schemes are prevalent; supervised, unsupervised, and hybrid. In the supervised learning like training under an instructor, the output is shown to the network, and the prediction is updated according to this actual value. The weights are continuously adapted to minimize the error between the real and predicted value and only those results are incorporated which converge efficiently to the actual value (Kamruzzaman et al., 2006). Our study is based on the supervised learning technique.

Unsupervised learning is just like learning without a teacher, i.e., the network is not provided with real output. The system works by using the correlation between variables and setting data patterns. Hybrid learning systems combine supervised, and unsupervised learning whereby the weights come from supervised learning and others are obtained through unsupervised learning. Capacity, sample density, and computational complexity are the three most important issues in this regard (Kamruzzaman and Sarker, 2003) (Kamruzzaman and Sarker, 2003).

The underlying patterns in the Data set are emulated by the network along with the decision rule and training function. The training time of the network is huge in the presence of sophisticated observations because the system takes more time for validation of its results. On the other hand, the system becomes localized on the smaller data set. The network performs well on the training data set (In Sample) but presents poor results on the testing (Out sample) observations.

The complexity of the network computation refers to the time taken by it to arrive at an appropriate approximation of an underlying problem. The algorithmic selection plays a vital role in this computational complexity (Fonseca and Navaresse, 2002). The designing of efficient algorithms for the NN system is an active research topic, and presently four types of learning rules are available for network learning including Error correction rules, Boltzmann, Hebbian, and competitive learning. Here we discuss the error correction rule to be used in the present study.

2.3.5 Error Correction Rules

In the supervised method of the ANN learning, Error correction are the primary rules of learning. The target output is provided to the ANN system for each set of input variables. The system generates its output and compares it with the already available example. In the case of larger error between the generated output and the actual output, the errors are back propagated, and the input weights are changed to minimize the error. The error correction rule is the basis of the perceptron learning, and it provides validity for the concept of the perceptron. A perceptron contains a single neuron with adjustable weights wj = 1,2, ...,n and threshold U. Given an input vector X = (x1, x2, ..., xj t) the net input to the neuron is

$$v = \sum_{j=1}^{n} w_j x_j - u \tag{2.3}$$

The generated result y of the perceptron is + 1 if v ¿ 0, and 0 if v ¡ 0. The classification problem has a different pattern wherein the perceptron labels an input shape to one class if y = 1, and to the second class if y=O. The linear equation is:

$$\sum_{j=1}^{n} w_j x_j - u = 0 \tag{2.4}$$

The back propagation learning algorithm is based on this error-correction principle. The research studies in finance sphere are mostly using the Multilayer Feed Forward Neural Networks, and according to Dase and Pawar (2010), more than 90% research in finance is based on Multilayer feed forward neural networks with back propagation training method. The Multilayer perceptron models are organized on the principle of supervised learning.

The network in this method is presented with a target value against which it adjusts its performance. The design has three layers, i.e., an input layer, processing layer and target layer (output). The input variables are provided to the network' first layer, and these are processed through a linear function to assign appropriate weights. The weighted inputs are read into the next and important hidden layer. The processing of this layer is conducted through the sigmoid function.

The number of hidden layer neurons is a matter of the experimentation of the researchers. Each neuron in the hidden layer produces its output, and the generated outputs are organized in the form of one output. It is important to mention that the outputs of one layer act as the inputs for the proceeding layer. The outputs of the hidden layer are the data for the next layer, and these are then compared with the already supplied targets. The generated outputs are compared with the actual outputs, and the errors are back propagated to refine the results. This process continues until the network arrives at an optimum output beyond which there are no chances of minimizing the error (Hornik et al., 1989, 1990).

2.3.6 Transfer Functions

The number of variables in the input and output layers determines the required number of neurons in these layers, while the hidden layer neurons are defined by the experimenter based on the complexity of the problem. Every neuron in any layer applies a mathematical model to its inputs to process it. These mathematical functions are called the transfer functions of the network and play a crucial role in the success or failure of the system. The major purpose of the transfer functions is to process its corresponding inputs, convert it into the outputs and move it to the next layer as inputs. This whole process is considered as a black box operation by the theory of ANN and is called the transformation, activation or squashing function (Levich and Thomas III, 1993).

The application of the transfer function has a significant role to play as it prevents the network to be trapped into a situation of local minima and also check the resultant output to reach an undefined value. These two problems create the situation of paralysis for the whole system and create little value for the researchers. The deployment of a linear and nonlinear transfer function depends upon the nature of the data. The linear functions can be deployed in any layer, and it makes the processing easy and less time consuming, but the presence of non-linearity in the data set makes the results less useful.

Some vital transfer functions are Arctan step, linear, hyperbolic tan, sigmoid and ramping function. The various squashing functions have applications in particular situations. For example, if the investigator is interested in calculating the deviation of observation, the hyperbolic tan function is utilized. On the other hand, if the purpose is calculating the averages of a data set, the nonlinear sigmoid function is applied (Klimasauskas, 1989).

The sigmoid squashing function has some features which make it more appropriate for a neural network system. Firstly, due to its nonlinear nature, it can successfully capture the underlying relationship between the dependent and independent variables. Secondly and most importantly its differentiation power reduces the error to a minimum level. The finance studies rely on the use of the sigmoid function in the hidden layer. The financial markets have a proven nature of nonlinearity with the added characteristic of long and short memory. This requires the use of nonlinear or sigmoid functions (Kao et al., 2013).

Every transfer function has its data normalization requirement. The neural work is efficient on normalized data although the raw data also does not create noticeable problems. The mean/ standard and linear scaling are the two widely used techniques of data normalization in the NN system. The sigmoid function process that data efficiently which is normalized between 1 and -1 or 0 and 1.The present research applies Feed Forward Neural Network system with Backpropagation as the training method. The input layer using the linear function and the hidden layer utilizes the sigmoid function. Mathematical Equation of Linear Function is given below

$$SV = \frac{tf_{min} + [tf_{max} + tf_{min}] * [d - d_{min}]}{d_{max} - d_{min}} \tag{2.5}$$

Mathematical Equation of Sigmoid function is

$$\varphi (v) \, tanh \, (v) = \frac{e^{v} - e^{-v}}{e^{v} + e^{-v}} \tag{2.6}$$

2.4 Forecasting: Technical and Fundamental Analysis under ANN

As a matter of practice, the researchers have mainly employed two types of financial variables in predicting the stock returns; technical and fundamental. The technical variables are generated by the market activity and based on the past prices of the markets or individual stocks. The prevailing notion is that the returns in the recent past have predictive power for the near future, i.e., technical analysis is utilized for short-term prediction. The fundamental financial variables are mostly drawn from the firm's performance and broad market indicators, representing the long-term predictive performance of the stocks (Vanstone and Finnie, 2006).

A vast repository of literature is present which concentrates on the application of ANN using technical and fundamental variables stock market forecasting. The selection of papers for our study is based on the notion that the articles should be appearing in the finance journals which can relate the findings to the core theory of investment.

2.4.1 ANN and Financial Variables

The fundamental and technical variables are engaged by Quah and Srinivasan (1999) to study the stock markets returns behavior in the presence of ANN. The study incorporates the technical and fundamental variables jointly and separately to investigate the performance of these variables. The principal finding of the study is that the ANN can successfully separate the value stocks from other stocks and this technique can develop the portfolios. The study poses a challenge to the existing procedures of portfolio formation. Kanas and Yannopoulos (2001) compares the forecasting performance of linear models and artificial neural networks on out sample data set. The findings suggest that the ANN forecasts are nearer to the actual outputs as compared to the linear model. The study confirms a nonlinear relationship between the fundamental analysis and stock returns and demonstrates similarity with the factors of asset pricing models.

A comparative study of the forecasting models based on the traditional and neural network approach is conducted in a study by (Olson and Mossman, 2003). This study is an exhaustive investigation, looking for long-term investment strategies based on the fundamental analysis of individual securities in the Canadian stock market. This research is considered as a hallmark of ANN application in the securities market and probably the first application of ANN and asset pricing factors. The findings have classified the securities into high and low earning returns and prove the superior performance of ANN as compared to the logistic regression techniques. However, the study lacks generalization regarding the selection of financial variables.

Brabazon and O'Neill (2006) examine the predictive ability of ANN with technical and economic variables of the financial times stock exchange-100 index of the London Stock Exchange. Ten financial variables are formed by inter-market activity to predict the fifth-day closing prices of the index. ANN show a keen ability to detect the variation in the stock returns, and the prediction error is minimum. The short coming of the study is that trading rules generate confused buy and sell signals

The investigation by Stansell and Eakins (2004) is perhaps the first attempt to apply some fundamental variables of the asset pricing models. The significant variables of Market capitalization, Dividend Yield, P/S ratio, P/E ratio and P/B ratios are used as inputs, and average stock returns are employed as the target output for the network. The portfolios selected by the neural network are composed of value stocks. The actual and forecasted returns are closer to each other, but the directional changes are against the expectations. The study comes out with an encouraging conclusion that the ANN can be utilized to select portfolios which ensure superior investment returns than the benchmarks.

A novel method of ANN is introduced by Jasic and Wood (2004) using a univariate neural work model on a non-normalized data set. The study generates trading signals based on ANN and related to profitability; finds the forecast to be statistically significant to make profits for the investors on out sample dataset. However, the study uses an inconsistent method of defining the parameters of the neural network. Majhi et al. (2007) investigate the performance of the neural network and compare it with a random walk and linear autoregressive models. The major findings are that neural network outperforms linear autoregressive and random walk models in both in sample and out sample forecasting. The empirical work, however, is not sufficient to support the major findings.

Carvalhal and Ribeiro (2008) compare the predictive power of ANN with three traditional forecasting models, i.e., random walk, Autoregressive moving averages, and generalized autoregressive conditional heteroskedasticity models in Latin American stock markets. Technical variables are employed as inputs to the network system. The study provides substantial evidence for ANN as a useful technique in predicting the indices. De Faria et al. (2009) compare the forecasting performance of neural networks to the adaptive exponential smoothing method in the Brazilian stock market. The authors state that the neural network performs better than the adaptive exponential smoothing method. Additional tests reveal that the results are also consistent across more developed markets.

Mostafa (2010) employs two ANN architectures, a multi-layer perceptron ANN and a generalized regression ANN, to forecast the closing price movement of the Kuwait Stock Exchange, and conclude that ANN models are valuable tools in predicting stock exchange movements in developing markets. The findings suggest that the estimated index returns firmly follow the actual returns of the index. The study period of the study is short which creates problems in ANN technique. Kara et al. (2011) investigate the changing direction of Istanbul Stock Exchange (ISE) National Index. The findings suggest that the neural network forecasts the direction of the index with 75.74% accuracy, while the other model demonstrates 71.52% accuracy.

Kumar et al. (2011) notice ANNs to resist the noisy environments like stock market data and demonstrate a high tolerance to fuzziness. These characteristics make ANNs suitable for making informed investments decisions in the share markets. Dunis et al. (2011) conduct a comparative analysis of ANN and other traditional techniques to assess the predictive performance of both these sets of the model in Athens stock markets. The study constructs various autoregressive technical variables as inputs to the network, and the findings recommend the adoption of the neural network by the fund managers for enhancing their returns in the volatile markets.

Al-Jarrah et al. (2011) reports the long-term predictive ability artificial neural works in Jordanian Stock Market. The conclusions of the researchers propose that the long-term prediction of the proposed system is 80% accurate. This study suffers from many weaknesses including the use of raw data in the artificial neural networks. This drawback has probably reduced the forecasting accuracy of this research. Qi (1999) documents supportive evidence for ANN as compared to the linear forecasting models. The study finds supporting evidence for in sample and out sample forecasting accuracy as compared to the traditional techniques.

Idowu et al. (2012) points out that although ANNs do not allow perfect estimations on volatile data such as the stock exchange market, they indeed provide closer results to the real ones compared with other techniques. Maknickiene and Maknickas (2013) suggest a forecasting model for foreign exchange markets based on artificial neural works. The findings of the study consider the ANN as a useful tool for the investors, making his portfolio construction process more profitable. Jabbari and Fathi (2014) provide a comparative analysis of the least square regression and ANN in predicting the excess returns on Tehran stock exchange. The study finds empirical evidence for a strong predictive power of average returns for the investors, based on ANN as compared to the regression tool.

Fadlalla and Amani (2014) investigate the short-term predictive performance of Artificial Neural Networks. The findings provide evidence that the one day ahead forecasting of the index is closer to the actual closing price. All these studies suggest the successful application of ANN in stock market forecasting in most of the stock markets in the world and provide a solid rationale for the present study to apply ANN in the portfolio returns by using asset pricing models . All these studies have some common features i.e these studies mostly concentrate on the technical analysis and the linkage with the established theory and models of investment strategies is the major shortcoming. It seems that these studies ignore the ultimate users of the research.

2.4.2 Artificial Neural Networks and Pakistan' Equity Market

The application of ANN in Pakistan's equity is taken up by many scholars. The primary shortcoming of these studies is that the authors belong to the disciplines of statistics, computer science or engineering. These endeavors lack the definition of ANN forecasting regarding the investment theory. The study of Fatima and Hussain (2008) is perhaps the first contribution in this regard. This paper compares the forecasting performance of ANN, ARIMA, and GARCH and assesses the prediction performance by using forecast mean squared error. The study affirms ANN to be a better model for predicting the stock returns in this volatile market.

Haider and Nishat (2009) apply the feedforward neural networks to the stock values of a single firm. The input variables include the three days lagged return and the next day's returns are estimated. Particle swarm optimization is applied for portfolio construction. The study successfully achieves excess returns as compared to the market. Iqbal et al. (2013) undertake the application of several neural network models to predict the returns of a single stock in Pakistan stock exchange and. use The findings suggest that the neural networks have successfully predicted the returns with more accuracy. The scope of these studies is limited and the time periods are also very short.

2.4.3 Asset Pricing models and ANN

The first attempt to evaluate the forecasting ability of the asset pricing model, using artificial neural networks is taken up by (Cao et al., 2011)[19]. The study compares the forecasting performance of single factor dynamic Capital asset pricing model, Fama and French three factors model, and ANN. The dynamic version of CAPM and Fama and French three models are first used for forecasting the stock prices prediction in Shanghai Stock market, and then the predictor variables

[19] Cao et al. have applied the artificial neural networks in three research studies in the year 2005,2009 and 2011.

of these asset pricing models are used by the neural network system to predict the stock returns.

This research utilizes the variables of beta, market capitalization and book-to-market ratios for 367 listed firms for ten years. The performance of both the linear and nonlinear models is measured by the Mean absolute deviation, Mean absolute percentage error, and Mean squared error. The study utilizes the feed-forward neural network design for arriving at the minimum error of the network because 90% of the prediction studies in finance employ this architecture. The findings suggest that the ANN has predicted the returns more accurately on the asset pricing models which prove that linking of the investment theory with ANN improves the prediction performance of the system in the long run. The networks also outperformed the linear models on the above performance parameters.

Another attempt is initiated by (Gokgoz and Sezgin-Alp, 2014), evaluating the predictive performance of the asset pricing models, using artificial neural networks. The macroeconomic indicators as suggested by multifactor factor Arbitrage pricing theory are employed as the predictor variables to predict the returns of the sectoral indices in Turkish stock market. The Feedforward neural network structure of ANN with back propagation is applied to the prediction system, and the performance of the network is evaluated by the mean squared error (MSE). The findings suggest that ANN has successfully predicted the future returns of all the indices with a minimum error both on in sample and out sample dataset. The standard method of portfolio formation is not considered in this study.

Aldaarmi et al. (2015) investigate the predictive ability of Fama and French three factors model and value-based management model (VBM) using artificial neural networks, enabling investors to make investment decisions. The monthly returns of the stocks are used as the predicted variables, and six portfolios are formed on the basis of Fama and French model. The predictor variable of market returns, Size, and value, are constructed for five years. The results suggest that the difference between the actual and predicted portfolio return is significant and the predictive power of high B /M and big firms portfolios are weak. The real and predicted values in case of medium B / M and small firms are very close, implying a strong predictive power for portfolio returns. The basic theory of ANN states that the performance of the system is optimal on large data set and smaller data set creates the problem of over fitting.

Besides these studies, the author of the present study spent long hours in search of investigations on asset pricing and artificial neural networks and the renowned publishers, for example, SCIENCE DIRECT, TAYLORS, AND FRANCIS, EMERALD, JSTOR, INFORMS, and HINDAWI, but no other studies are located on this subject.

2.5 Hypotheses of the Study

The rigorous literature review in the present chapter has provided a solid background for the following testable hypothesis in this thesis.

1. H1: the single factor CAPM can predict the stock returns using artificial neural networks in Pakistan's equity markets.
2. H2: The three factors Fama and French model can predict the stock returns using artificial neural networks in Pakistan's equity markets.
3. H3: The five factors Fama and French model can predict the stock returns using artificial neural networks in Pakistan's equity markets.
4. H4: The application of CAPM and its major variants along with the artificial neural networks is a successful exercise in the emerging markets.

2.6 Conclusion

The chapter on literature review documents the presence of predictability in the financial markets worldwide by providing evidence from the recognized research articles. Research-Based support is presented for the consideration of technical, financial variables in predicting the stock returns in the stock markets of the developed and developing markets. The results of the studies based on linear and nonlinear processing techniques are presented, providing supportive evidence for the use of nonlinear systems in the present study.

The relationship of the investor's profitability with the asset pricing models is being developed in detail, and the primary model of asset pricing, i.e., CAPM is explained in detail along with applicability in the leading financial markets. An organization of the early tests of CAPM validates the main predictions of the model while the latter tests contradict the primary theoretical basis of the model. The anomalies of the CAPM are reviewed along with evidence, and the development of the different asset pricing models is undertaken in details. Notable studies in the finance journals supporting the FF3C and FF5C models and their predictive ability are displayed.

Most of the forecasting studies regarding the stock markets in this review have relied on the use of technical or fundamental analysis for long and short-term investment strategies by employing the neural networks. Some well-recognized studies also confirm the superiority of ANN over traditional forecasting techniques. The review further demonstrates a remarkable fact about the use of ANN in the asset pricing theory. Very few articles have applied ANN in this primary area of investment. This research gap is evident from the literature review, and our study is a pioneering attempt to implement the neural networks in the asset pricing theory, as such, the use of fundamental variables of asset pricing models as inputs for ANNs is well within the remit of this study.

Chapter 3

Methodology and Research Design

Introduction

We aim to estimate the predictive ability of various asset pricing models by using Artificial Neural Networks in Pakistan's equity markets. The time series of stocks returns is measured by the financial factors of the single factor Capital asset pricing model, three factors, and five factors CAPM. The success or failure of the models is assessed with the help of t-statistics.

The application of technical, financial and state variable in forecasting, although, is a prevalent practice among the stock market researchers but This approach lacks the ability of generalization in other markets. On the other hand, some renowned studies, for example,(Graham and Harvey, 2001; Grinold and Kahn, 1995; Javid and Ahmed, 2008; Simin, 2008), provide evidence of robust forecasting in favor of the composite factors of the asset pricing models.

This chapter discusses the methodology and data used for the present study and formally state the hypothesis of the research. We also address other issues, such as the definition of relevant input variables, definition and formation of portfolios and the composite factors of the asset pricing models, the model specification in terms of the artificial neural networks and the software (programs) developed for this study. Section 3.1 describes the population, sample and the period of the study; Section 3.2 elaborates the data required for the formation of various factors of asset pricing models. Section 3.3 the three models of asset pricing along with a brief introduction of the factors. Section 3.4 discusses the portfolios formation. Section 3.5 describes the detailed method of the construction of the composite factors of the asset pricing models. Section 3.6 provides the details of the ANN modeling in terms of the asset pricing models and concludes the chapter.

3.1 Population and Sample

The experimentation and analysis presented in chapter 4 are based on the financial indicators of stocks listed on the Pakistan Stock Exchange (previously known as Pakistan Stock Exchange). We select Pakistan Stock Exchange as the universe of the study, and a clear criterion is applied to the selection of firms. This criterion is based on the established guidelines developed by some renowned names in stock markets sphere.

Pakistan's equity markets have attracted massive investments in the recent past from all parts of the country and globally, reaffirming the confidence of the investors in the bourse's markets. This is in contrast to the past years when the stock market's investors belonged to the major cities of the country only; the presence of investment firms in small towns of the country is the evidence of the increased interest, knowledge, and confidence of all classes of investors in the equity markets of the country.

Significant reforms have been introduced in the regulatory structure of Pakistan.The market has gone through a development process in the past two decades. The continuous enhancement of infrastructure, re-engineering of the operational process and effective trading system and the automation of most of its functions, have placed this market in the list of well-organized and technologically advanced exchanges of the world . Pakistan stock exchange ranked third in the year 2014 among the top ten best-performing markets in the world, securing a place in the top ten for the third consecutive year. In the MSCI Asian Frontier Markets, Pakistan ranked number one – outpacing Sri Lanka, Vietnam, and Bangladesh by a significant margin. In 2014, the KSE-100 index gained 6,870 points, generating a handsome return of 27 percent (31% return in US dollar terms) for the investors (Pakistan Economic Survey, 2014).

The Bloomberg (2015) categorizes Pakistan's equity market as a larger market, while a recent report by the Indian edition of Quartz (2016) reveals that Karachi stock market has beaten the major Asian equity markets and KSE-100 is the 5th best performing market in the world ranking. The Bloomberg (2016) report declares Pakistan as the "tiger" of Asia and reaffirms KSE-100 as the best in the world. Some critics, on the other hand, attribute this growth to the portfolio investment by foreign investors; their claim is refuted by the Central Bank of the country, which issues the composition of investors and the volume of their investment as an investor's guide. The analysis of the SBP report (2015) reveals that 80% of the investors are indigenous with 70% share in the daily turnover of the market.

The cumulative market capitalization of all the listed Companies is approximately 87$Bnwith$166 mn average daily turnover, and the average daily turnover of shares is 379.1 mn (SBP; 2016). The turnover of shares implies that this number of shares is changing hands during the year. This average becomes higher if the two weekends are not included. For the year 2015, the benchmark index of KSE posts 49.4% (37% in dollar terms) annual return (Bloomberg report, 2015). The KSE-100 index registers a growth rate of 48.9% and the market positions itself in a significant place in different indices managed by MSCI. The listed capital witnesses a growth rate of 5.8% while the market capitalization demonstrates 21% average growth rate in the last five years as shown in Table 3.1 (Annexure A) .

The MSCI Pakistan index (an independent equity research index) gains 38% in 2015, higher than any other emerging markets in Asia including, Sri Lanka, Bangladesh, and Vietnam. KSE-100 index returns are closely following the Japanese index in absolute percentage terms (MCSI, 2015). A graphical comparison of KSE-100 and India Sensex stock in Figure 3.1 reveals that the KSE-100 is closely matching the Indian stock market growth. The index of Pakistan Stock Exchange stands at 29,653 while Indian Sensex is at 27,011 only. The growth of KSE-100 is 13.17% while the Indian Sensex has registered only 6.30% growth rate.

The performance of KSE-100 index as compared to other markets is presented in Table 3.2 (Annexure A). The Table shows a very encouraging picture, i.e., KSE outperformed Standard and Poor's 500, Bombay Stock Index Sensex, Australian index AORD, Srilankan index CSE, London Stock exchange index FTSE 100 and Indonesian Index JCI for the year 2015 (Pakistan Economic Survey, 2015). The Chinese Stock Market index Shanghai Composite, however, registered a growth rate of 116.9% and gained 2394 points. This market has beaten all the indices in the global financial markets and performed very well during this period.

All these gauges contribute momentous value to Pakistan Stock Exchange. The extent of Investment and trading size validate the desire of the investors to invest in the equity markets and earn an above average return.

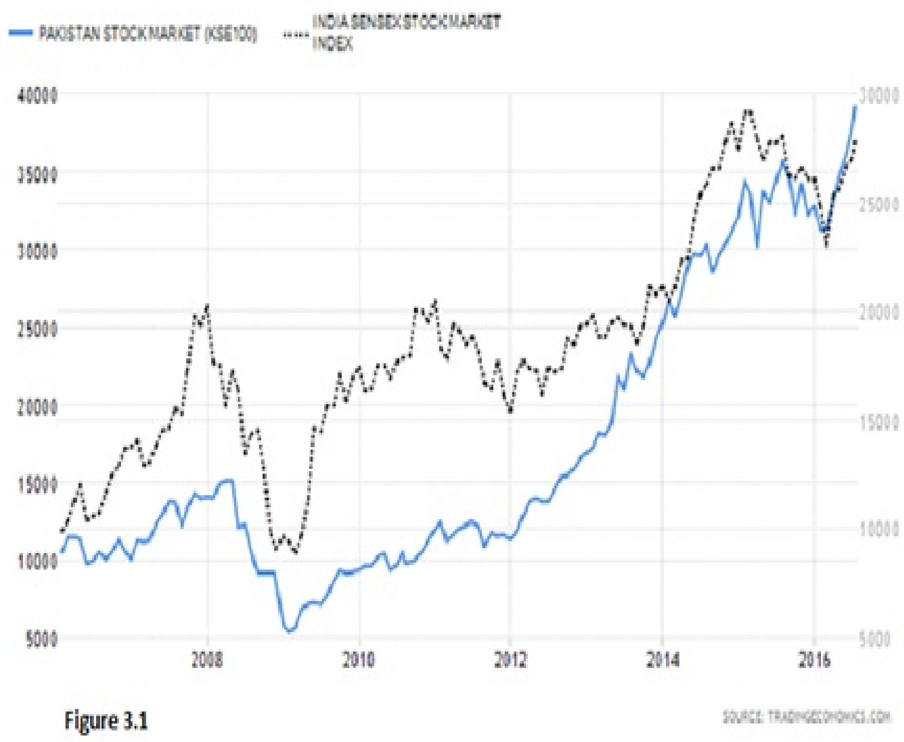

Figure 3.1: Comparison of KSE-100 and Sensex.

Most of the financial sector reforms including the stock market have taken place during the decade of 90's. Better infrastructural changes and automation of the primary processes were put in place during that decade. Pakistan Stock Exchange has employed the latest database management system in the last ten years. The market is closely matching the developed markets in terms of investor's education and information, analytical reports, Market trends and online trading system. Due to these reasons, we have selected the last sixteen years' time interval for the present study.

We use the data from January 01, 2000 to December 2015.However, in August 2008 Pakistan Stock Exchange (PSX) starts to follow an extreme downward trend, and the stock market is unable to normalize for about four months. This is the time of weak trading and has the potential to create a discrepancy in the final analysis. Therefore, to avoid extreme results, the period of four months is excluded from the study. The sample firms include companies from all the industrial sectors listed on KSE-100. However, enterprises of the financial sector including banking, insurance, brokerage houses, Modarba companies and mutual funds are excluded from the analysis following (Fama and French, 2015). The criteria for the selection of stock from the remaining firms from various sectors are adopted from (Javid and Ahmed, 2008) with some modification and according to these criteria.

• The selected stock must be listed at KSE. • The data of monthly price index and the book value, market equity, total assets, profitability and volume traded by the sample companies must be available for the stocks. • During the sample period, the selected stocks must be traded for more than 90% of Trading Days. • As the history of KSE-100 index is short, therefore only those companies are selected which are listed throughout this period.

3.2 Data Sources and Financial Indicators of Firms

This thesis employs the monthly returns as the target or predicted variable of stocks listed on Pakistan Stock Exchange. The selection of monthly data instead of weekly or daily data is that the study follows the standard method of Fama and French (1993) for the formation and selection of target returns. The data on monthly returns are obtained from the official website of Pakistan Stock Exchange.

The database of PSX contains data on all the listed Companies. The thesis includes reference to the reports, mentioning the development of the equity markets in Pakistan. These reports and bulletins are issued by the Central Bank and the Economic survey of the Central Government. These reports are published on the quarterly and annual basis and carefully track the development and regulatory framework of the financial markets including the capital markets. The research repository of these institutions makes these reports available online, and a written request to these databases can obtain the additional information.

The price related data including opening, high, low, and closing is obtained from the database of Pakistan Stock Exchange. The composite factors of the asset pricing models include the market risk, size, value, and profitability and investment premiums. The required data for the formation these factors include 1) Net assets 2) of shares 3) Market Price per share (closing prices) 4) Total investments 5) profitability and 6) Book value of equity. The data for these company-specific variables are obtained from the Thomson Reuters' database, i.e., Data Stream to avoid the element of inaccuracy of the Data set. Other sources are the Companies financial reports and the State Bank of Pakistan.

3.3 Model Specification and Asset Pricing Models

The starting model is the cornerstone model of Capital asset pricing model and its significant variants, i.e., three factors CAPM and five factors CAPM. These models are used to see whether the predictive power of these models can be magnified by employing a state of the art technology of artificial neural works. However, whether these models are valid or not is not under the scope of this study.

A detailed discussion of the CAPM regarding its initial modeling, testing, and validation is provided in section 2.2 of chapter 2. The model states that asset returns are described by its systematic risk relative to the market return. The CAPM has the following specification

$$R_p = R_f + \beta_1 \left(R_{PSX} - R_f\right) + \varepsilon_p \tag{3.1}$$

where β_m is defined as $\beta_{im} = \dfrac{\sigma_i r_m}{\sigma_m} = \dfrac{cov\left(r_i, r_m\right)}{var\left(r_m\right)}$

The CAPM incorporates the market return factor of Rm which is composed for the proposed model of this study.

The second model of this study is the Fama and French three factors model. This model incorporates the impact of size and value factor along with the market return factor. The model requires the formation of SMB and HML factors for the size and value effects. The discussion of the three-factor model is earlier presented in section 2.2.10 of Chapter 2. Mathematically the Fama and French three factors model is represented as

$$R_p = R_f + \beta_1 \left(R_{PSX} - R_f\right) + \beta_2 \left(R_{SMB}\right) + \beta_3 \left(R_{HML}\right) + \varepsilon_p \tag{3.2}$$

The Fama and French five factors model incorporate two additional factors of profitability and investments. The theoretical and empirical background of this model is produced in section 2.2.11 of the previous chapter, and the mathematical representation is given below.

$$R_p = R_f + \beta_1 \left(R_{PSX} - R_f\right) + \beta_2 \left(R_{SMB}\right) + \beta_3 \left(R_{HML}\right) + \beta_4 \left(R_{CMA}\right) + \beta_5 \left(R_{RMW}\right) + \varepsilon_p \tag{3.3}$$

3.4 Portfolios of Asset Pricing Models

The portfolio formation is a central activity in any investment strategy; the asset pricing models employ the monthly portfolio returns as the dependent variable instead of individual stock returns mainly due to cost effectiveness and profit orientation. This procedure is first proposed by (Black, 1972) and then reconfirmed by (Fama and MacBeth, 1973). The primary analysis of this thesis is based on the

(Fama and French, 1992) methodology for portfolio formation. Data on market capitalization, book-to-market ratio, total assets and operating profit is used to construct factors used in multi-factor CAPM. The factors of Size, value, investment, and profitability are constructed using the criterion of Fama and French (2015).

$$R_{it} = \frac{P_{it}}{P_{it} - 1} \tag{3.4}$$

The monthly rate of return for each stock in the sample is calculated as follows.

Where R_{it} : is the rate of return on stock i at month t. Pit: is the monthly price index of the stock i at month t. $P_{it} - 1$: is the monthly price index of the stock i at month t-1. To measure the market rate of return, this study used the equally weighted index for KSE (Karachi Stock Exchange) as the proxy for the market portfolio rate of return. We use e the 12- month treasury bills as a proxy for the risk-free rate of return which is taken from the website of state bank of Pakistan.The target portfolio returns on monthly basis are used as the benchmarks for the ANN system to compare them with the output (predicted portfolio returns) generated by the Neural Networks. These portfolios are formed following (Black, 1972) and (Fama and French, 2015).

Firstly, we estimate the coefficient beta for all the securities included in the sample window and then sort these securities from high beta to low beta. These securities are then grouped into 30 equally weighted portfolios and then divided into three groups based on high, mid and low betas. The high beta portfolios include portfolios 1-10 while the mid and low beta portfolios include portfolios 11-20 and 21-30 respectively. The same procedure is followed for the next sample window until the end of the sample period to yield a rolling window.

The monthly portfolio returns for each portfolio is calculated for a 12 months period starting from Jan 2000. The portfolio formation in this way is repeated for all the years from Jan 2000 to Jan 2015. This procedure enabled us to obtain the monthly portfolio returns of 15 years for all the securities included in the sample. For each year all those securities are included whose data is available, therefore the number of securities for each year varied and ranged from 250-300 securities. The number of firms in each year also varied in the respective portfolios.

3.5 Factors Definition and Formation

The traditional regression models require the definition of the dependent and independent variables. These variables are called input and output variables in artificial neural networks system. The input variables for this study are the market Beta (Rm), size factor or SMB (small minus big), value factor (high minus low), profitability factor RMW (robust minus weak, and investment factor CMA (conservative minus aggressive). According to Fama and French (2015), the investments conducted on the basis of these factors can beat the buy and hold strategy and ensure excess returns as compared to the market. These five factors are used as inputs (based on the three models) to the neural network system for predicting the portfolio returns in the present study.

3.5.1 Market Risk

Market risk is measured by taking the difference of market return and risk-free return. Market return is calculated from the market index from KSE-100 for the years 2001 to 2015, and risk-free return is the return which is offered on the treasury bills. The risk-free return is taken from the available data on the official website of State Bank of Pakistan (SBP). According to the sample of this study, the risk-free rate of treasury bills is taken from the year 2000 to 2015. The market return less the risk-free rate of treasury bills is the proxy to measure the market risk. It is pertinent to mention here that this is the most influential factor of any asset pricing model as outlined by the CAPM and it is believed by the finance researchers that most of the stock or portfolio returns are the functions of this factor.

3.5.2 Size (Small minus Big) and Value (High Minus Low)

The market capitalization is used to calculate the size factor. By market capitalization, the firms are classified as small and big capitalization companies. This ranking generates the SMB factor and is referred to as the difference between small and big capitalization companies. The second grouping of the firms is based on the ratio of book value to market value of the firm's equity. The firms with a high ratio are referred to as the high B/M ratio firms, and the small B/M ratio represents the low firms. This grouping results in the HML factor. These factors are used to calculate the risk premiums for the size and value factors.

The SMB and HML factors are calculated according to the methodology proposed by (Fama, 1991). The sampled firms are sorted by their respective market capitalization from low to high ranking order. The first 50% of the group represents those firms whose market capitalization is low and are considered as small (S)firms, while the second 50% describe the big firms (B). This is called the first sort and a second sort is applied by their book-to-market ratio.

The second sort is based on high and low B / M ratio. After the second sort, the firms are now placed into three groups. The first group is 30% of the sample, and consists of those firms whose book-to-market ratio is high (B) and market capitalization is low (S). The second cluster is 40% of the sample and consists of those firms, having medium B/M ratio (M)and small capitalization (s). The last group is the remaining 30% of the sample, and their grouping is based on the small capitalization firms with low B/M ratio. This procedure results in the formation of portfolios, and they are referred to as S/H, S/M, and S/L. The return of these portfolios is calculated by taking the weighted average of the monthly returns of the participating firms.

The same procedure is applied to the companies which have high market capitalization and are referred to as big caps (B) firms. These big caps (B) companies are again sorted on the basis of their high book to market ratio (H) to low book to market ratio (L). They are divided into three groups and applying the 30%, 40% and 30% criteria results in the portfolios called B/H, B/M, and B/L. The weighted average returns are calculated for these portfolios for each year. These six portfolios are now used for the formation of SMB factor, and the factor is calculated from 2000 to 2015 each year.

SMB = Small minus Big = Average Returns of Small Size firms minus Average Returns of Big Size companies

$$SMB = \frac{(SH + SN + SL) - (BH + BN + BL)}{3} \tag{3.5}$$

3.5.3 Value Effect (High minus Low) premium

The value effect segregates the value stocks from growth stock, and it is the difference between the returns of the high book to market ratio (B/M) of the assets and low book to the market ratio (B/M) of the stocks. HML (High minus Low) represents the risk factor of return rate that involves s the ratio of book to market value (B/M) effect. The HML factor is calculated as the return to a value-weighted portfolio of the 30% of stocks with the highest book-to-market equity ratios, minus the return to a value-weighted portfolio of the 30% of stocks with lowest book-to-market equity ratios, again re-balanced on the last trading day of the month. HML is calculated with the help of below-written formula.

HML = High minus Low = Average Returns of High Book to Market Ratio (B/M) minus Average return of companies having a Low book to market ratio (B/M) ratio

$$HML = \frac{(SH + BH) - (SL + BL)}{2} \tag{3.6}$$

3.5.4 Profitability (Robust minus weak) Premium

Profitability is measured according to the procedure adopted by the (Fama and French, 2015). The annual revenues are taken as the starting indicator and the cost of goods sold, interest expenses, general and admin expenses during the financial year are deducted. It is then divided by book equity at the end of the year, which is earning per share. Earnings per share are applied as a proxy for the profitability.

The portfolio of the stocks with robust profitability less the portfolio of the stocks with weak profitability gives RMW (robust minus weak). To calculate the RWM the following procedure is followed. First, all the companies are sorted according to their market capitalization (small to big) and then divided these companies into two groups by establishing cut off at 50% as it was done to calculate SMB.

The small companies (S) which are obtained from the previous sorts are again sorted on the basis of earning per share (EPS) from robust to weak. This group of small companies sorted on earning per share basis is divided into three clusters. The first group consists of thirty percent small companies (S) with robust profitability (R). The second group includes the middle forty present small caps (S), and the third cluster consists of last small caps (S) having weak profitability (W). In this way, we calculate SR and SW by taking a weighted average of monthly returns of the companies.

The big caps (B) are also sorted on the basis of robust profitability to low profitability as in the case of small caps (S). These big caps (B) sorted on the basis of profitability are divided into three clusters. The first cluster comprises of thirty percent big caps (B) which have robust profitability (R) the last thirty percent big caps (B) which have weak profitability (W) and middle forty percent big caps (B) which have medium profitability. This method enables us to calculate B/R and B/W by taking the weighted average of monthly return of the companies.

RMW = Robust minus Weak = Average of high earning per share minus Average of Low earning per share

$$RMW = \frac{(SR + BR) - (SW + BR)}{2} \tag{3.7}$$

3.5.5 Investment (Conservative minus Aggressive) Premium

The CMA factor is calculated as the Portfolios returns of the low investment stocks less the returns of the portfolios of high investment stocks. The growth of assets of a firm is used as the proxy for investment factor. Growth in assets is calculated by dividing the assets in the current year by total assets in a previous year and then a log-normal value is taken (Fama and French, 2015) according to the following formula.

$$A_{it} = ln\left(\frac{A_{it}}{A_{it}-1}\right) \tag{3.8}$$

Ait is growth in assets of the companies for year i. Ait is the assets of the companies i for year t.

The following procedure calculates CMA. First, the companies are sorted on the basis of their market capitalization and formed two groups. The first group consists of fifty percent of small firms referred to as small caps (S) and the second group comprises of remaining fifty percent big firms. The small firms (S) are again sorted on the basis of annual growth in assets from aggressive (A) to conservative (C). Then these small caps (S) sorted on the basis of growth in assets is divided into three groups. The first group consists of the thirty percent of the small companies (S) which have aggressive growth in assets; the second group consists of last thirty small companies (S) which have conservative growth in assets (C).

SC and SA are calculated by taking a weighted average of monthly return of the companies. The big companies (B) are also sorted on the growth in assets from aggressive (A) to conservative (C). By annual growth in assets, the sorted big companies (B) are divided into three groups. The first group comprises of thirty percent of big companies (B) which have aggressive annual growth in assets (A) and the second group consists of last thirty percent of the big companies which have conservative (C) growth in assets. Forty percent companies have medium growth in assets. From above procedure, BA and BC are calculated by taking the weighted average of monthly return of the companies from 2000 to 2015.

CMA = Conservative minus Aggressive = Average of High growth in assets minus average of Low growth in assets

$$CMA = \frac{(SC+BC)-(SA+BA)}{2} \tag{3.9}$$

According to some authors, the asset pricing factors can emulate the impact of the fundamental indicators of the firms. Besides this, these factors also offer an excellent explanation of the major economic indicators of a country. We expect that the inclusion of these factors will contribute high value to the asset pricing theory.

3.6 Artificial Neural Networks and Asset Pricing

Artificial intelligence is taking over the traditional linear and nonlinear techniques. The artificial neural network is successfully employed to predict stock returns, directional changes in the index and trend prediction. The primary purpose of ANN forecasting is to reduce the difference between the actual and predicted values (minimize error). As mentioned in the literature review in Section 2.3, neural network techniques have shown promising results in stock markets, and researchers are resorting to this technology to solve the uncertainty problems of financial markets.

ANN with Back Propagation training method has been implemented in most of the finance research. The dependent and independent variables are treated through linear, and nonlinear functions and each neuron calculates its output with the help of these mathematical functions. The neurons in the hidden layer and other layers are connected with each other through a system of weights, and the networks adjust these weights for achieving better forecasting results. The interconnection of the neurons stores knowledge of the processing mechanism giving rise to the short and long memory feature of the network. Specialized neurons exist between the hidden and output layer which is called the bias neuron (Sharma and Chopra, 2013). The bias neuron is equivalent to the intercept term of the regression theory.

Like any other forecasting tool, the artificial neural networks require the declaration of parameters before putting into operations. The primary parameters of the system include firstly, the normalization and preparation of the Data set in a particular tabular form, secondly, the training methods and its algorithm and finally the design of the network. The literature suggests many guidelines on developing a neural network for the prediction and exploratory research and the guidance provided by (Masters, 1993; McCord-Nelson and Illingworth, 1991)[1] are worth noting. The instructions suggested by these studies are combined by (Kaastra and Boyd, 1996) in their eight-step methodology for designing any ANN system for all types of studies. This method is adopted, simplified and modified for the present study and the details of the steps are explained below.

3.6.1 Step 1: Identification and Declaration of Appropriate Variables

In step 1, the declaration of dependent (target output) and independent (input) variables is required. The composite factors of market return, size, value, investment and profitability factors are applied as the inputs and excess monthly portfolios returns as the output for the neural network system in the present study. All the three original asset pricing models are translated into ANN, and the mathematical representation of ANN regarding single factor, three factors, and the five factors CAPM are given below:

$$R_p - R_{Rf} = G\left(\alpha + \sum_{j=1}^{h}(\alpha_i)\right) + F\left(\beta_{0j} + \beta_{1j}\left(R_{PSX} - R_{Rf}\right)\right) \tag{3.10}$$

$$R_p = G\left(\alpha + \sum_{j=1}^{h}(\alpha_i)\right) + F\left(\beta_{0j} + \beta_{1j}\left(R_{PSX} - R_{Rf}\right) + \beta_{2j}\left(R_{SMB}\right) + \beta_{3j}\left(R_{HML}\right)\right) \tag{3.11}$$

$$R_p = G\left(\alpha + \sum_{j=1}^{h}(\alpha_i)\right) + F\left(\beta_{0j} + \beta_{1j}\left(R_{PSX} - R_{Rf}\right) + \beta_{2j}\left(R_{SMB}\right) + \beta_{3j}\left(R_{HML}\right) + \beta_{4j}\left(R_{CMW}\right)\right. \tag{3.12}$$

[1]These authors advise that the neural networks can be designed in many ways. The organization of the neural network system is a function of the Neurodynamics and architecture. Neurodynamics is the feature of an individual artificial neuron and includes the definition of input and output variables, transfer functions and learning algorithm, etc.

3.6.2 Step 2: Data Preprocessing

In step 2, the process of normalization or transformation which is called pre-processing in the neural network system is followed. This process enables the network to learn the fundamental relationships between the variables and present better forecasting and analytical results for analysis. The widely used methods of transforming the raw data are the log-normal process, differencing techniques and the use of ratio. The ANN has its standards of transforming the data depending upon the mathematical function in the hidden layer, and the data is normalized between the upper and lower limits depending upon the transfer function (Jasic and Wood, 2004). We use the sigmoid function, and this function requires the data to be normalized between 0 and 1 for this study. The mathematical equation of the sigmoid function for data normalization is provided below:

$$Sig\,(t) = \frac{1}{1+e} \tag{3.13}$$

A common practice in the traditional forecasting modeling is to divide the time series data into an in-sample and out sample data sets. The equivalent terms for the in-sample and out sample data is training and testing, while the validation data set is an additional step used explicitly by the neural network system to control the asymptotic nature of the neural network model. Some widely used methods of distributing the data set is the cross validation method and random assignment. The cross validation method is applied on huge and sensitive data sets i.e. weather forecasting and marine operations. Under this method, the convergence of results is slow on commonly used gadgets and it requires supercomputers for successful results. On the other hand the random selection method is the optimal convergence method in most of the stock market analysis.

The basic theory of ANN requires the training data set for the network to be the largest one as compared to the testing and validation. The testing data is set in the range of 10% to 30%. The testing data is used to evaluate the generalization (out of sample) ability of the system after the training is completed (Wang et al., 2011).

3.6.3 Step 3: Data Distribution among Training, Testing, and Validation for ANN

In step 3, in the preliminary analysis, this study identifies the best ANN system for the equation (6). ANN system is flexible and offers many solutions to a specific forecasting problem. However, the challenge to identify a cost and time effective optimal solution is examined in the present study in a comprehensive manner. We take almost all the possible combinations regarding neurons, data combinations (training, testing, and validation) and portfolios types in terms of the level of risk.

We divide the data into a series of combinations to achieve the optimal data sets. The first set is divided into 60-20-20 combination for training, validation and training set. After this first data set distribution, a five percent variation is allowed to the data set. The generated datasets are presented in Table 3.3, Table 3.4 and Table 3.5 (Annexure A). These tables show that the data set contains the combinations of 60-20-20, 65-15-20, 65-10-15,70-10-20,70-15-15,70-20-10,75-10-15,75-15-10,80-10-10,85-05-10,85-10-05,90-05-05.

Likewise, the ANN also describes the number of neurons and the transfer function for a given hidden layer (Adebiyi et al., 2014). The neurons process the data in the hidden layer, and this process is believed to be a black box for the analyst. The number of iterations is decided by the network to arrive at the optimal results (Krollner, 2011). This term transfer function is used to describe the empirical formula that calculates the outputs of a particular hidden layer or neuron. Other terms used for the process are activation, transformation or squashing functions5.

3.6.4 Step 4: Neural Network Prototypes

Step 4 is the decision on the network designs including the number of layers, number of neurons, and transfer function. We use the sigmoid function as the transfer function. The resultant curve of the function is " S-shaped," and Mathematically it is represented as

$$S(x) = \frac{e^x}{1 + e^x} \tag{3.14}$$

The detailed network paradigm for this study is executed by initialization architecture and includes three layers, i.e., an input layer, a hidden layer and an output layer. The input layer utilizes five neurons and the linear function (logistic function) to assign the appropriate weights to the input variables. The five neurons represent the five factors of the asset pricing model. The logistic function assigns the optimum weights to these variables and the output from the input layer is used by the hidden layer. The maximum limit of neurons in the hidden layer is placed at 50, and the output layer consists of a single neuron in the form of desired target output. These neurons work in a series, and the programs compile the best results for each neuron under each combination of the data set.

3.6.5 Performance Measurement

In step 5, the performance of the neural network system is assessed. Many performance evaluation techniques exist to evaluate the neural network system. These measures are used along with a benchmark to compare the performance of the metric itself. We use Mean Squared Error performance measurement method to avoid some of the pitfalls of other evaluation techniques. This error function may not be the final evaluation criteria, but other standard forecasting evaluation methods, i.e., mean absolute percentage error (MAPE) is typically not minimized in neural networks, the proposed parameter is selected. The mathematical equation of MSE is given below.

$$MSE = \frac{1}{N} \sum_{t=1}^{N} \left(R_t - \widehat{R}_t \right)^2 \tag{3.15}$$

Where R_t and $\widehat{R}_t$ are, respectively, the actual returns and forecasted returns, and N is the size of the testing data set. The default performance function for feedforward networks is mean square error—the average squared error between the network outputs and the target outputs Rt. Forecasting errors need to be less for forecasting accuracies for financial time series. The minimum MSE score is chosen as the best lag point for each network system.

3.6.6 Step 6: Training Method

Step 6 requires the selection of training methods including the number of training iterations, learning rate, and momentum. The objective of training is to find the set of optimal weights between the neurons that determine the global minimum of the cost or error function with lesser computational power. Unless the model is habituated for the local observation or over fitting, this set of weights should provide good generalization ability to be applied to the situation outside the sample data (Ruxanda and Badea, 2014). The superior training methods are Scaled Conjugate Gradient descent, Gradient descent with momentum, Levenberg-Marquardt, Newton technique, and Bayesians regularization method.

The performance of these training methods is advised for differing situations. For example Newton method is mostly used in scientific research while Bayesians regularization method is efficient on huge data sets like weather forecasting. The BR (Bayesians regularization) takes huge amount of time to produce results. Due to these reasons, we select the Levenberg-Marquardt (LM) method of training the network as most of the stock market research utilizes the back propagation architecture along LM method (Burney et al., 2005). Furthermore, the LM algorithm is acknowledged as an alternative to the ordinary least squares method in computational finance.

This is the most efficient training method as compared to other techniques, requiring lesser time to minimize the error between actual and predicted values and also need minimum computational power but more storage space (Hagan and Menhaj, 1994). It is known as the damped least square equation and is used to solve the nonlinear problems in finance. The method is also considered as the best curve fitting tool in financial analysis and is a robust method of calculating the minimum error in forecasting studies. A comparative analysis of results is provided with Bayesians regularization method and applicable to FF5F model only.

There are two schools of thought regarding the point at which training should be held. The first stresses the danger of getting trapped in a local minimum and the difficulty of reaching a global minimum. The second view advocates a series of train-test interruptions. Training is stopped after a predetermined number of iterations, the network's ability to generalize on the testing set is evaluated, and training is resumed. We use the second approach and set the maximum iterations limit at 1000.

3.6.7 Step 7: Instruction Scheme for MatLab

In step 7, we compile the schemes of instructions for the MATLAB program. The first set of instructions estimates the relationship between the dependent variable (actual or the monthly target returns) and the returns (outputs) produced by the neural network system. This relationship is described as the R-value (regression value) in the ANN setup. If the R-value is substantial, then MSE value is much smaller than the mean target variance. This indicates that the neural network has successfully managed to model most of the variations in the input-output transformation. An R-value of 1 or 100% shows a close dependence while an R-value of 0 means poor or random relationship.

The second set of instructions in Matlab calculates the minimum error between the actual and predicted portfolio returns by 16 data sets and 1-50 neurons. This program is based on simple step ahead observation reading scheme and generates 800 results for a single portfolio. The third program processes the data generated by the second code in the form of a graph to arrive at the optimal number of neurons and the best data set. The decision on various parameters of the neural networks is a matter of the intuition of the researcher or the trial and error method of data combination. Once a model is selected and trained on the training data set, its performance is evaluated by the testing data set since the network model is biased towards the training data and this creates the problem of over-fitting the data.

When the error terms for the validation and testing data sets have wide variations, the model is considered to be overfitting and is of little use for an investment purpose (Hall, 1994; Rechenthin, 2014). The fourth program is based on the rolling window scheme; a widely used technique used in investments analysis and forecasting studies. Under the rolling window scheme, the program reads the first 48 monthly observations of all the five input variables; forecasts its portfolio returns and compares it with the target portfolio returns in the output layer. In the second reading, the program ignores the first observation and takes another group of 48 observations and vice versa. The purpose of this step is to evaluate the in-sample and out-sample accuracy and the difference between the actual and forecasted portfolio returns by the network system.

3.6.8 Step 8

In step 8, the required MATLAB programs are designed, and the computational power is applied to compile the desired results for analysis.

Chapter 4

Data Analysis and Results

4.1 Descriptive Analysis of Portfolio Returns

Descriptive analysis of the data set is carried out to take a preliminary suggestion of the nature of the research data. These include the plots of the data in terms of time, histograms, and measures of central tendency and distribution. We present the distribution of the normalized monthly portfolio returns for the high, mid and low beta portfolios in Figure 4.1, 4.2 and 4.3. A program in MATLAB conducts the normalization. The analysis of these Figures shows that the returns of the KSE-100 demonstrate wide variations in terms of positive and negative signs. Table 4.1, 4.2 and 4.3 shows the descriptive statistics of the high, mid and low beta portfolios.

The average mean of high beta portfolios is 0.21% with a range of 0.38% - 0.07% while the average standard deviation of this group is 0.0832. The average minimum and maximum returns of the group are -47.49% and 21.80%. The distribution of the returns shows that 60% of the values are falling on the left side of the mean, while 40% values fall on the right side of the mean value. Table 4.1 (Annexure B) presents these statistics, and it further shows that the average kurtosis and Skewness of this series is 6.2408 and -1.2788 respectively.

Figure 4.1 presents the data in graphical form. It shows that the monthly returns fluctuate widely in some years but stabilizes in the few years. The average mean

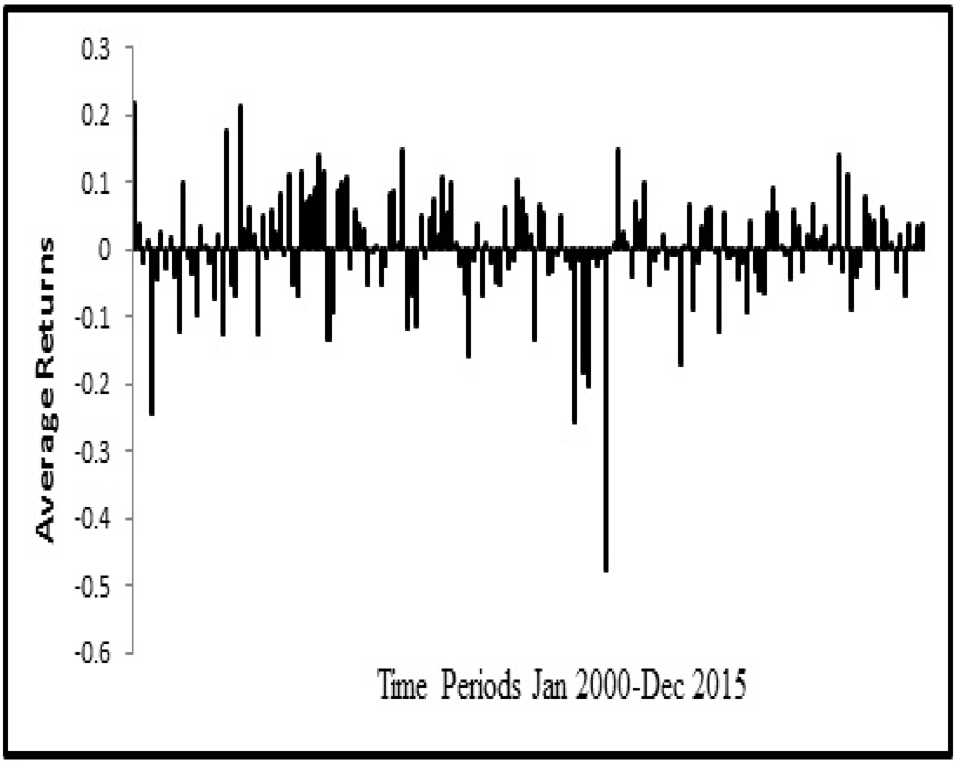

FIGURE 4.1: Distribution of Monthly Returns (High Beta Portfolios).

of the medium beta portfolios is 0.23%. The mean values are falling in the range of 0.28% - 0.11% showing low fluctuation as compared to the high beta portfolios. The minimum and maximum values of the monthly returns are -49.60% and 26.51% while the standard deviation of the series is 0.0912 (Table 4.2, Annexure B). The average kurtosis and Skewness is 4.6572 and -.8550 respectively.

Figure 4.2 is the graphical representation of this group and shows a comparatively stable picture of the monthly returns of the medium beta portfolios.

Table 4.3 (Annexure B) shows that the low beta portfolios are showing an average mean of 0.52% with a range of 0.67% - 0.40%. The maximum returns of this series are 35.36%, and the minimum returns are 26.49%.These values show that the low-risk portfolios are returning low compensation to the investors as compared to the other two groups of portfolios. The average standard deviation and kurtosis are 0.0928 and 1.582 respectively, while the Skewness is -0.2291. These statistics show that the returns data of the low beta portfolios show more normality than the other two series of data.

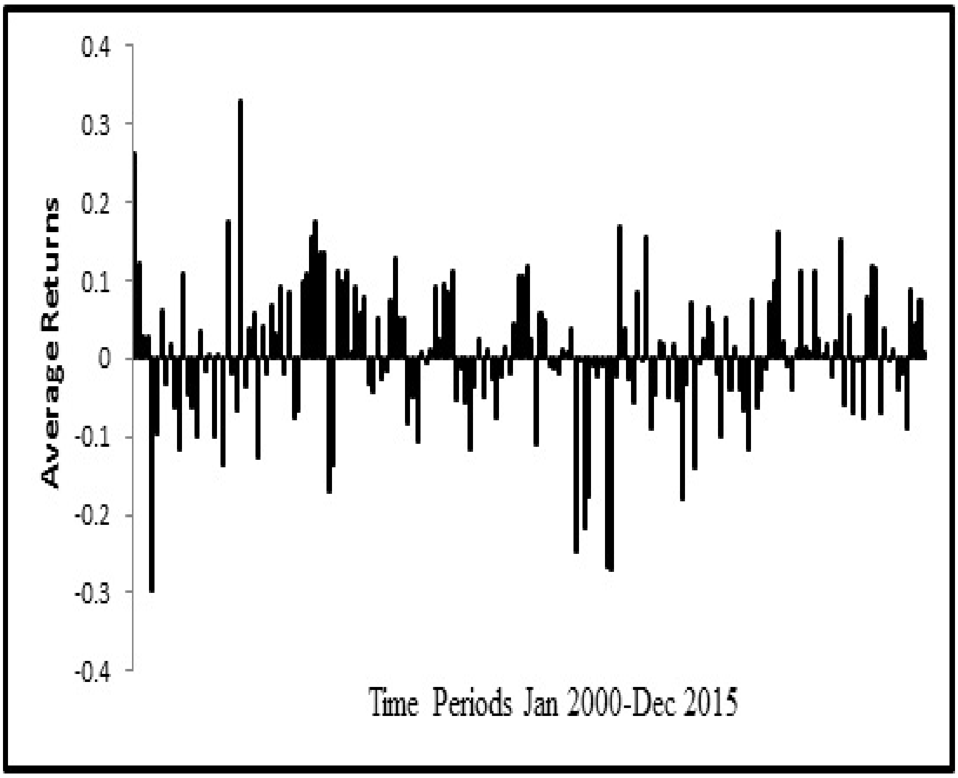

Figure 4.2: Distribution of Monthly Returns (Mid Beta Portfolios).

Figure 4.3 is the graph of the monthly returns of the low beta portfolios and presents a stable situation of the returns. The last few years have witnessed more promising and stable returns for the investors and the periods of the negative values are less as compared to positive returns values.

4.2 An Overview of the Results and Analysis

The experimentation by the criteria mentioned in the implementation section of chapter three generated a total of 800 forecasted results for a single portfolio based on the 16 combinations of Data set and 50 neurons. Each model utilized 180 monthly returns for the 30 portfolios with one time step. This shows that the ANN program used the first 179 monthly returns to predict one-month ahead returns.

In this way, the network predicted fifty values for one combination of the data set, and the difference between the anticipated returns and realized returns is estimated in the form of mean squared error. Initially, the models display only

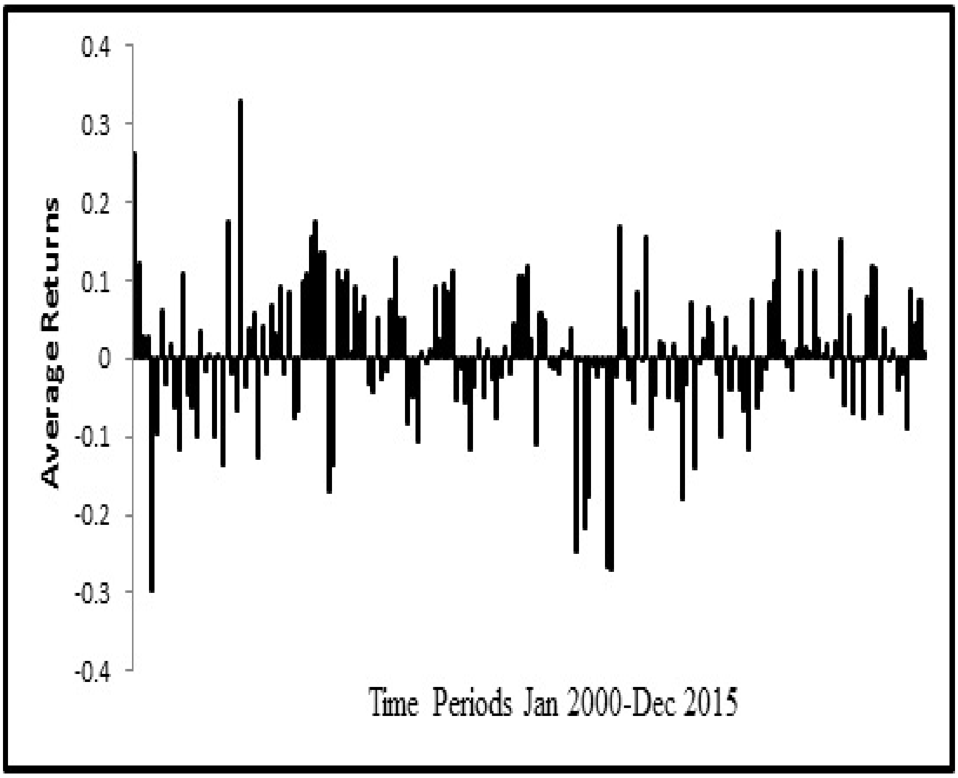

FIGURE 4.3: Distribution of Monthly Returns (Low Beta Portfolios).

the best results for all the three performance measures. The experimentation has been designed in such a way that the system displays the best MSE results as an average of training, validation, and testing. The experimentation produced a total of 24000 models for CAPM, Fama and French three factors and Fama and French five factors models each: totaling 72000 neural networks models with different parameters.

4.2.1 Performance Analysis: Asset Pricing Models and Neural Network System

A histogram of the performance of all the three asset pricing models is exhibited in Figure 4.4. This Figure represents the performance of various factors of the three asset pricing models in the neural networks and is based on the lowest MSE score predicted for each model, for all the 24000 network architectures. The analysis of the systems on market risk shows that the lowest score of MSE is ranging from 0.38% to 0.99%. This range of MSE results is produced by a total of 11578 models out of 24000 networks while the MSE score of all other network models is beyond our threshold score. The CAPM-based networks models have predicted 48% of the periods of the target returns accurately.

The lowest MSE score of 0.38% is produced by portfolio 15 at 75-05-20 data set. The ANN response on this portfolio is maximum as 378 NN models have produced MSE score of 0.38% to 0.484%. Similarly portfolio 14 has responded favorably generated o the NN system generating a minimum error of 0.484% and maximum of 0.53%. The constituent portfolios of mid beta class including portfolio 11-15 have responded favorably to the NN system while portfolio 16-20 falls in the unfavorable results range. The low beta portfolio i.e. portfolios 21-30 have generated MSE score of 17.8% to 469.5%. This shows that low beta portfolios have low chances of accurate prediction in ANN. This finding is in line with the investment convention that low risk stocks returns low returns.

The neural networks system based on FF3C model returned 94% periods accurately for the monthly returns and the range for the MSE score is lying from 0.22% to 0.99%. 22560 network models produce this range of MSE results, which means that the three factors CAPM has predicted 94% time intervals accurately. Low beta portfolio have responded well to FF3C model. The lowest MSE score of 0.22% is produced by portfolio 30. The High beta and low beta portfolios have generated favorable results while the mid beta portfolios generated high MSE score. This means that mid beta portfolios have poor chances of meaningful forecasting with ANN and the three factors of FF3C model.

The five factors model predicted actual returns for 98% of the time periods correctly, and the MSE range of the results is between 0.10% to and 0.99%. The high beta portfolios have registered the lowest score of 0.10% along with portfolio 30 and 14. Portfolio 9 and 11 have generated poor results only. All other classes of portfolios have better chances of successful prediction in case of FF5F model. It is important to mention here that the reported errors, presented in this section, represent the individual portfolios only while the analysis in the coming section has utilized the averages of the high, mid and low beta portfolios with all the 16 data sets in a group form.

These results imply three conclusions; firstly, the neural network system provides closer results to the actual values and can be employed for prediction purpose in stock markets. This result is in line with the conclusion of Idowu et al. (2012). Secondly, the performance of the Neural Networks in the presence of some financial variables is a matter of experimentation, and generally, it increases with the addition of more input variables. This finding is in line with the Coupelon (2007). Thirdly the addition of innovative factors in the asset pricing models provides a better picture of the predicted values of the portfolio returns.

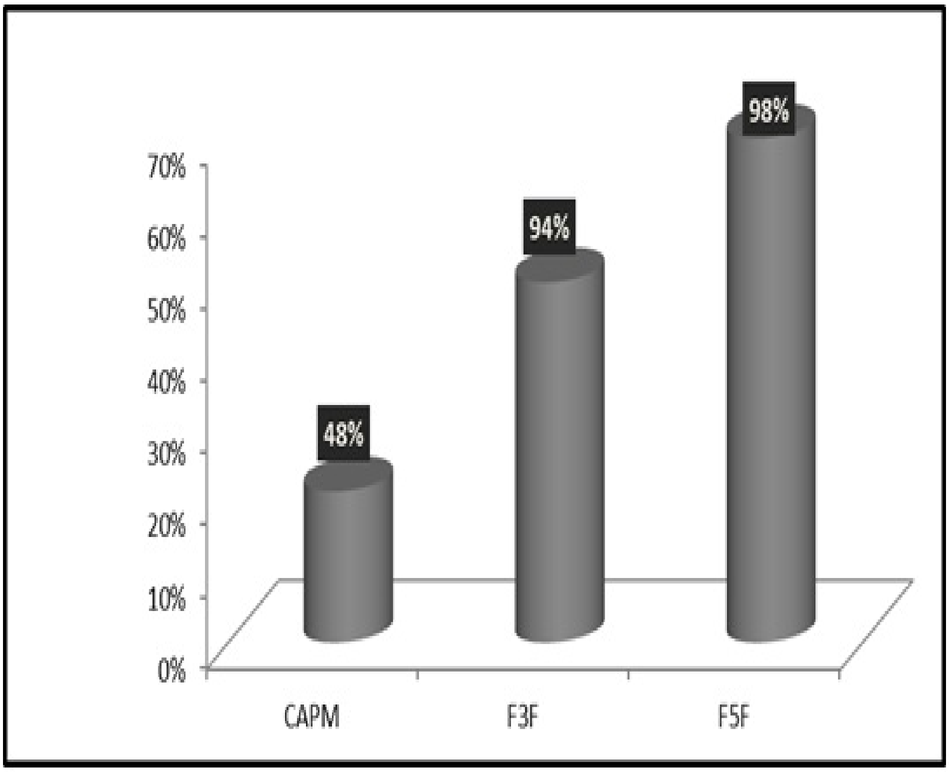

FIGURE 4.4: Histogram of Input Variables Performance.

This is a significant finding of the present research which will enable the investors to earn an above the market rate of returns on their portfolio investment.

4.2.2 Identification of the Best ANN Design for Asset Pricing Models

Table 4.4 (Annexure B) represents the results of the Neural Network models of all the data sets based on CAPM factor. The data sets are distributed among training, validation, and testing and processed through neurons ranging from 1-50. Table 4.4 shows that the MSE results for the data sets 60-20-20, 65-15-20, 65-20-15, 70-15-15, 70-10-20, and 70-20-10, are almost identical: ranging from 0.63% to 77.3% for the whole range of neurons. These are the average MSE scores for all the thirty portfolios. The MSE score for the data set 75-10-15, 75-15-10, 80-15-05 and 75-20-05, are identical and falling in between 0.64% to 77% for all the neurons of the models. The errors reported by other data sets, i.e., 80-10-10, 85-05-10, 85-10-05 and 90-05-05 are ranging from 0.66% to 77.4%.

The forecasting results of the Fama and French three factors model are presented in Table 4.5 (Annexure B). The same procedure has been implemented for processing the market returns, size, and value factors as inputs for a neural network system and monthly returns as the output for all the thirty portfolios. The analysis of this Table shows that the data sets 65-15-20, 70-15-15, and 75-20-05 have reported similar results, producing the MSE score in the range of 0.51% to 15.88%. The data sets of 75-10-15, 75-15-10, and 75-20-05 come out with identical MSE score ranging from 0.53% to 15.9% while other combinations have produced varying results ranging from 0.50% to 16.9%. The search for the best ANN model emulating the size and value factors was conducted through the second processing of the generated data, which helped us to identify the best neural network model.

The predictive ability of the five factors CAPM and artificial neural networks is shown in Table 4.6. The results show a marked improvement in the forecasting performance of the portfolio returns. The response of the networks models as a result of the increased factors has improved, and the analysis of Table 4.6 (Annexure B) indicates that the data sets 60-2-20, 65-15-20, 70-20-10, 70-15-15 and 75-20-05 have estimated the forecasted returns identically. Other combinations of data sets have generated varying results in terms of mean squared error. The MSE range for the data as mentioned above is between 0.35%-0.64%. The MSE scores for other combinations are in the span of 0.37% to 0.80%.

The original programming in MATLAB produced 24000 results for each asset pricing model. This high number of generated network architecture made it very complicated to analyze each model separately and come out with the best representative model. Therefore another set of instructions was applied in MATLAB program to identify the optimum models range for all the three asset pricing models. The purpose of this exercise was to search for the best combination of data distribution and model architecture, which should suggest the best neural network models for all the three asset pricing models.

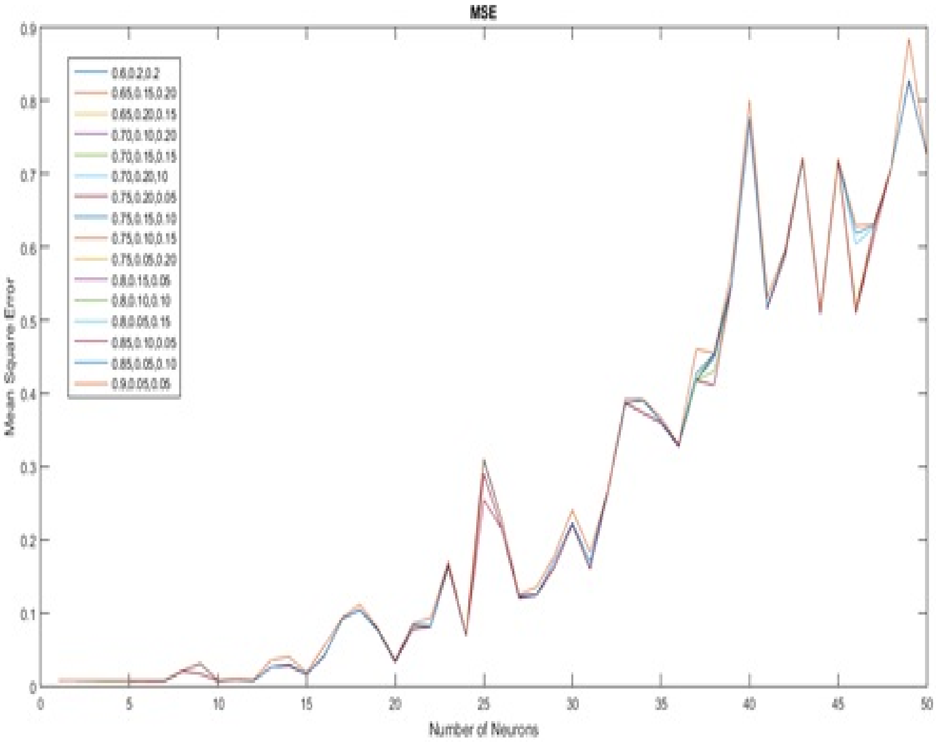

FIGURE 4.5: MSE Results of All datasets under ANN using CAPM.

Figure 4.6 presents the results of this exercise for CAPM. The analysis of Figure 4.6 indicates that almost all the neural network models generated the best results up to 16 neurons all data sets. A thorough search for the best network model in a data management software comes out with the 75-10-15 data set and 16 neurons for the single factor CAPM as the best ANN model. The results of all other models started deteriorating after reaching the threshold number of the optimum neurons.

The generated networks of the three factors CAPM are presented in Figure 4.7. This Figure shows that the size and value factors magnify the performance of the models. Almost all the models have accurately predicted the target returns: the flatness of the curve up to 27 neurons supports the previous findings that the size and value factors can better explain and predict the future returns (Fama and French, 1995). The data set 60-20-20 along with 27 neurons is the best ANN model under FF3C model.

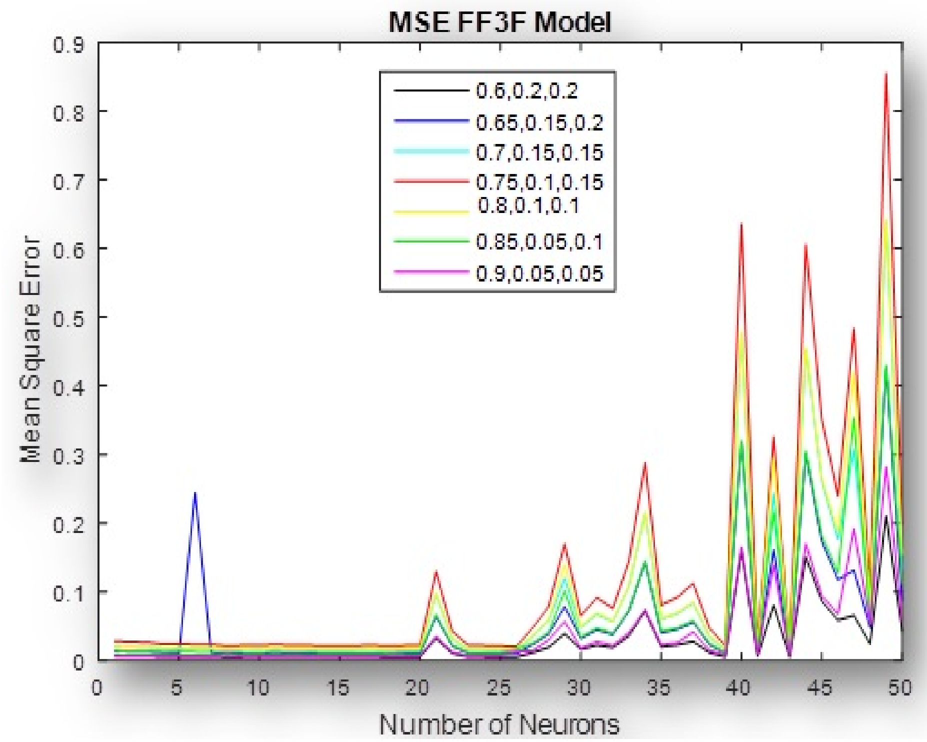

FIGURE 4.6: MSE Results of All datasets under ANN using FF3C Model.

The literature review on ANN suggests that the predictive power of the neural network system increases with the increasing number of independent variables. The comparison of our results with some of those papers identifies an impressive guideline for stock market researchers utilizing ANN. In my view "it is not merely the increase in the number of technical or financial variables that increase the performance of the network, rather the construction of composite indicators like the size and value factors can ensure the maximum accuracy in stock market prediction studies."

Figure 4.8, representing the results of the ANN models using Fama and French five-factor model. This model has produced the most promising results for the time series of returns in terms of mean squared error, and a marked improvement can be noted. All the combinations of the data set have yielded outputs very near to the actual value of portfolio returns except for the 65-15-20 combination.

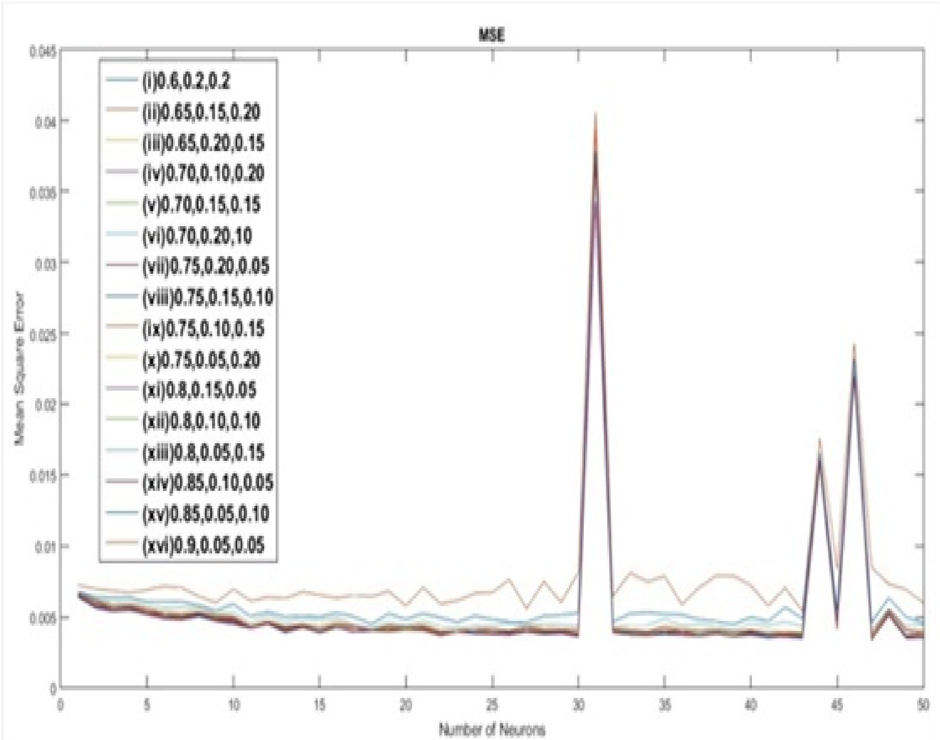

FIGURE 4.7: MSE Results of All datasets under ANN using FF5F Model.

It can be noticed that up to 30 neurons the ANN models decrease the MSE. After it, the systems show instability at intervals to inference the choosing of neurons less than 30. This phenomenon is the standard for all the training, testing and validation combinations in our study. The results for neurons 30, 40 and 50 shows that the neural network system loses control beyond the threshold level for these data combinations. This variation of the system seems to be the black box phenomenon of the neural network system beyond the control of the researchers. The average MSE score of all the data sets is ranging from 0.35% to 0.81% up to 28 neurons.

The analysis yield that the response of the networks models on the composite factors is encouraging. The processing of this level of neurons and the search for the best data combination in a spreadsheet showing that the data set training 75%, validation 20%, and testing 05%, along with 28 neurons is the best neural network model for our sample market. The MSE results of this data combination and number of neurons are optimum.

These results are well in line with Basu and Ashwood (2014) and lead us to two established heuristics about the hidden layer size. First, the optimum number of neurons does not follow some mathematical rule. It is based on the presentiment of the researcher to apply an exhaustive search for the number of optimum neurons, and secondly, there is an inverse relationship between the number of neurons and the performance of the network. The last outcome is well in line with the findings of (Hall, 1994; Swales Jr and Yoon, 1992) which mention that unnecessary use of too many neurons in the hidden layer slows down the performance of the models.

The literature review suggests that the performance of the ANN remain optimal up to ten neurons. The majority of those studies have either used the tailored made software or the toolbox in MATLAB. This software has limited capability to process the extensive experimentation of the neural network system. The magnification of the performance with the increase in the number of neurons is a useful heuristic for the future researchers.

The discussion as mentioned above shows that CAPM is producing minimum forecasting error at a maximum of 16 neurons and 75-10-15 dataset. The FF3C and FF5F models are minimizing the difference between actual and forecasted returns at 27 neurons on 60-20-20 and 28 neurons with the 75-20-05 data set respectively. Our results are backed by the principal findings of (Fadlalla and Amani, 2014).

4.2.3 Goodness of Fit Test and Regression analysis of the CAPM-based ANN

The decision on various parameters of the neural networks is a matter of the intuition of the researcher or the trial and error method of data combination. Once a model is selected and trained on the training data set, its performance is judged by the testing data set since the network model is biased towards the training data and this creates the problem of over-fitting the data. When the error terms for the validation and testing Data sets have wide variations, the model is considered to be overfitting and is of little use for an investment purpose (Rechenthin, 2014). A network that suffers from overfitting is believed to be non-useful (Hall, 1994).

Another important aspect of the appropriateness of a model is the regression value R-value which depicts the relationship between the actual and estimated (target) portfolio returns. The average monthly returns of the high, mid and low Beta portfolios are regressed on the factors of the three asset pricing model. The results of the fitness of CAPM based ANN system are exhibited in Figure 4.9. These tables indicate that the difference between the testing and validation error is subtle and the show an excellent fit of the model for high beta portfolios. This analysis refers to a major theoretical foundation of CAPM that the high-risk stocks have more chances to be predicted accurately with a neural network system. The results of high beta portfolios confirm the finding of (Jabbari and Fathi, 2014).

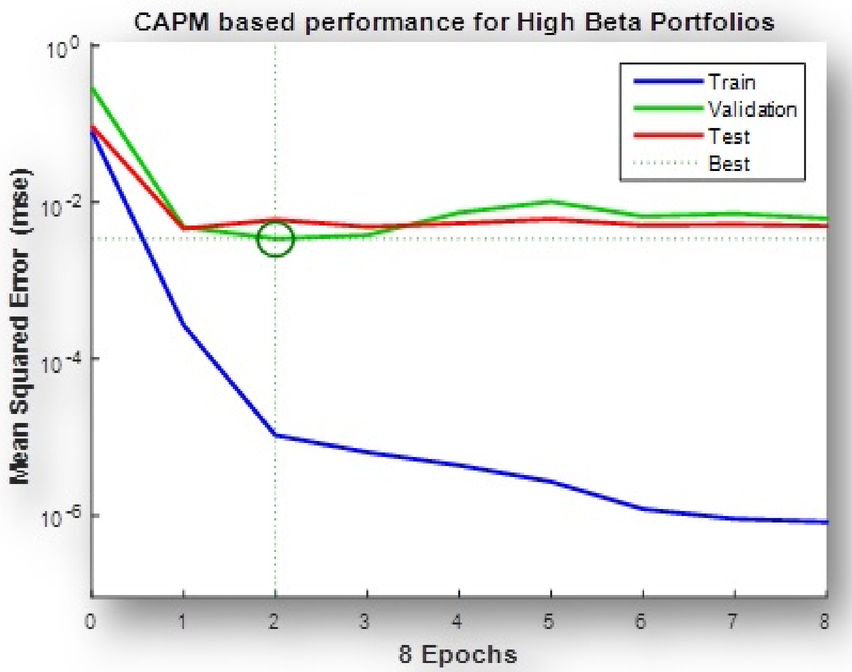

FIGURE 4.8: CAPM Based Performance of High Beta Portfolios.

The results of the mid-Beta portfolio are presented in Figure 4.10 depicting widespread distance between the testing and validation error. The wide gap between the testing and validation data set shows an over-fitting of the network system. This over fitting in terms of the investment analysis means that the predictability of the mid beta portfolios has little chances of being accurate through a neural network system. This description is also confirmed by the regression analysis and other graphs in the coming pages.

The goodness of fit test results of the low beta portfolios presented in Figure 4.11 illustrates that the results are according to the expectations and the resultant distance between the testing and validation data sets is low as compared to the mid beta portfolios. These results are in line with the basic theory of the neural network system which states that the error between the testing and validation data set should be as small as possible. The time taken by the network is longer because the number of calculations is high as compared to the previous two systems.

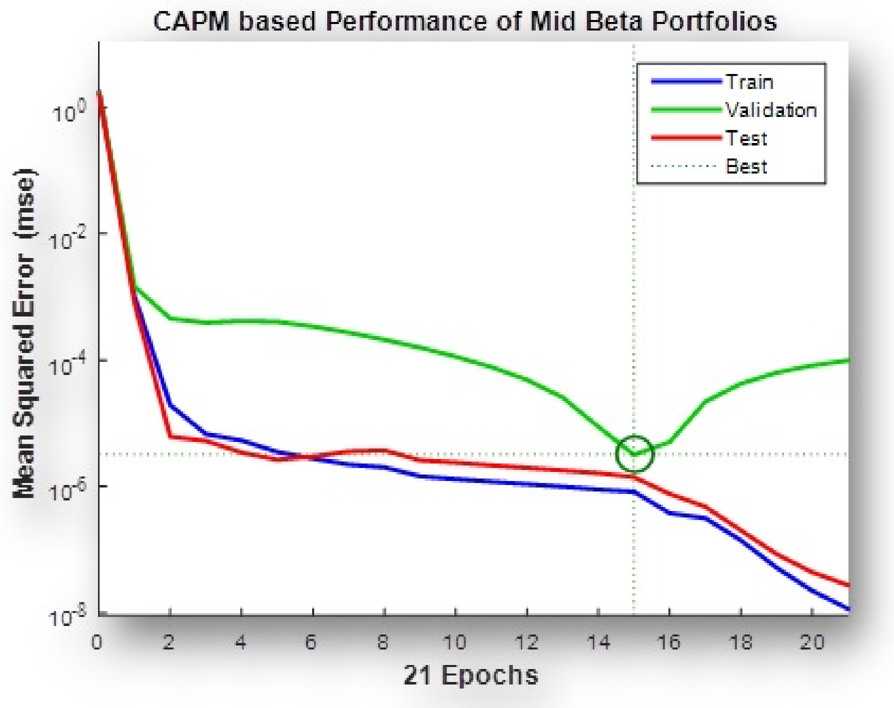

FIGURE 4.9: CAPM based Performance for Mid Beta Portfolios.

The R-value of the regression for the three classes of portfolios is described by Figure 4.12, 4.13, and 4.14. These Figures show that the regression line is lying at 45 degrees demonstrating a perfect relationship between the dependent and independent portfolio returns. The R-value for the high, mid and low beta portfolios is 99.99%, 90.52%, and 99.99% respectively. This also confirms the results

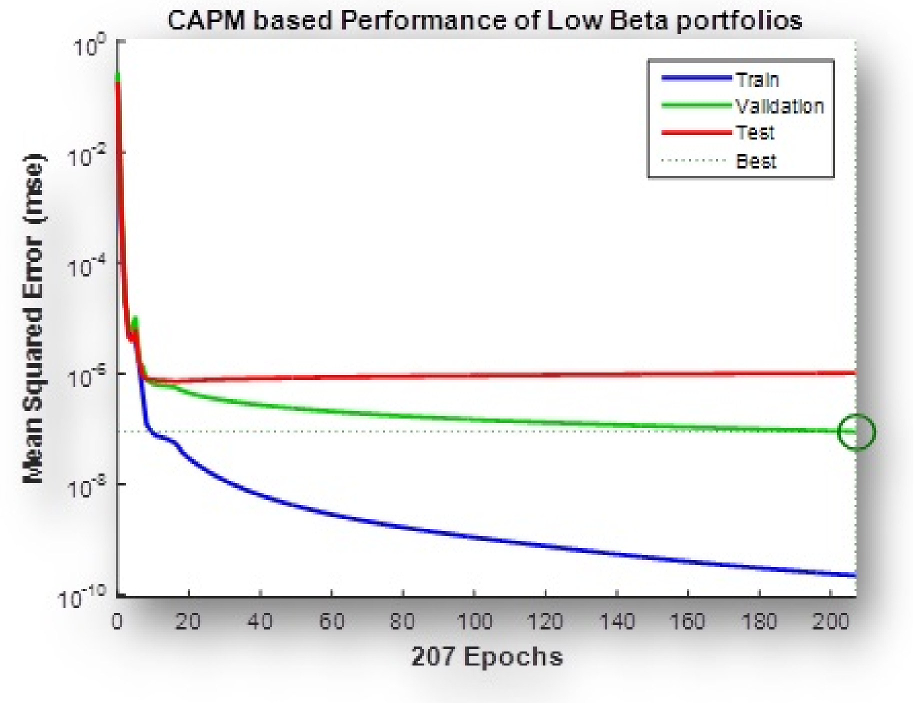

FIGURE 4.10: CAPM based Performance for Low Beta Portfolios.

of the graphs previously discussed and shows the correlation between actual and predicted portfolio returns for the three classes of portfolios.

The overall accurate performance of the ANN in predicting the upward and downward returns enables us to infer that the factors of asset pricing models have performed well in predicting the returns. The use of these established factors, instead of random Company's indicators has more profitable use along with ANN.

One of the theoretical postulations of the CAPM is that the high beta portfolios generate high returns while the low beta portfolios generate low returns. This conclusion has been contradicted by many authors as mentioned in the literature review. Our findings suggest that the use of ANN in the capital asset pricing has successfully verified this theoretical foundation. The high beta portfolios have returned maximum predictability as compared to the mid and low beta portfolios. The corresponding Figures 4.11, 4.12 and 4.13 also validates the theoretical postulation of CAPM. The regression score of the high beta portfolios is better than the mid and low beta portfolios. The regression value of high beta portfolios

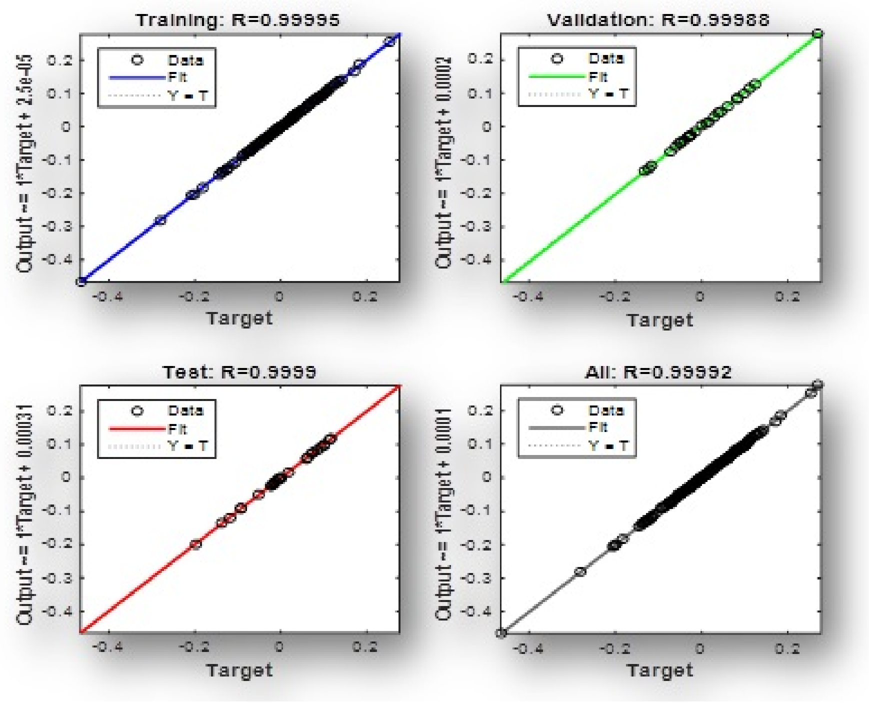

FIGURE 4.11: CAPM based Regression Analysis for High Beta Portfolios.

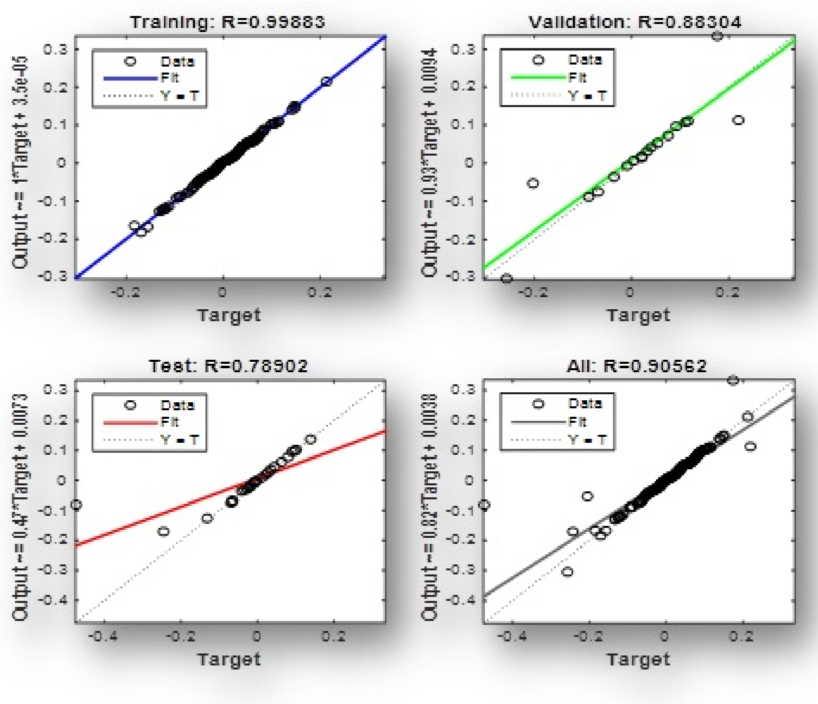

FIGURE 4.12: CAPM based Regression Analysis for Mid Beta Portfolios.

is almost 100% while the same score for mid and low beta portfolios is less than 100%.

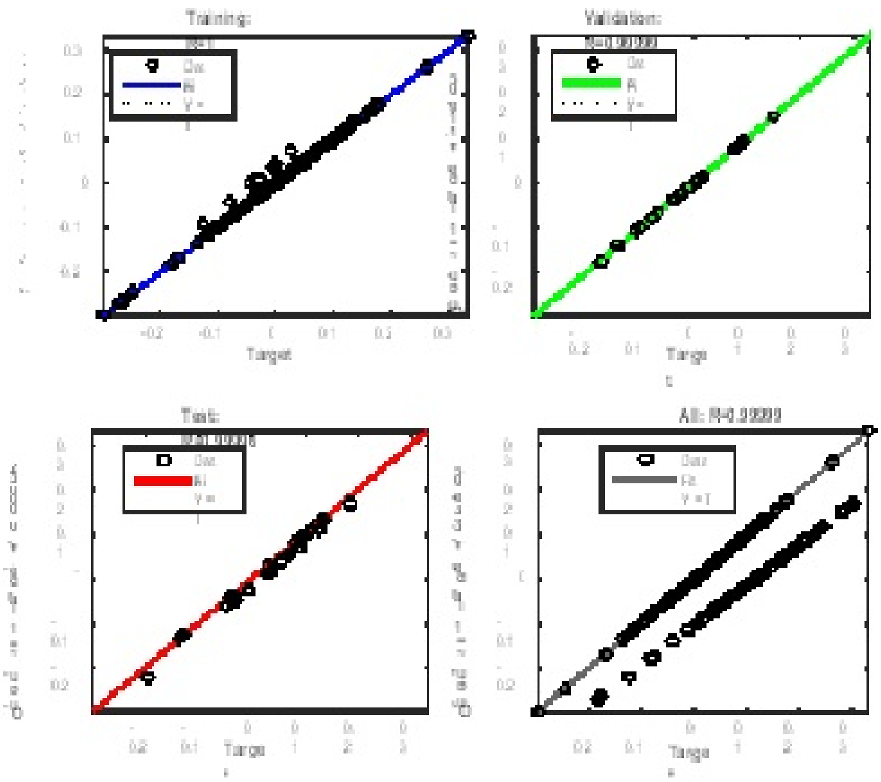

FIGURE 4.13: CAPM based Regression Analysis for Low Beta Portfolio.

4.2.4 Goodness of Fit test and Regression Analysis of ANN-based FF3C model

The three factors Fama and French model incorporates the impact of market premium, size and value to explain the cross-sectional returns of portfolios. These composite have an inbuilt capability to describe the impact of most of the state variables. Therefore, the use of these financial variables in a neural network system, instead of randomly chosen technical or fundamental variables of choice by many researchers, is a pioneering and daring attempt. It is expected to have a notable academic impact and more significant addition to the bottom line of the investment strategies in the emerging and developed markets.

Figure 4.15, 4.16, and 4.17 have been sketched to illustrate the fitness of the independent variables of the market, size and value premium for predicting the

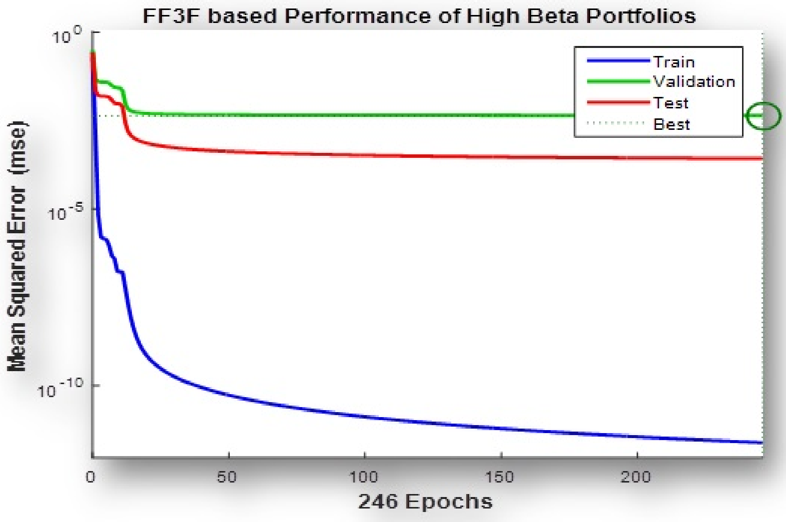

Figure 4.14: CAPM based Performance for Low Beta Portfolios.

dependent variable of the high, mid and low beta portfolio returns. Figure 4.15 shows that the error minimization process has successfully performed on the three factors model and the validation data set has controlled the resultant error continuously on the high beta portfolios. The mid beta portfolios have also responded well to the neural network system, and the training error has shown a gradual decrease (Figure 4.16).

Although the neural network model has performed well on the high and mid beta portfolios, the low beta portfolios have produced a substantial difference in MSE results for validation and testing. The reason for this discrepancy is the low-level riskiness, demonstrating small non linearity in the data set and we arrive at a conclusion that the low-risk stocks or portfolios should use linear approximation function in the neural network system. Figure 4.17 shows this wide variation in the testing and validation errors.

The regression graphs shown in Figures 4.18, 4.19, and 4.20 describe the relationship between the input and output variables for the FF3F model. Figure 4.18 represents the relationship between the dependent and independent variables of

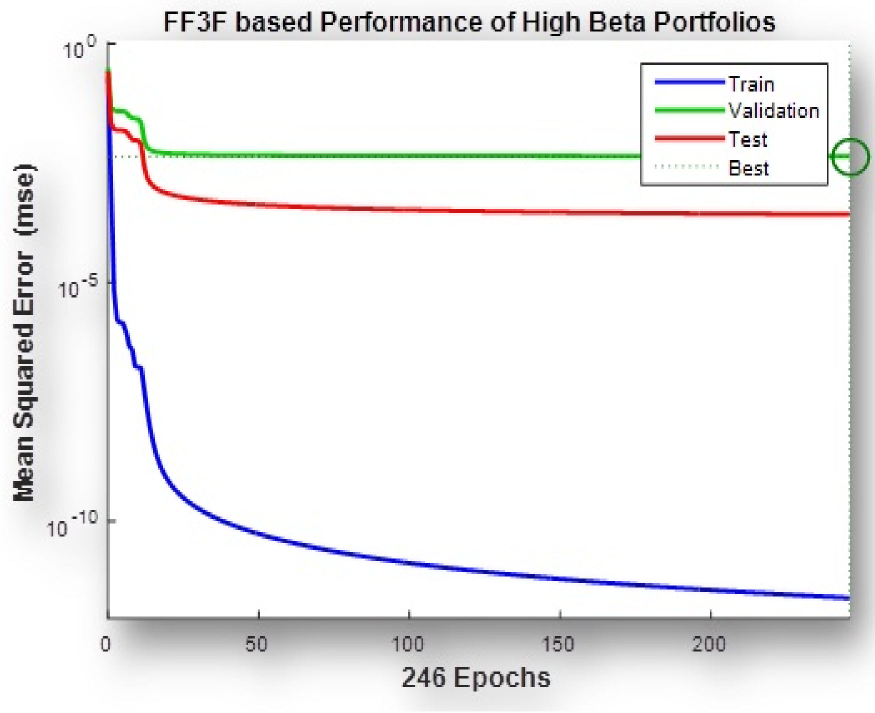

FIGURE 4.15: FF3F based Regression Analysis for Mid Beta Portfolios.

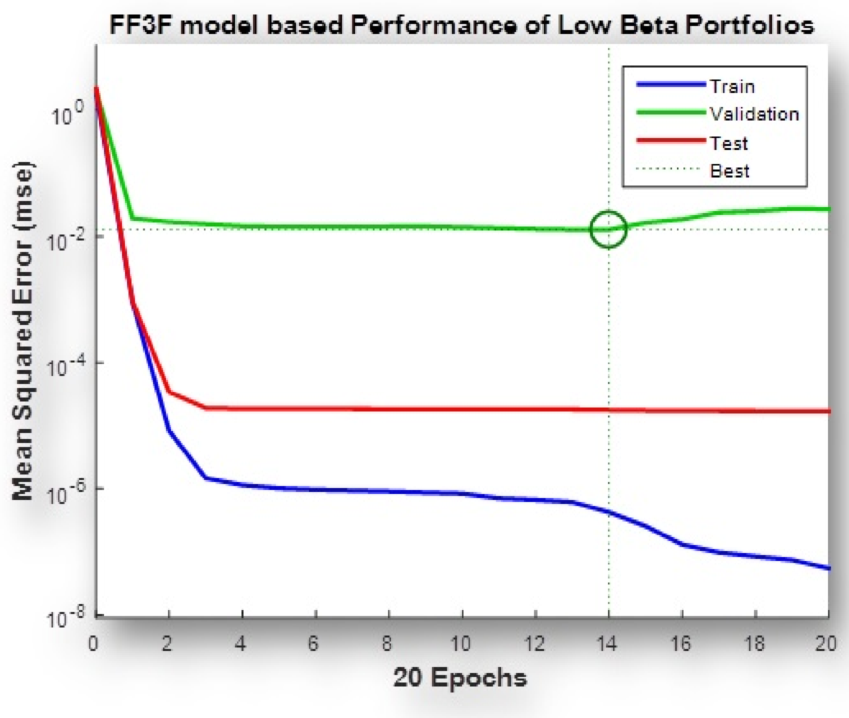

FIGURE 4.16: FF3F based Regression Analysis for Low Beta Portfolios.

the high beta portfolios. This figure shows that the average regression score of the high beta portfolios is 94%, presenting a closer match between the dependent and independent variables.

The mid beta portfolios show a regression score of 89.7% and the validation curve is deviating from the 45% normalcy. Figure 4.19 shows a clustering of the error in the mid beta portfolios. This clustering is pointing towards an unfavorable sign for the low-risk portfolios. The low R-value of 78% for low beta portfolios shows that the NN system is unable to compensate the low-risk portfolios and stocks (Figure 4.20).

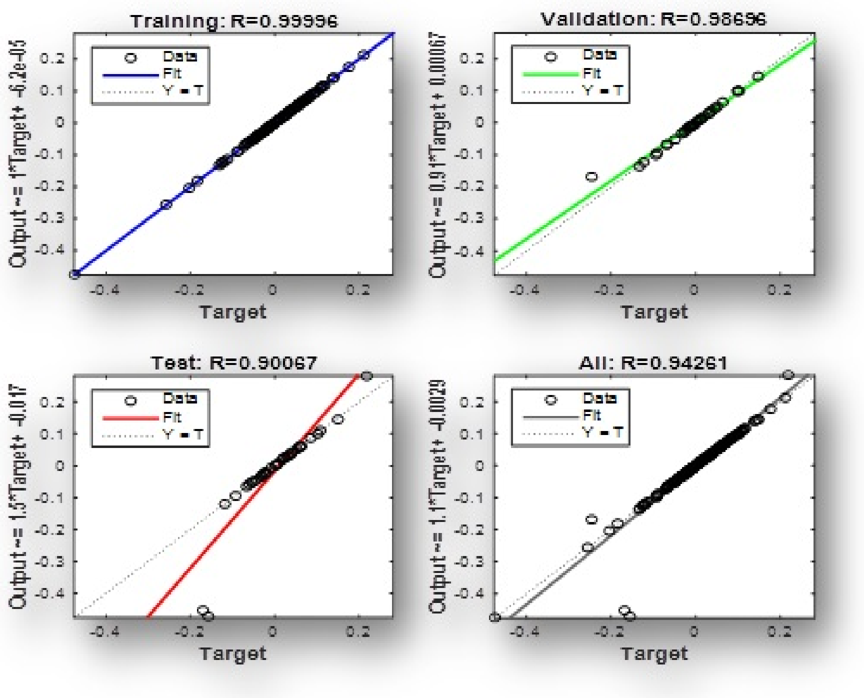

FIGURE 4.17: FF3F based Regression Analysis for High Beta Portfolios.

4.2.5 Goodness of Fit and Regression analysis of ANN-based FF5F model

Some leading market analysts criticize the FF3F model for not offering an adequate explanation for the cross-sectional returns of portfolios. These investigations suggest that the three factors model ignore the capital investment and dividend

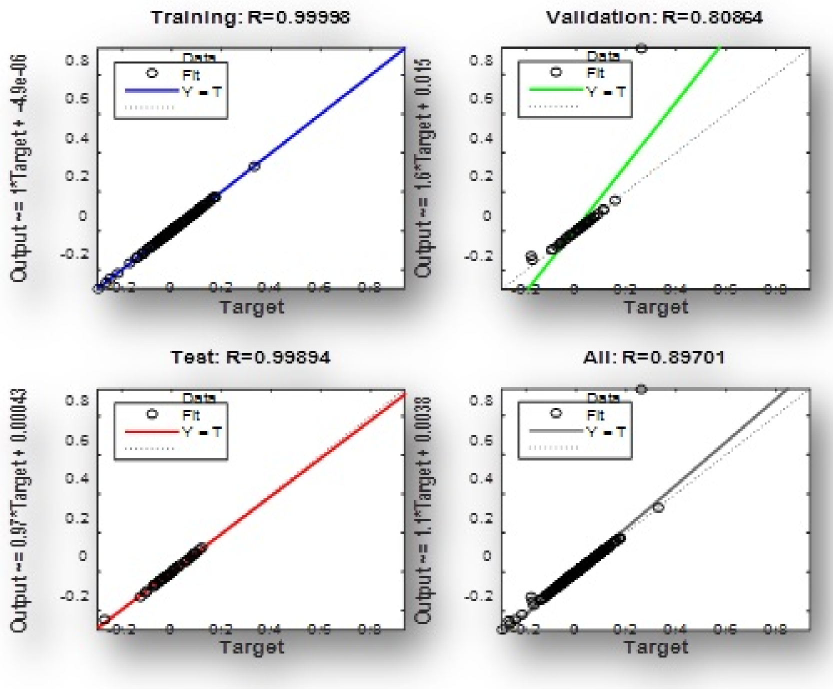

FIGURE 4.18: FF3F based Regression Analysis for Mid Beta Portfolios.

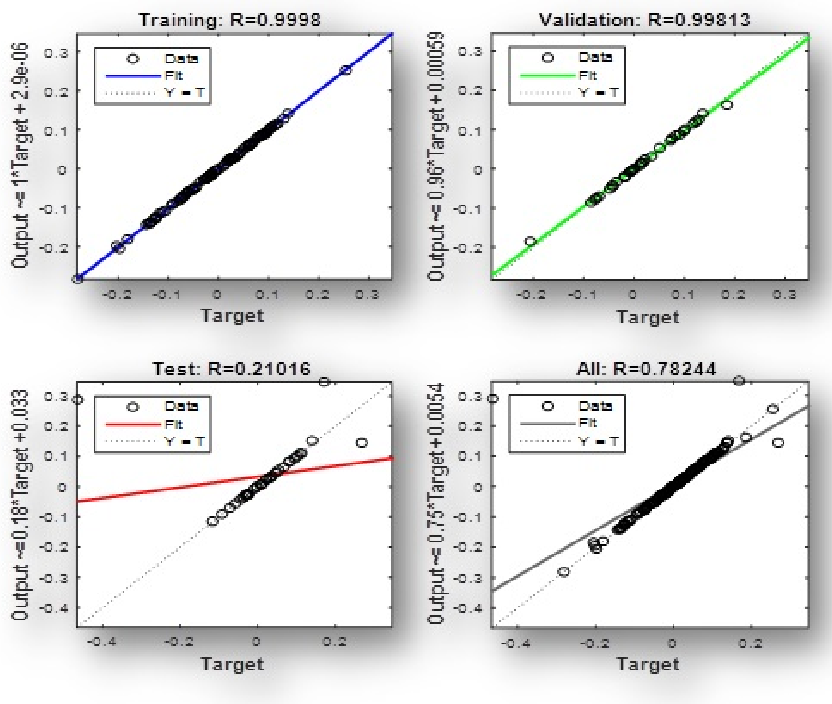

FIGURE 4.19: FF3F based Regression Analysis for Low Beta Portfolios.

aspects of the Companies. This debate on additional anomalies prompted the authors of the three factors model to emulate the profitability and investment parameters in a new paradigm called the FF5F model. The FF5F model attempts to explain the average returns of the portfolios with the size, value, profitability and investment premiums.

The authors of the model have pointed out one drawback of the model related to low average returns on small stocks. According to the authors " The five-factor model's main setback, however, is its failure to capture the low average returns on small stocks whose returns perform like those of firms that invest a lot in spite of low profitability. The model's performance is indifferent to the way its factors are defined (Fama and French, 2015)." As pointed out earlier, the present research is a first ever attempt to test the predictive capability of the traditional asset pricing theories in an emerging equity market like Pakistan.

The initial testing of the FF5F model using ANN is presented in Figure 4.21, 4.22, and 4.23 for high, mid and low beta portfolios. These Figures show that the behavior of the five factors of market premium, size and value premium and profitability and investment premium is very favorable in predicting the portfolio returns. The training error has followed a consistent path of minimization, and the difference of the error between the validation and the testing data set is also at the minimum, which elaborates a good fit of the all the factors with its dependent variable of portfolio returns.

These figures depict a systematic error minimization between the training, testing and validation data sets. The training is according to the nature of the ANN. The distance between the other two data sets is minimum which makes the proposed system under the five factors CAPM well fit for prediction of the portfolio returns. The prediction behavior of the mid beta portfolios is the same as that of the high beta portfolios (Figure 4.22).

Wide variation can be noted in the fitness of the low beta portfolios. The ANN system has shown low performance in predicting the portfolio returns of the low beta portfolios which mean that the investors have lower chances of accurate prediction of returns in the low-risk stocks and portfolios (Figure 4.23). This result comes

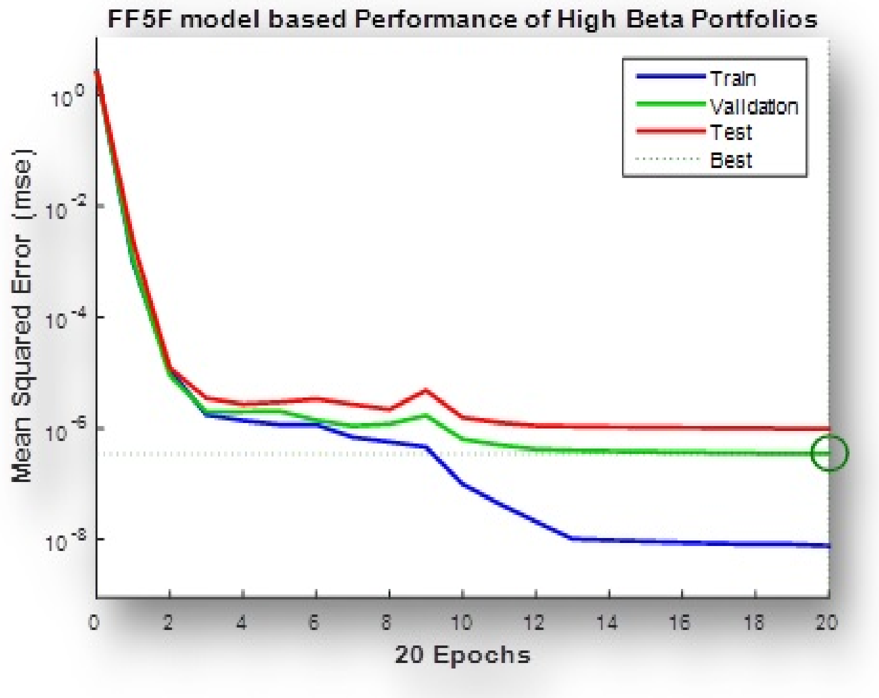

FIGURE 4.20: FF5F based Performance for High Beta Portfolios.

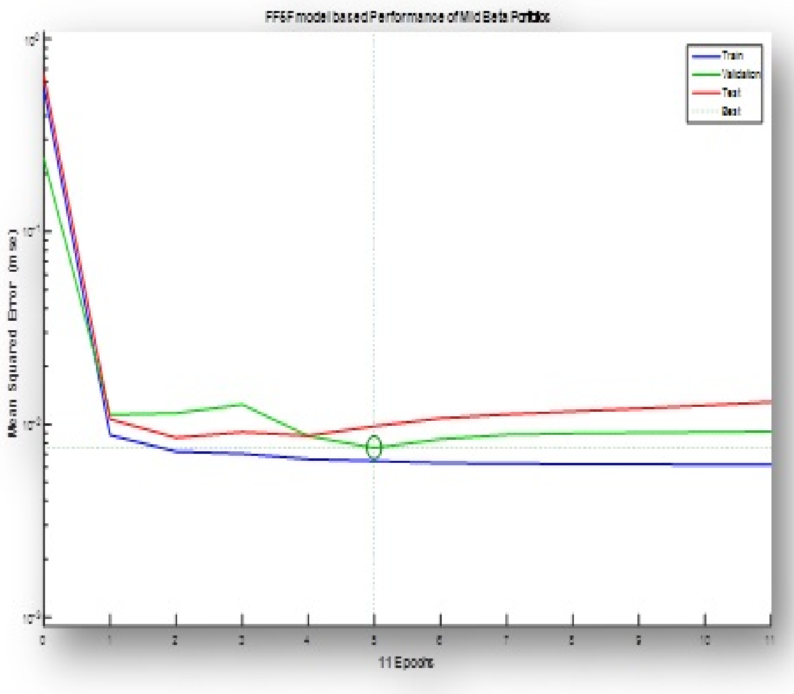

FIGURE 4.21: FF5F based Performance for Mid Beta Portfolios.

out to be a natural verification of the claim of the authors of the FF5F model which says that the average returns of low earning firms are poorly explained by the model (Fama and French, 2015).

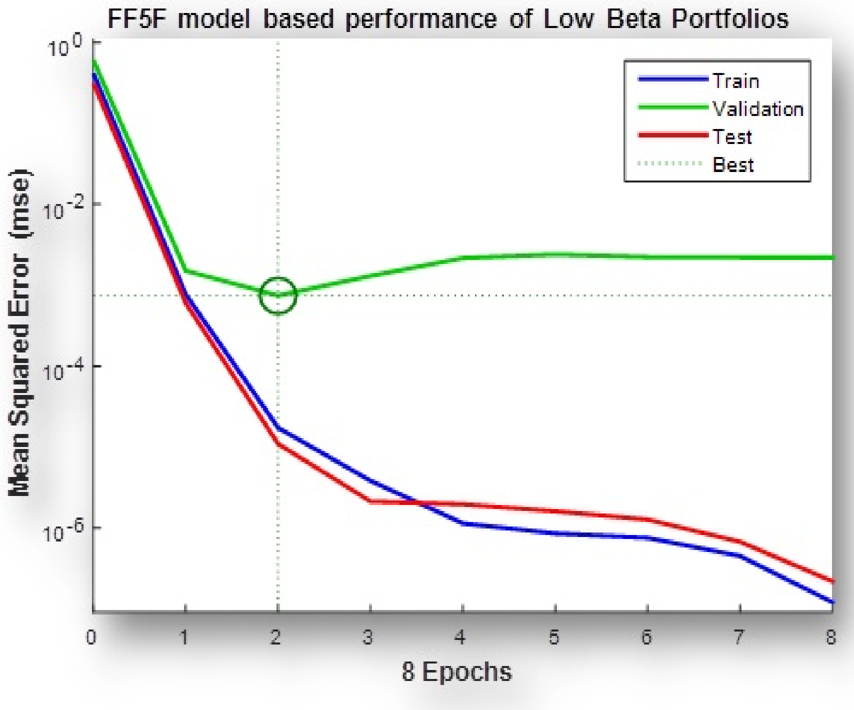

Figure 4.22: FF5F based Performance for Low Beta Portfolios.

The Regression graphs of the five factors CAPM are shown in Figures 4.24. 4.25, and 4.26 for the three classes of portfolios. The regression value of the high and mid beta portfolios comes out to be 100% and all the actual and predicted returns are matching each other at 45 degrees to the regression line. The low beta portfolios have shown only 78% regression value depicting a weak relationship between the actual and forecasted portfolio returns.

4.3 Forecasting and Rolling Windows scheme in Asset Pricing

The results as mentioned above and the subsequent sorting of findings by the spreadsheets software opened a new horizon for processing of the data in another

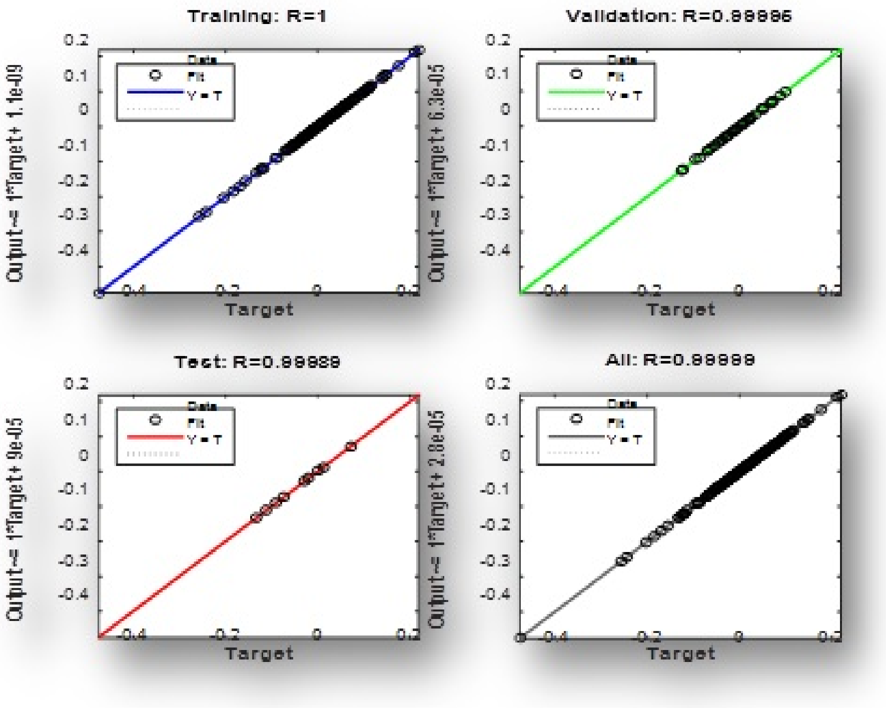

FIGURE 4.23: FF5F based Regression Analysis for High Beta Portfolios).

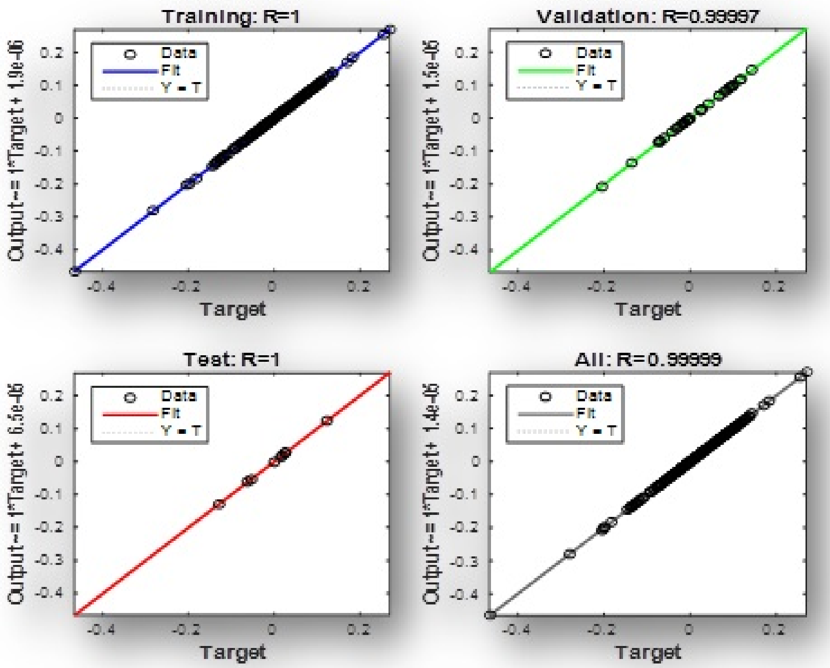

FIGURE 4.24: FF5F based Regression Analysis for Mid Beta Portfolios.

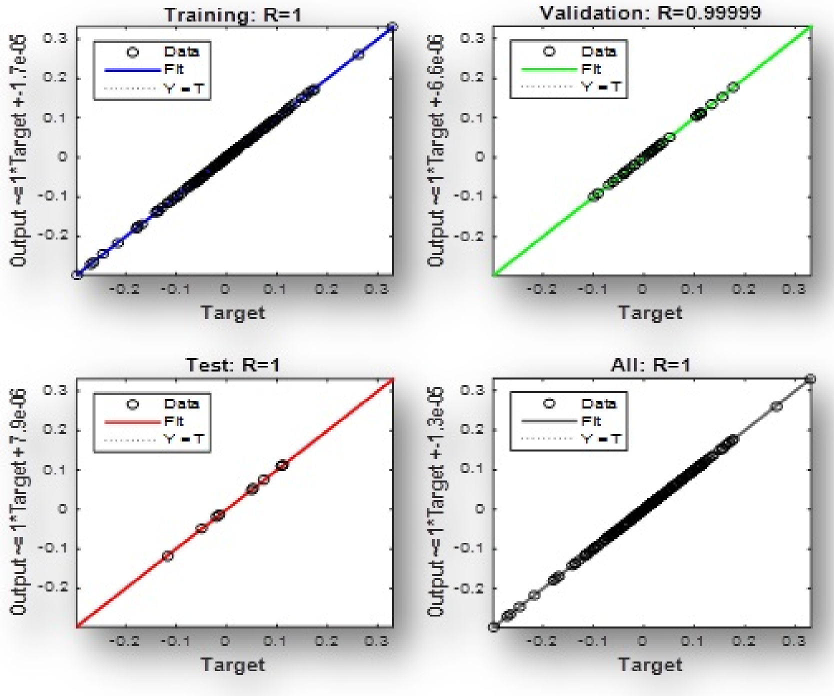

FIGURE 4.25: FF5F based Regression Analysis for Low Beta Portfolios.

MATLAB program. The new program is based on the concept of the rolling schemes in the investment studies. It is believed that this scheme ensures maximum accuracy in forecasting studies. The following criteria have been applied to incorporate the new regime in the remaining analysis of the present study. This strategy is adopted from (Refenes, 1994) and administered to the sample data of portfolio returns to get a close value for the predicted returns. • Under the new scheme of testing and training the network, a rolling approach is applied to the sample data. This rolling scheme has been designed for four years monthly returns. Thus the neural networks take the values of monthly returns of the first 48 months as a training set and predict the 49th value for the monthly returns. The neural network system then takes the next 48 observations (leaving the first value and predicts the 50th value of monthly returns. This scheme of iterations generates a total of 133 values for loss functions of mean squared error. It is appropriate to mention that the program returns the best results only for the three loss functions on an average basis (the average of training, validation, and testing). The rolling of the results on 48 months' returns is the standard for the investment analysis in forecasting of the future values.

• The traditional finance theory suggests that the performance of forecasting techniques is evaluated on the out sample data because the in sample evaluation is of little use for the investors. Therefore, we have designed this new program wherein it returns the best results for the in sample and out sample (training, validation, and testing) separately for the loss function of MSE. This rolling method is adopted from (Inoue et al., 2017).

4.3.1 Analysis of the results based on CAPM under rolling window scheme

This analysis rests on another experiment using the forecasting capacity of the market returns Rm of the CAPM in predicting the returns of the portfolios. The portfolios were divided into three groups, i.e., high, low and mid beta portfolios returns and these returns were regressed against the market risk premium. The purpose was to separate the forecasting characteristics of the market premium on the high to low-risk portfolios. The distribution of the data set among the in sample and out sample observations is critical to the success of regressive as well as neural networks techniques, and these are also presented in the coming sections. The forecasting performance of the neural network system on the actual and forecasted value is an integral analysis of the prediction studies.

4.3.2 Actual vs. Predicted Returns of Portfolio of CAPM based ANN

The performance of Neural networks using the market returns as a factor of CAPM to predict the returns of the portfolios is given in Figures 4.27, 4.28 and 4.29. These Figures are generated by using the returns of the low beta, mid-beta and high beta portfolios as output targets. This input-output relationship is processed in a separate MATLAB program as mentioned previously. The program anticipated the returns for the last 133 months, and the predicted returns were compared with the actual average returns of the corresponding months for the three groups of portfolios. The monthly predicted returns have been converted to the annual returns to get a meaningful picture of the results.

As shown in the Figures 4.27, 4.28 and 4.29, the ANN's generated outputs are closer to the actual returns of high, low and mid beta portfolios. A significant finding is that the neural network system has been able to capture the pattern of portfolio returns moments in Pakistan Stock Exchange, and this technology can be successfully deployed in Pakistan's equity market to predict the future returns, thus enabling the investors to beat the market and earn excess returns in this volatile market.

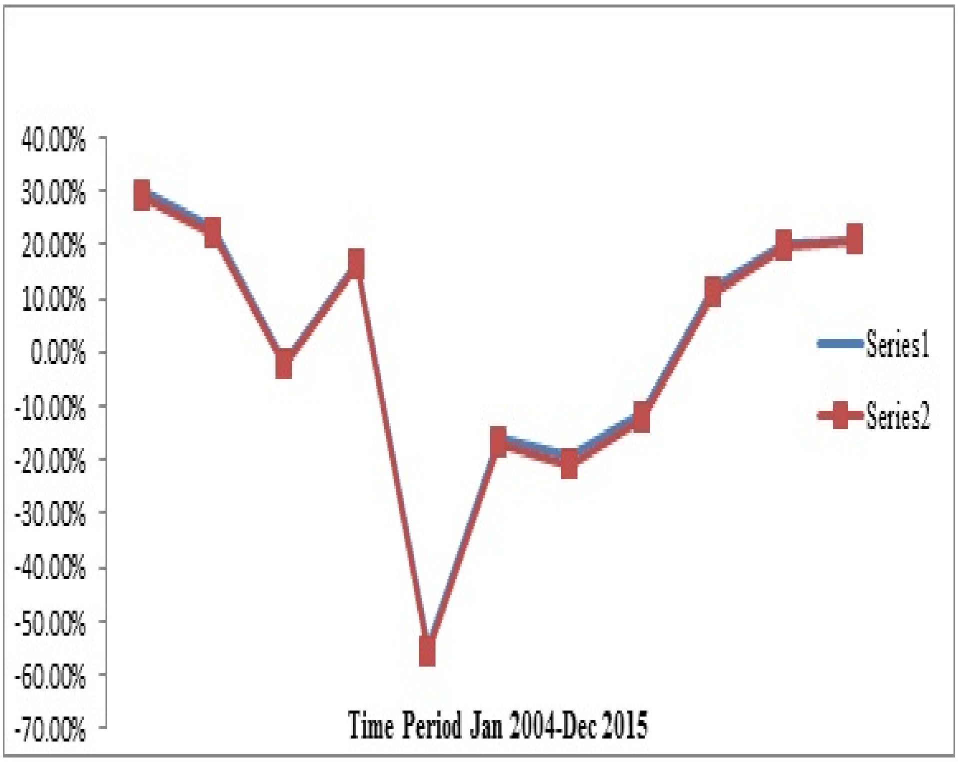

FIGURE 4.26: CAPM Based Actual Vs. Predicted Returns (High Beta Portfolios).

The conclusion from the graphs is reinforced by the data Tables 4.7, 4.8, and 4.9 (Annexure B) which show the MSE scores for each year's returns. The actual annualized returns of the high beta portfolios are ranging from -11.00% to 30.09% and the corresponding range of the predicted values of portfolio returns is -12.07% to 29.10% (Table 4.7). These results are obtained from the optimal data set

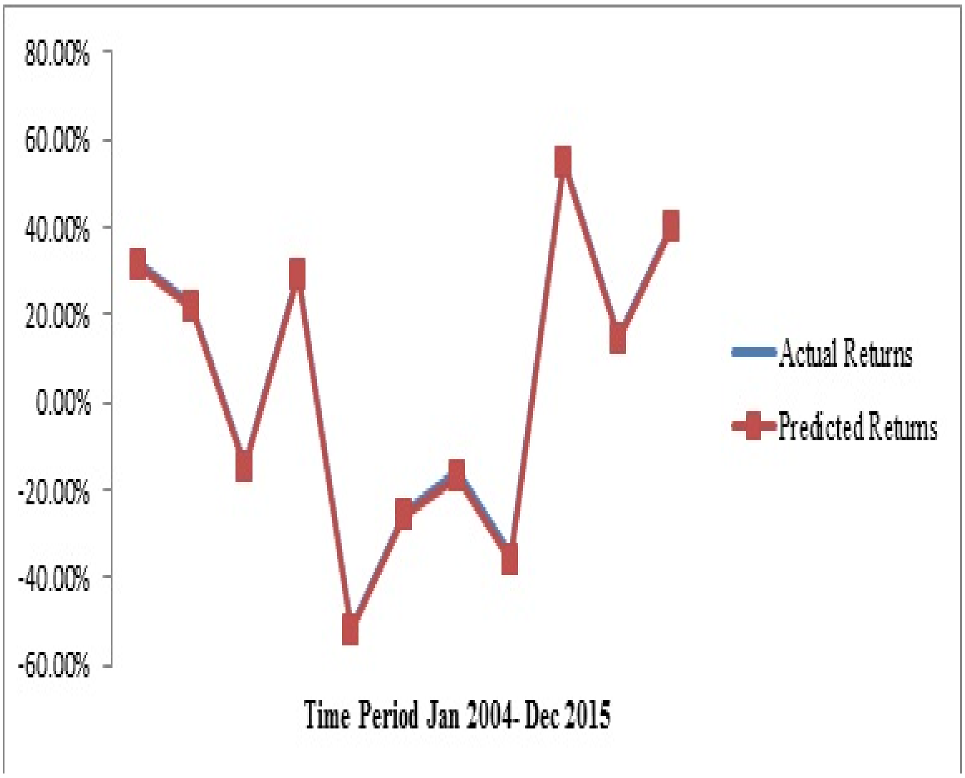

FIGURE 4.27: CAPM Based Actual Vs. Predicted Returns (Mid Beta Portfolios).

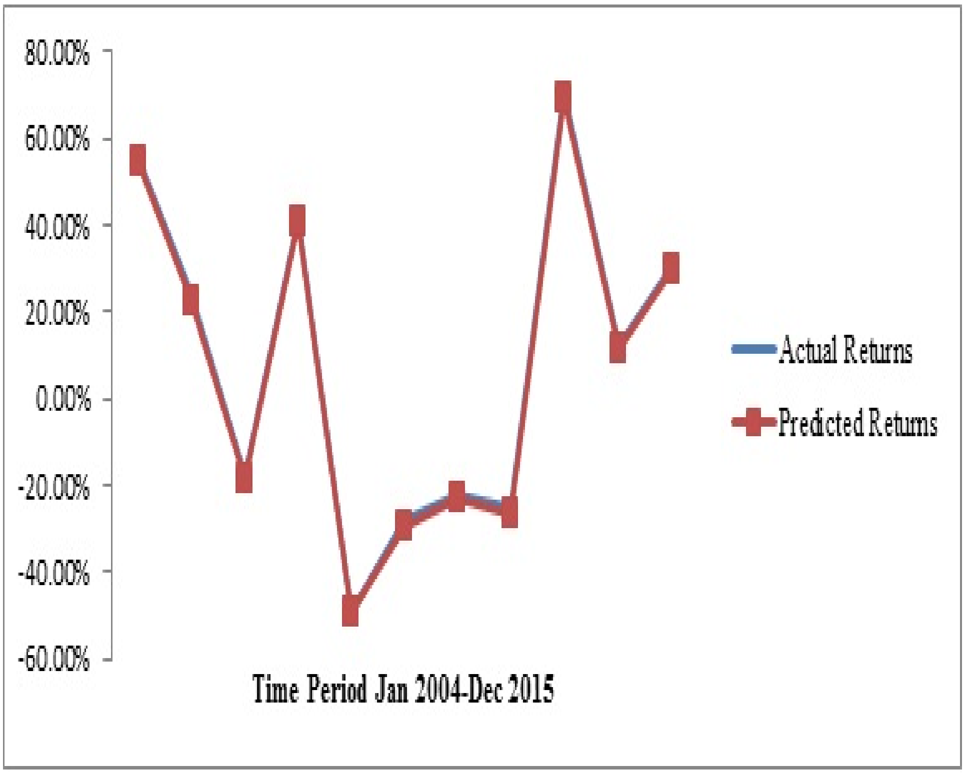

FIGURE 4.28: CAPM Based Actual Vs. Predicted Returns (Low Beta Portfolios).

of 75-15-15 and 16 neurons. The mean squared error is ranging from 0.37% to 01.161%. The neural networks have proved its learning ability by predicting the negative and positive signs of the portfolio returns.

The actual and predicted annualized returns of the mid beta portfolios are shown in Table 4.8. The real and predicted returns are ranging from -51.85% to 55.68% and -52.53% to 54.33%. The data set is 75-15-15, and the optimal number of neurons is 16. The low beta portfolios are in the range of -49.03% to 70.56% and -49.72% to 69.32%.(Table 4.9). These results and findings are in line with (Fadlalla and Amani, 2014; Jasic and Wood, 2004).

An important conclusion of these Tables is that the volatility in the actual and predicted values for high beta portfolios is small as compared to the low and mid beta portfolios. The actual returns of the mid beta and low beta portfolios are highly skewed and show a fat tail. Due to these reasons, the predicted values of low and mid beta portfolios have shown more volatility as compared to high beta portfolios. This conclusion is according to the established finance practices which say that the market assigns higher compensation to highly risky stocks as compared to low-risk portfolios. The results are also in line with (Gokgoz and Sezgin-Alp, 2014).

4.3.3 In sample and Out sample Analysis of CAPM Based Results

This section presents the analysis of in sample and out sample performance of the neural networks on the market risk premium. The econometrics theory and the literature on neural networks suggest that the performance of a testing tool should be assessed on in sample and out sample basis. According to the econometrics theory, the in-sample data is used to estimate the parameters of the model while the out sample data set is used for actual forecasting. The artificial neural networks use the in sample data for training the system which results in the estimation of the network weights while the test set data is used for forecasting. The validation data set serves as a controlling the forecasting accuracy of the ANN. The point at which the validation error starts rising, the network compiles the error results on training and testing (Carvalhal and Ribeiro, 2008).

As mentioned earlier, a rolling horizon is applied with 48 rolling which read the latest returns data into the ANN system. When the network forecasts the next month's returns by this rolling, the training data set slides forward for one period, and this process continues until the whole data set is exhausted by the program. According to the literature when the performance of the neural network is acceptable for in sample data but not favorable on out sample observation, the model has been trapped into local minima. The generalization capability of the model is limited which means that the model is of little practical use.

This concept of in sample and out sample is represented in terms of training, validation and testing results. When the difference of errors on the training set is small but enormous on the testing data set, this means that the model has not performed well and needs to be reprogrammed, or data set needs to be revised.

The MSE results for training, validation, and testing for high beta portfolios are shown in Tables 4.10, 4.11, and 4.12 (Annexure B). The analysis of these results indicates that the MSE score for high beta portfolios is high on the initial rolling but gradually decrease for the training or in sample data set, and the model has successfully reduced the testing or out sample error. The network's learning capability has steadily increased, and the model has not been trapped into local minima. The MSE score for training set is ranging between 0.15% - 1.01%.

This enables us to conclude safely that the neural network system can efficiently train the stock market returns in a volatile market. The performance of the system on test data is even lower than training and validation data sets, and MSE score for the experimental data set is ranging between 0.04% - 0.17%. These results verify the basic theory of ANN which says that the performance of the neural network systems increases when there is high non-linearity in the data set. Pakistan's equity market is considered as the most volatile capital market, and our results are leading us to the inference that the application of ANN in this market can successfully capture the high non-linearity trends in this market which can ultimately beat the passive buy and hold strategy. Tables 4.11 and 4.12 (Annexure B) show that the mid beta and low beta portfolios have shown more variation regarding the forecasting error, but the model has performed in the same way as it did for the high beta portfolios.

These Tables show that the forecasted error for mid beta portfolios on the training set is ranging between 0.35% to 1.87% and the testing error is ranging from 0.04% to 0.05 %. The low beta portfolios generated MSE score of 0.12% to 0.96% for training and 0.05 % to 0.62% for testing. The corresponding Figures 4.31, 4.32, and 4.33 of the three categories of portfolios confirm that the training curve shows an upward trend initially but gradually decreases which indicate that the network designed for this analysis has enabled the system to learn the patterns of the data. Once it is adept in its learning process, it can generalize its parameters to any data set. These findings are according to the theory of the neural network system which says that the learning behavior of the system is a reflection of the human training, and it can adapt to the changing circumstances as humans behave.

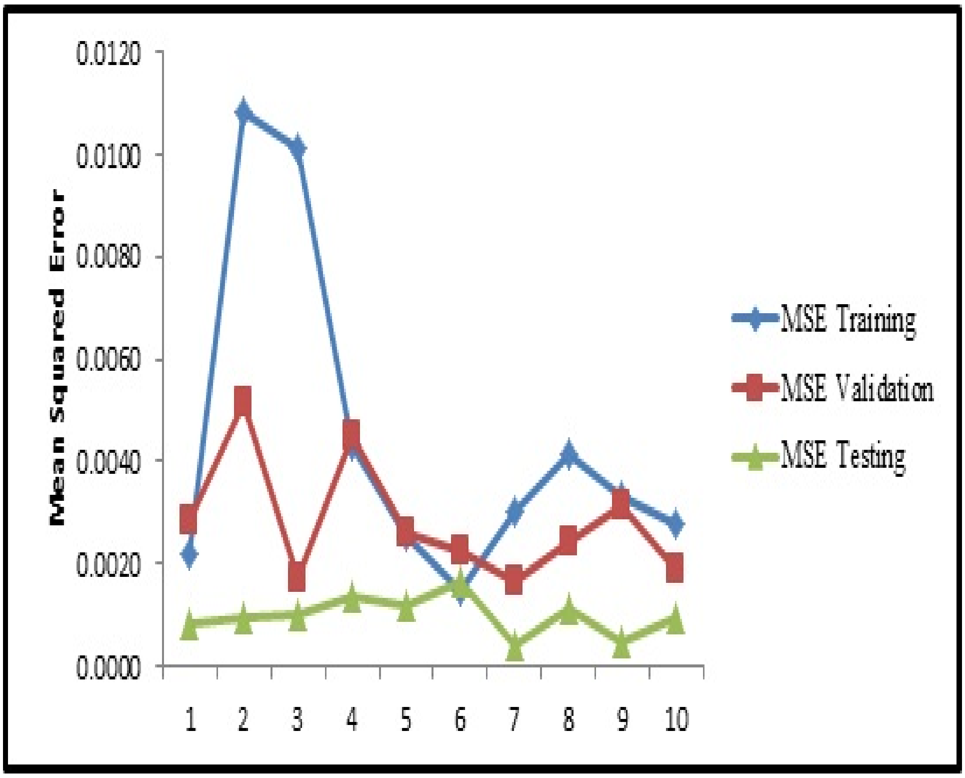

FIGURE 4.29: CAPM In sample and Out sample Results (High Beta Portfolios).

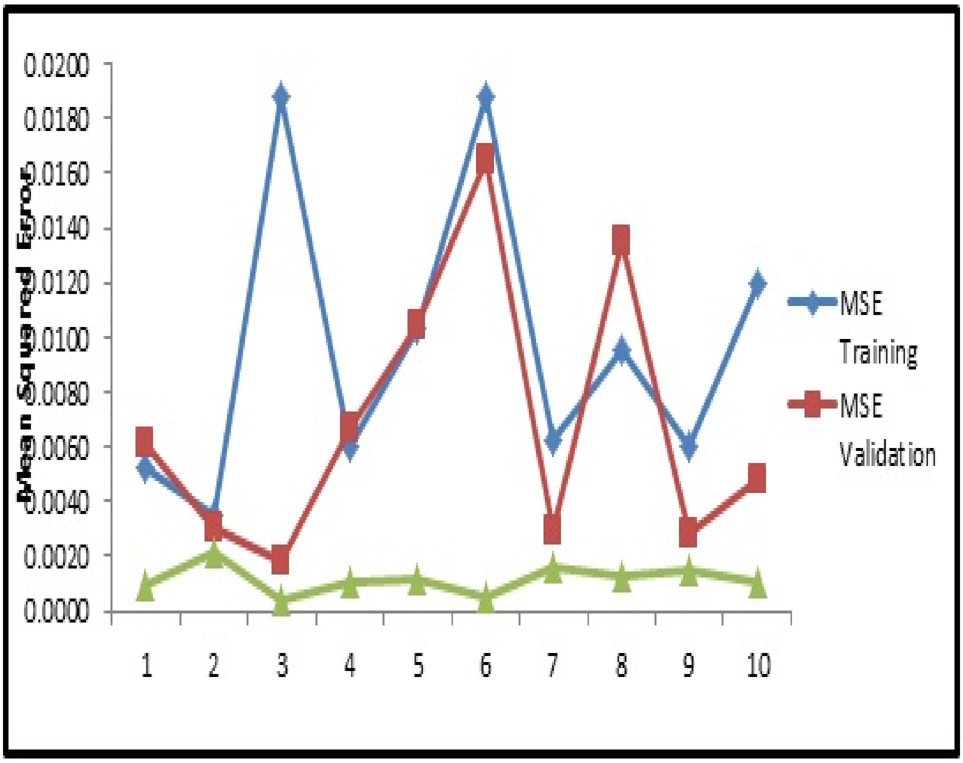

FIGURE 4.30: CAPM In sample and Out sample Results (Mid.Beta Portfolios).

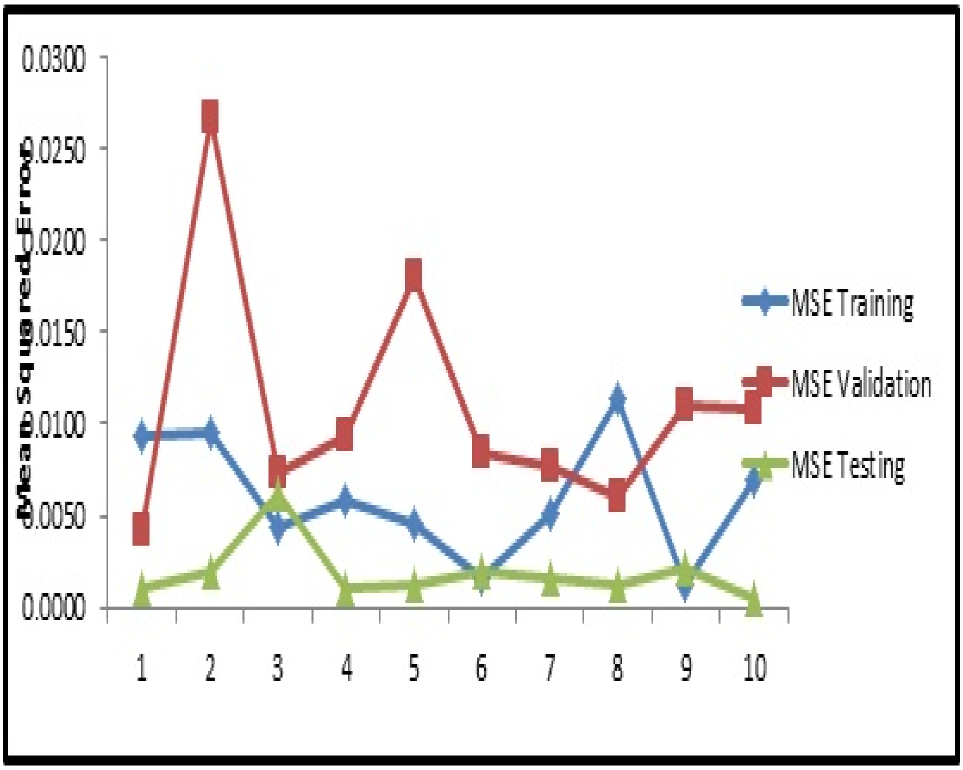

FIGURE 4.31: CAPM In sample and Out sample Results (Low Beta Portfolios).

4.4 Fama and French Three Factor Model and and ANN

This experimentation is based on the processing of market returns, size and value effect to predict the future returns of the portfolios. It is believed in the asset pricing studies that the size and value effects have more explanatory capability along with market returns and the aspects of asset pricing, left unattended by CAPM, are well addressed by the Fama and French three-factor model.

4.4.1 Actual vs. Predicted Portfolio returns based on FF3F and ANN

Table 4.13, 4.14 and 4.15 (Annexure B) presents the results of FF3F model. The neural network models have used Rm, Rsmb and Rhml as the predictor variables to forecast the returns of high low and mid beta portfolios, The corresponding Figures of the performance of neural networks using the market risk premium, size premium, and value premium are provided in Figure 4.33, 4.34 and 4.35. As mentioned earlier in section 4.2.1, This input-output relationship simulation is based a rolling scheme of 48 months, and the windows slide one step ahead to predict the 49th month's return. The generated 133 results are compared with the actual returns of the portfolios. The data tables report the portfolio returns on an annualized basis.

The analysis of Tables 4.13, 4.14 and 4.15 depict a somewhat different picture of the actual and predicted returns for the three classes of portfolios. The actual and predicted values of high beta portfolios category show unfavorable results where the actual returns are positive but show almost exact results in the case of negative returns. The lowest means squared error results for high, mid and low beta portfolios are .0.22%, 0.22%, and 0.18% respectively. The three factors model has generated the best results at 60-20-20 data set and 27 neurons. The large-scale variation in results of high beta portfolios but stable results for the low and mid beta portfolios show that the emerging markets have not yet incorporated the impact of size and value factors in explaining the behavior of stock returns for high-risk stocks and portfolios. Results of the mid beta and low beta portfolio returns seem to be better than high beta portfolios.

The actual and predicted returns of the three classes of the portfolios are shown in the Figures 4.33, 4.34, and 4.35. These Figures show that the ANN generated outputs are closer to the actual returns of high, low and mid beta portfolios. The three factors model through neural network system has been able to capture not only the direction of portfolio returns but also calculate the magnitude of the change in returns. The negative and positive signs of the portfolio returns along with the one month ahead predicted values would enable the investors to hold, buy or sell a particular stock. These results again confirm the notion that the concept of the application of modern and established asset pricing theories can take a new direction of successful implementation when the nonlinear processing tools like artificial neural networks are applied in an emerging and volatile markets like Pakistan. The investors can earn excess returns even in the presence of market manipulation in this volatile market.

4.4.2 In sample and Out sample analysis of Fama and French Three Factors Model

The training and testing results of the three factors models are presented in Table 4.16, 4.17, and 4.18 (Annexure B). These results are based on the factors of market premium, size and value effects. The best results are reported at 60-20-20 data set and 27 neurons for all the three types of portfolios. The analysis of this Table 4.16 reveals that the resultant error of the training, validation, and testing has gradually decreased. The validation error has controlled the network successfully with little deviation in some years. The lowest score of MSE for high beta portfolios is 0.4%, 0.17% and 0.13% for training, validation, and testing thus confirming the basic theory of in sample analysis that resultant error should be minimal on successive iterations while training. It is also evident from figure 4.36 where the validation curve has shown a small distance from the testing error.

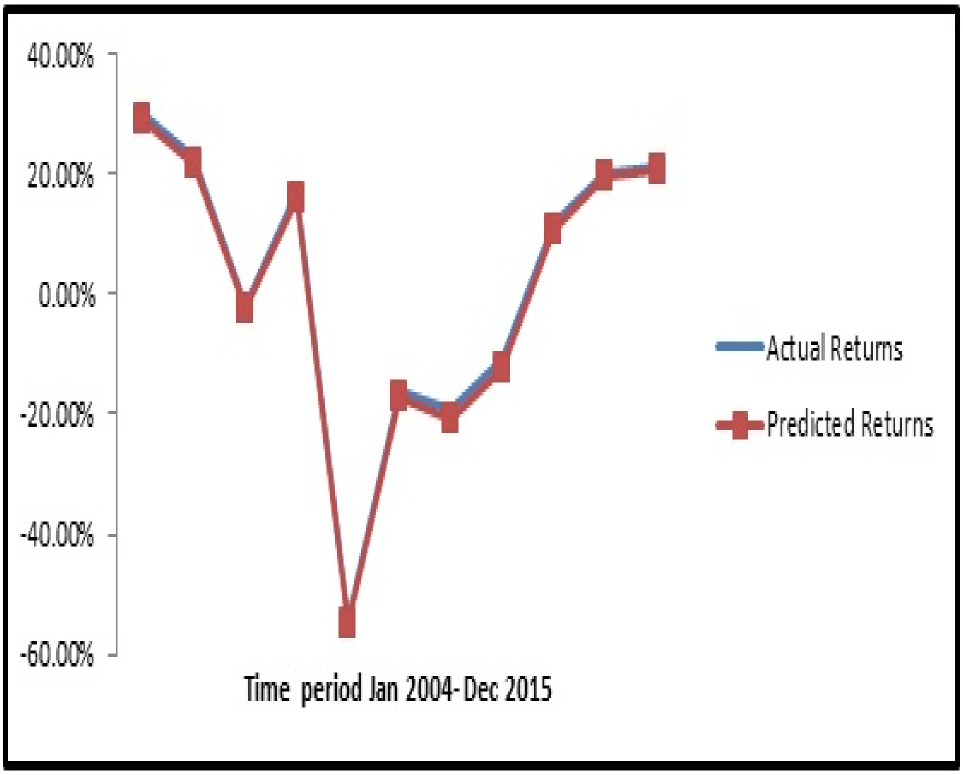

FIGURE 4.32: FF3F model based Actual Vs. Predicted Portfolio returns (High Beta Portfolios).

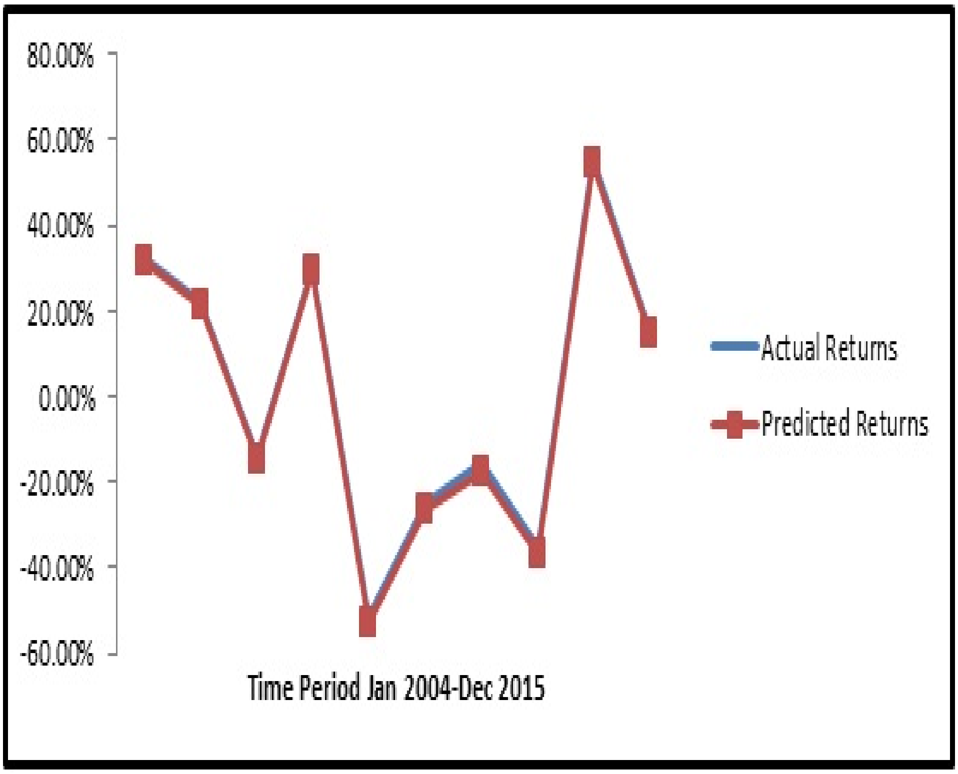

FIGURE 4.33: FF3F model based Actual Vs. Predicted Portfolio returns (Mid Beta Portfolios).

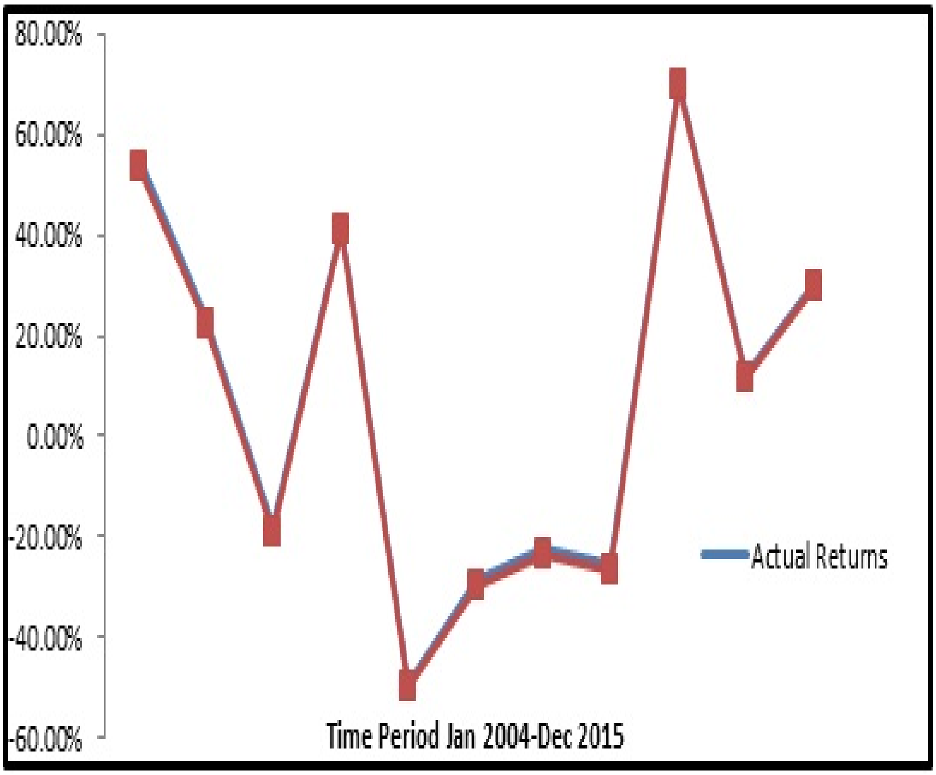

FIGURE 4.34: FF3F model based Actual Vs. Predicted Portfolio returns (Low Beta Portfolios).

The corresponding graph in Figures 4.36, 4, 37, and 4.38 exhibits another significant finding related to the training time horizon. The training curve has shown wide variations even at the end of the training in all the three categories, and this confirms another concept of the neural network that the addition of more variables, although refines the forecasting performance of the system the learning time also increases.

Our purpose here is to look for the best performing asset pricing model using more robust technology. The out sample (testing) predictive performance of the network on FF3F is even better than the CAPM as the lowest testing score for high, low and mid beta portfolios is 0.13%, 0.14%, and 0.13%. The out sample result shows that with the help of artificial neural networks, the Fama-French three-factor model can predict asset returns and correctly distinguish the portfolios with different expected returns. These findings are consistent with(Hu, 2007), and the performance of the network on out sample data set is encouraging. The results point toward the application of this state of the art technology for a volatile market

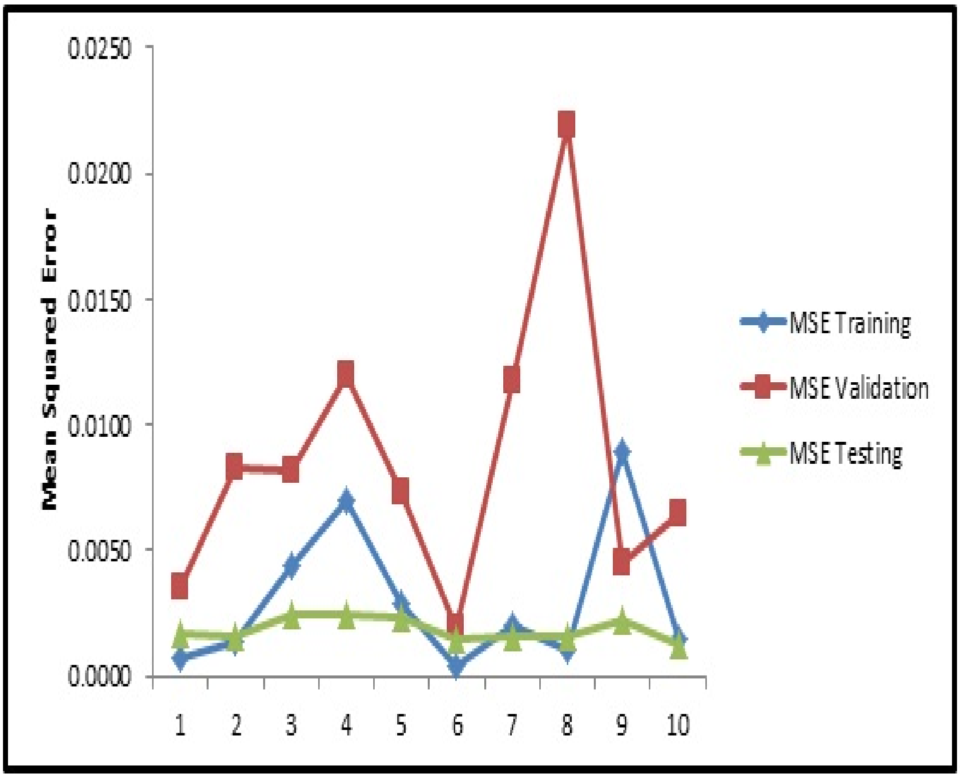

FIGURE 4.35: FF3F In sample and Out sample Results (High Beta Portfolios).

like Pakistan will hopefully decrease the losses of investors.

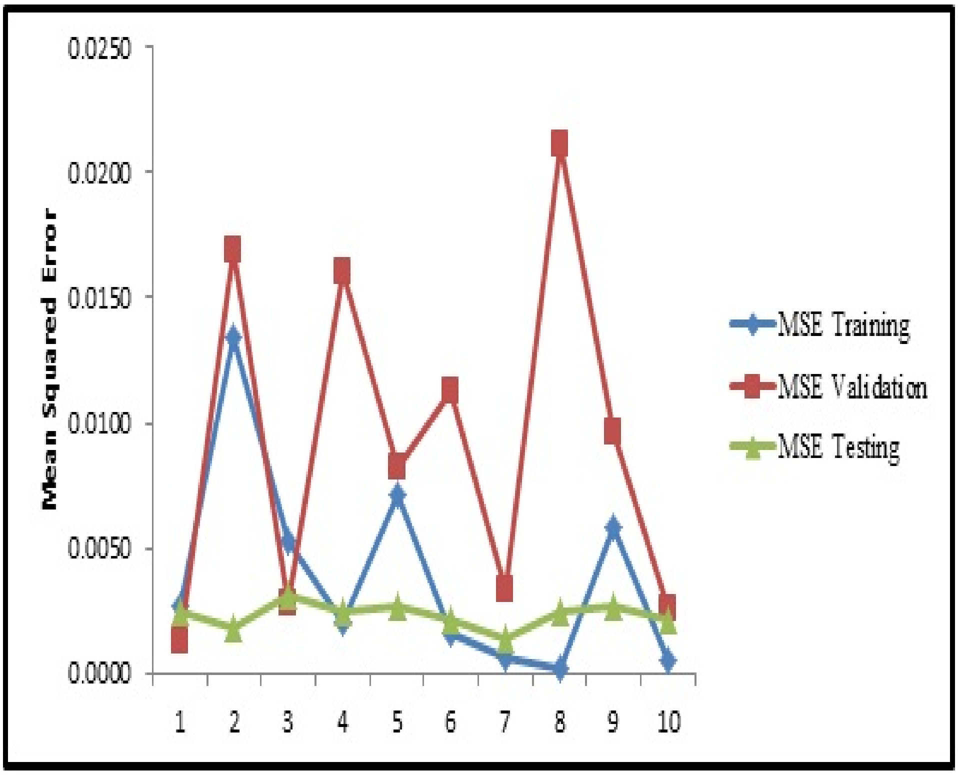

FIGURE 4.36: FF3F In sample and Out sample Results (Mid Beta Portfolios).

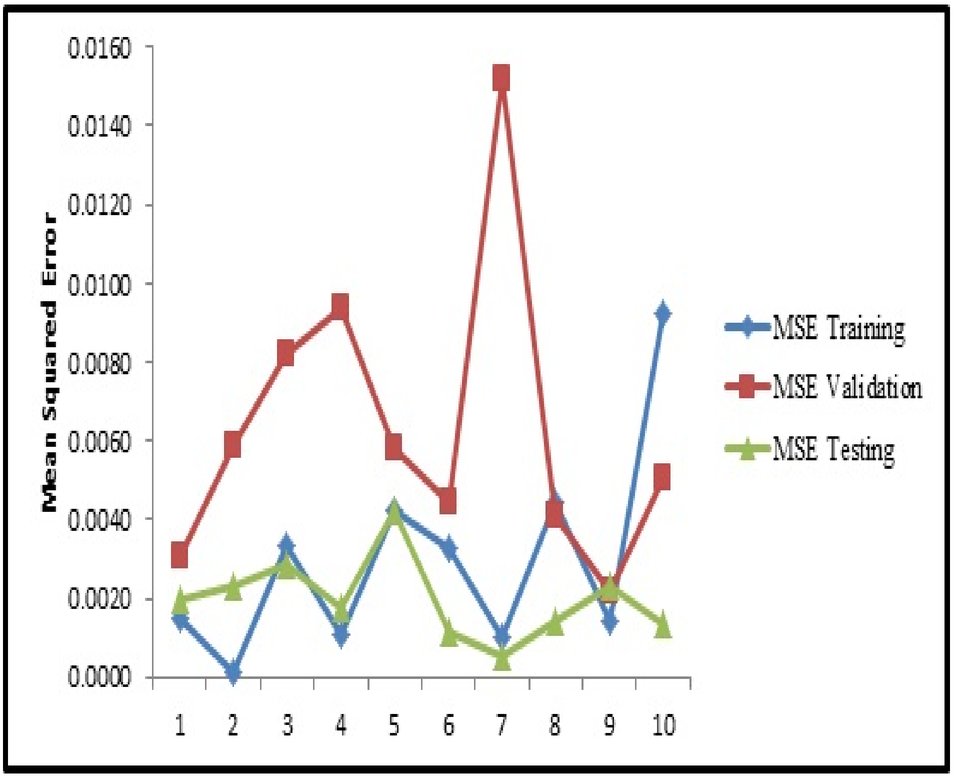

Figure 4.37: FF3F In sample and Out sample Results (Low Beta Portfolios).

4.5 Fama and French Five Factors Model based ANN Result

The application of FF5F model is a pioneering attempt in Pakistan's equity market along with ANN as a processing technique. The model is tested by looking at the predictive power of its factors on an annual basis. The In sample and Out sample performance of the model is also investigated with different combinations of Data sets and various mathematical equations. The results are also compared with the previous models to examine the difference in performance of all the models.

4.5.1 Actual vs. Predicted Portfolio Returns based on FF5F Model and ANN

A comparison of the actual and predicted portfolio returns is a key finding in any forecasting study, and this aspect of forecasting is appreciated much by the traders and Investors. This comparison should not only present the magnitude of change in returns but also identify the direction of the market because sometimes the size cannot be converted into profitability, but the estimation of directional changes can save the investors from potential losses. Table 4.19, 4.20, and 4.21 (Annexure B) demonstrate that financial variables of FF5F model have generated very close results for the predicted values on high beta portfolios along with the negative and positive signs of the market. This is an encouraging illustration for the decision makers regarding the use of ANN and FF5F model. . The annualized predicted returns of the high beta portfolios are in the range of -55.34% to 29.30%. The best model of the neural network system is identified at the 75-20-05 data set, and the optimal number of neurons is 28 for the all the three portfolios. The analysis Tables 4.20 and 21, depicting the performance of low and mid beta portfolios, demonstrates almost the same results as the high beta portfolios and the resulting lowest MSE scores are 0.0019 and 0.0020 respectively. The annualized predicted returns of the mid and low beta portfolios are in the range of -52.85% to 54.73% and -49.72% to 54.37% respectively (Table 4.20, Table 4.21, Annexure B).

The corresponding Figures 4.39, 4.40, and 4.41 also show that the predicted values very nearly follow the actual returns and this performance is superior to the previous two models of CAPM and FF3F. The lowest MSE score for the high beta portfolios is 0.42%.

4.5.2 Statistical Significance of Actual and Predicted Returns-FF5C Results

Table 4.41 (Annexure B) provides the t-statistics under two-Sample Assuming Unequal Variances of high, mid, and low beta portfolios. The t-statistics of high, mid and low beta portfolios is High 0.143, 0.281, and 0.656 respectively under the actual and predicted analysis. On the basis of this statistics we accept all the three null hypothesis. This implies that there is no statistical difference between predicted and actual returns under FF5C model.

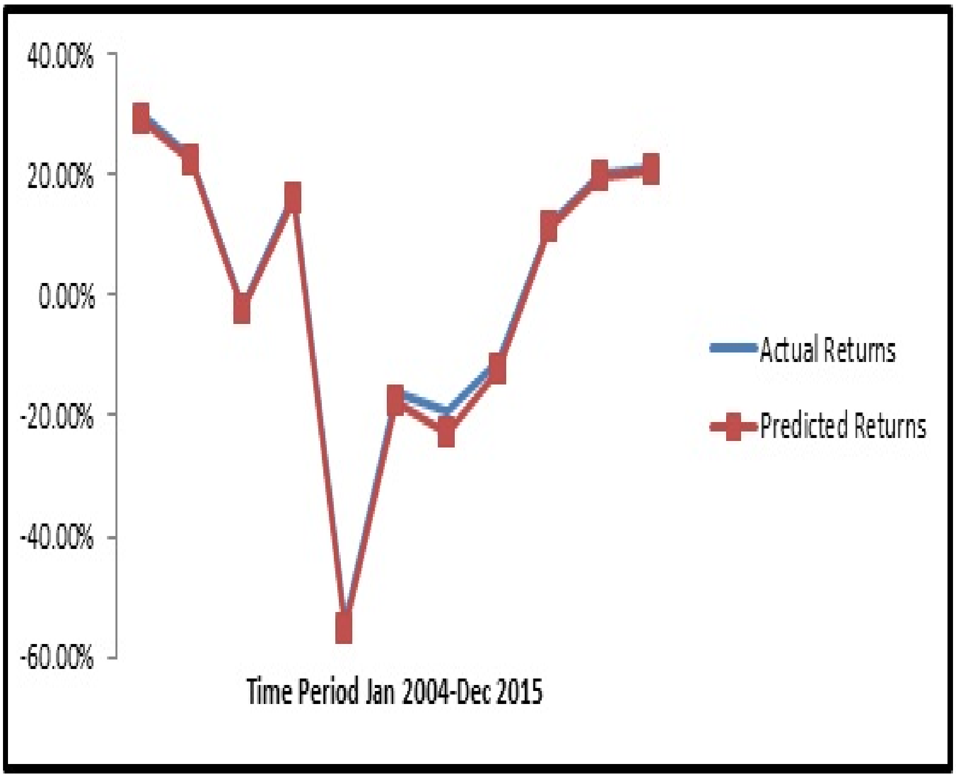

FIGURE 4.38: FF5F model based Actual Vs. Predicted Portfolio returns (High Beta Portfolios).

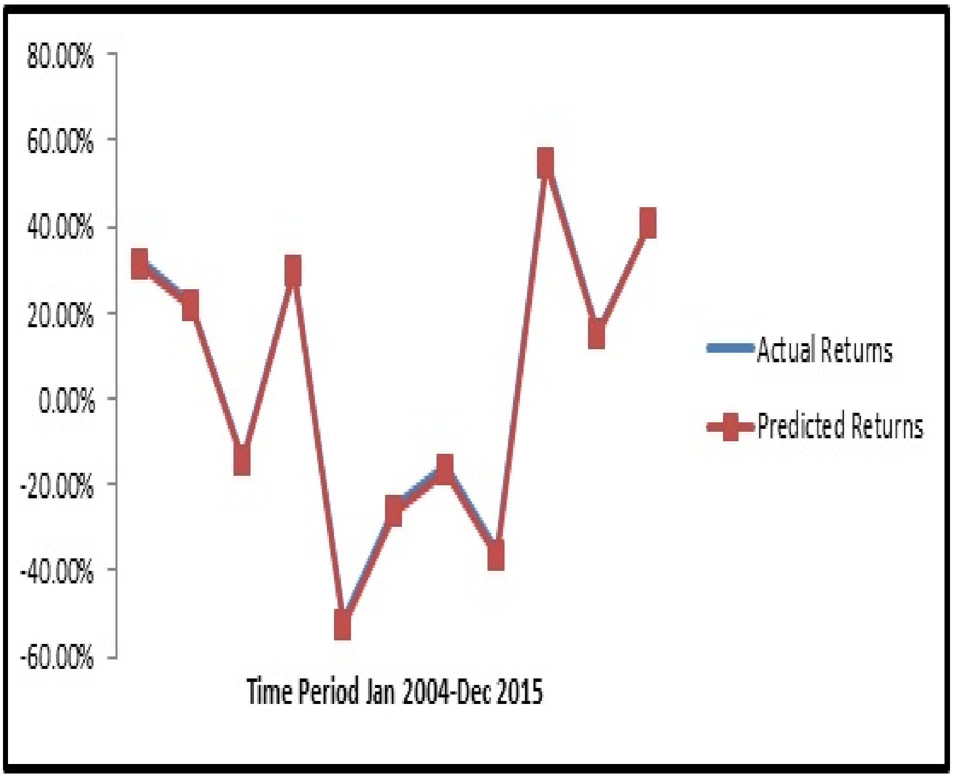

FIGURE 4.39: FF5F model based Actual Vs. Predicted Portfolio returns (Mid Beta Portfolios).

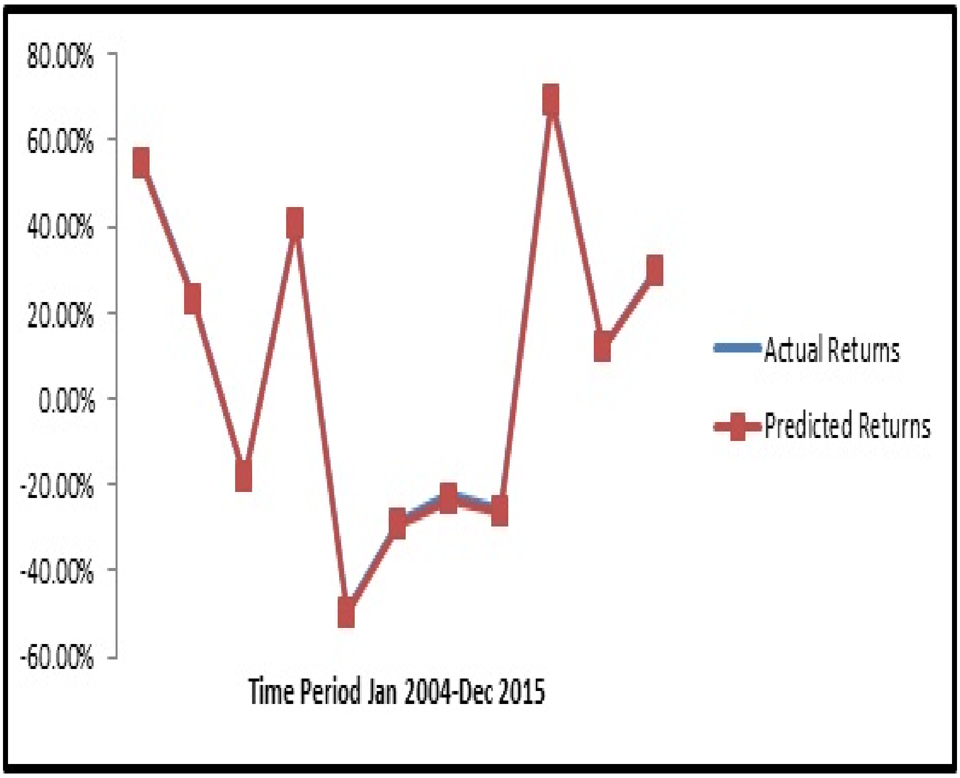

FIGURE 4.40: FF5Fmodel based Actual Vs. Predicted Portfolio returns (Low Beta Portfolios).

4.5.3 In Sample and Out Sample Analysis of FF5F based Results

The in sample and out sample data set results of the five factors CAPM are presented in Tables 4.22, 4.23, and 4.24 (Annexure B). The lowest score of MSE for high low and mid beta portfolios on in sample (overlapping training) Dataset are 0.04%, 0.02% and 0.02% thus confirming the basic theory of in sample analysis that resultant error should be minimal on successive iterations while training. The error is gradually decreasing in the training, validation and testing data set which corresponds to the model fitness of the neural network system.

The corresponding graphs in Figures 4.42, 4.43 and 4.44 exhibit another significant finding related to the training time horizon. The training curve has shown wide variations even at the end of the training in all the three categories, and this confirms another concept of the neural network that the addition of more variables, although refines the forecasting performance of the system the learning time also increases.

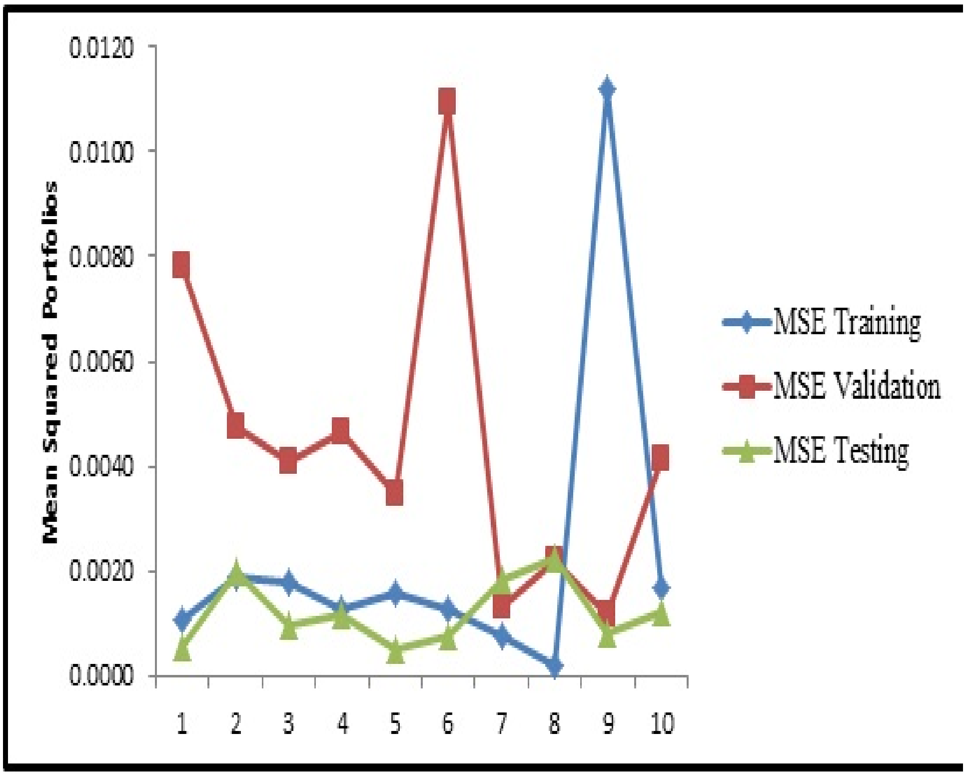

FIGURE 4.41: FF5F In sample and Out sample Results (High Beta Portfolios).

Our purpose here is to look for the best performing asset pricing model and the element of time can be offset by using more robust technology. The out sample (testing) predictive performance of the network on FF5F is even better than the CAPM as the lowest testing score for high, low and mid beta portfolios is 0.13%, 0.14%, and 0.13%.

The out sample result shows that with the help of artificial neural networks, Fama-French five-factor model can predict asset returns and correctly distinguish the portfolios with different expected returns. These findings are consistent with (Hu, 2007), and the performance of the network on out sample data set is encouraging. The results point toward the application of this state of the art technology for a volatile market like Pakistan. It will hopefully decrease the losses of investors.

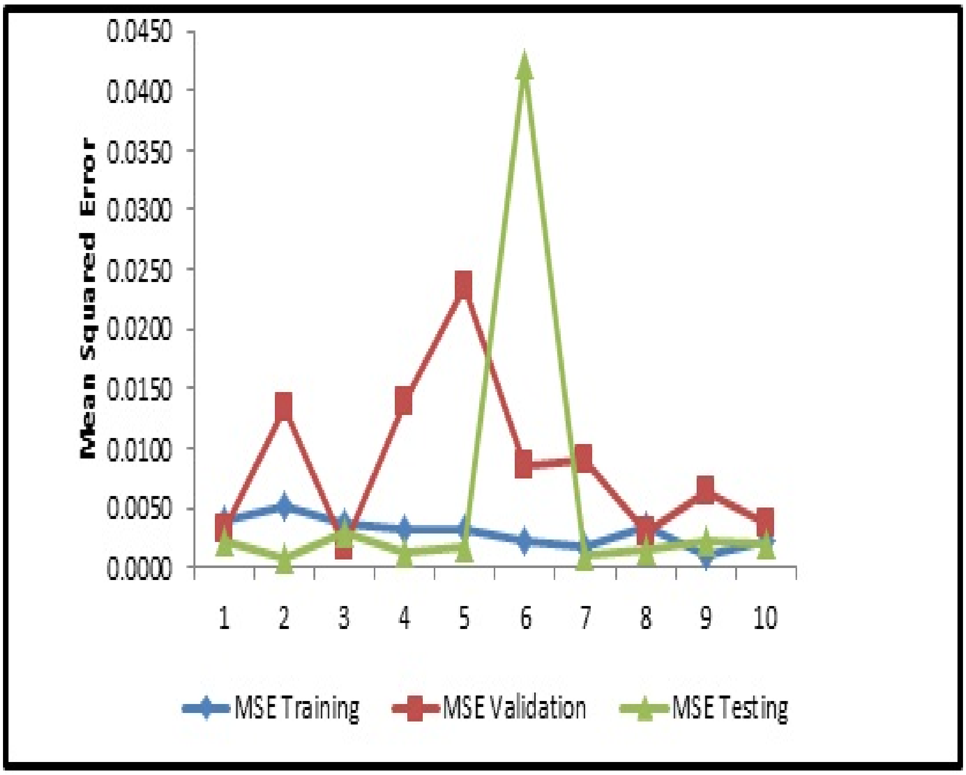

FIGURE 4.42: FF5F In sample and Out sample Results (Mid Beta Portfolios).

4.5.4 Comparative Analysis of Results of FF5C under various Training Methods

The Levenberg-Marquardt and Bayesian regularization are the two techniques which produces lowest results of MSE than any other approximation technique. In this section we present and analyze the MSE results of FF5C under Bayesian regularization method and compare it with the results of FF5C under Levenberg-Marquardt method. Table 4.40 (Annexure B) shows the results of MSE on the architecture of 1-50 neurons and 16 data set combinations. The BR method is more appropriate on large data sets and requires huge computational power.

Table 4.40 demonstrates that the BR algorithm has produced the best results at 13 neurons on all data sets. The minimum MSE of 0.64% is observed at 10 neurons and 60-20-20 data set. After this threshold level the performance of the neural network system deteriorates. On the other hand, the results of FF5C model under the Levenberg Marquardt algorithm are more promising. The FF5C model under all the data sets and 1-50 neurons has generated the lowest MSE score of 0.38%

on 28 neurons. Even beyond that level the performance of the network does not become worst rather it decreases gradually.

The literature review strongly supports the employment of LM in finance sphere studies. Our findings suggest that the use of Bayesian regularization (BR) is not appropriate for the stock market data as compared to LM.

Chapter 5

Conclusion

This thesis investigates the predictive ability of the major asset pricing models by using of Artificial Neural Networks in Pakistan's Equity market. The primary aim is to identify the model which provides the best description of future returns. ANN conducts the principal measure in the presence of three asset pricing models. A total of thirty portfolios are constructed and categorized as high, mid and low beta portfolios. The initial testing of ANN is conducted through a wide range of parameters, while a rolling scheme is applied to the portfolio returns to follow the method proposed by (Refenes, 1994).

The time series of returns is constructed with the help of regression, curve fitting, the difference between the actual and predicted values of annualized returns and the difference between the training (in sample) and testing (out sample) comparison.

5.1 Summary of Findings

Chapter 4 tests the predictive ability of market returns, size and value premium, and investment and profitability premiums on a wide range of ANN parameters. These factors are taken from the established asset pricing models and used as inputs for the neural network system. The artificial neural network parameters include the number of neurons, training methods, processing algorithm and performance parameters.

5.1.1 Findings of CAPM based Neural Network Models

We find that the accuracy level of forecasted portfolio returns of CAPM-based neural network models is low. The resultant errors of all the neural network models (CAPM based) are minimizing in a small the range of neurons.The goodness of fit test and the regression of the CAPM-based variable in the neural network system find a very close fit for the high and low beta portfolios but report a deviation for the mid beta portfolios. Under the rolling scheme of portfolio returns estimation, the MSE results for high, mid and low beta portfolios suggest that the CAPM-based ANN system can predict the future portfolio returns accurately.

The predicted annualized returns of the high beta portfolios report very close results to the actual performances. The real returns of mid beta and low beta portfolios are highly skewed and show a fat tail. Due to this reason, the predicted returns of these portfolios show high volatility as compared to high beta portfolios.This finding suggests that the market assigns higher compensation to risky assets. The high beta portfolios generate excess returns for the investors under the CAPM. These findings are in line with (Fadlalla and Amani, 2014; Jasic and Wood, 2004). The in sample and out sample results of the CAPM and artificial neural networks show that this exercise generates the variable results for the portfolio returns.

A major theoretical postulation of the CAPM is that the high beta portfolios generate high returns while the low beta portfolios generate low returns. This conclusion has been contradicted by many authors as mentioned in the literature review. Our findings suggest that the use of ANN in the capital asset pricing has successfully verified this theoretical foundation. The high beta portfolios have returned maximum predictability as compared to the mid and low beta portfolios.

5.1.2 Findings of Fama and French Three Factors Based Neural Network Models

The Fama and French three-factor Model presents improved results as compared to CAPM. The theory of ANN states that the performance of the NN system increases with the increase in the number of neurons. Almost all the models have accurately predicted the portfolio returns and the success rate of the neural network system on Fama and French three factors Model is high as compared to CAPM. Under the rolling scheme, the performance of the system also shows improvement as compared to the CAPM. The important finding of this analysis is that the performance of the system improves with the increase in the number of financial variables. The conclusion of this exercise validates the theoretical foundation of ANN.

The goodness of fit test and the regression values of the three factors model reveals that the high beta and mid beta portfolios have good chances of accurate prediction while the low beta portfolios have little probabilities of successful prediction.The ANN reports the actual and predicted results for Fama and French three models a little different for the high, mid and low beta portfolios. The low beta portfolios returns are unfavorable while the other two categories show consistent results. A large-scale variation in results is seen in this exercise which is the evidence that emerging markets have not yet incorporated the impact of size and value in the portfolio returns. A significant finding is that the market is not, however, assigning returns to the size and value factors.

Another significant finding of the Fama and French three-factor model processing is evident from the analysis of the In sample and Out sample performance of the networks. The reported errors for the training, testing, and validation have little variation and this points towards a sound fit of the ANN for this type of analysis that the resultant error should gradually decrease on successive iterations. The training curves show wide variation in the initial testing but show marked improvement afterward. The results suggest that the ANN algorithm along with asset pricing models decreases the losses of the investors in the volatile markets and these results are consistent with (Hu, 2007).

5.1.3 Findings Of Fama and French Five Factors model Based Neural Network Models

The five factors model has demonstrated more accurate prediction performance as compared to the previous two models, which implies that the addition of the investment and profitability factors demonstrate good predictive power in this market. Most of the data combinations produce a minimum error and the initial results are encouraging for this model and show excellent capability for the forecasting of portfolio returns. A notable finding of this analysis is that the five factors model has good forecasting ability along with ANN technology.

The regression analysis and goodness of fit test have also shown closer results. All the three classes of portfolios have demonstrated a consistent error minimization which again confirm the findings that the five factors model can successfully forecast the future returns with a minimum error. A significant outcome of these findings is that the additional and relevant factors of the asset pricing models increase the probability of accurate market forecasting.

The In sample and Out sample results of the five factors model shows a close convergence of results and the corresponding MSE score for training, validation, and testing shows a consistent minimization. A significant finding of these results is that the increase in the number of financial variables increases the performance of the system, at the same time the processing time increases.

Many fields including stock markets have recognized the forecasting capability of the artificial neural networks. The pattern recognition and learning abilities of the artificial neural network in a data-rich environment of the stock market present a valuable opportunity for the investors. The investors can modify their buy and hold strategy and adopt an active behavior in investments. The Neural network models based on the five composite factors of FF5F model opens new vistas for investors to organize their investment portfolios more efficiently and earn excess returns. The accepted conceptual foundation of the asset pricing models on the linear risk returns relationship also needs to be revisited in the presence of artificial intelligence techniques. The annualized predicted returns of the high, mid and low beta portfolios demonstrate a minimum error with the actual returns for 11 consecutive years. The mid beta portfolios show systematic variation in predicting portfolio returns, and the error is consistently minimizing implying that the mid beta portfolios have high chances of accurate prediction by the neural network system. A systematic minimization of error is reported among the three states of the neural networks verifying the theoretical foundation of the ANN. The performance of the system on the out sample data is also promising because most of the other techniques demonstrate well in sample performance but poor out sample ability.

Although the portfolios based on FF5F methodology using ANN models have accurately predicted the returns, it remains open to more experimentation. At this point, given the 'black box' nature of the ANN, it is difficult to offer any explanation beyond the well-known ability of the ANN to capture 'hidden' relationships between inputs and outputs. Future researchers should focus on clustering, classification, hybridization of other nonlinear techniques like GARCH and ARIMA with the neural network system. The portfolio selection can also be optimized using particle swarm optimization and other artificial intelligence techniques. We hope that future research in the fields of both asset pricing and artificial intelligence would be able to offer an opportunity for interdisciplinary research and present more challenges to the established investment theories.

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Annexure - A

Tables from Chapter 3

Table 3.1: Descriptive Statistics of Pakistan Stock Exchange

	2011	**2012**	**2013**	**2014**	**2015**
Total Listed Companies	639	591	569	557	560
New Companies Listed	1	3	4	5	6
Fund Mobilized (Rs. in bn)	31	115	30	48	29
Listed Capital (Rs. In mn)	943,733	1,069,840	1,116,005	1,100,341	1,177,766
Market Cap (Rs. In mn)	3,288,657	3,518,140	5,154,738	6,655,295	6,760,759
Avg Daily Shares Volume (mn)	112	150	221	229	186

TABLE 3.2: Comparison of KSE-100 and Some Major Indices of the World

Stock Name	**Index as on 01-Jul-14**	**Index as on 01-Jul-15**	**Growth**
KSE-100	29,653	33730	13.17%
S & P 500	1,960.23	2085	6.4
Sensex	25,413.78	27011	6.3
AORD	5,382	5635	4.7
FTSE 100	6,743.00	6960	3.2
FSSTI Index	3,255.67	3487	7.1
CSEALL Index	6,378.62	7179	12.5
JCI Index	4,878.58	5086	4.3
Composite	2.002.21	2127	6.2
Hang Seng	23,190	28133	21.3

Table 3.3: Distribution of Dataset in Training, Validation, and Testing for CAPM

Dataset Distribution	Network Architecture	Hidden Layer Neurons
60-20-20	1-1-1 to 1-50-1	Neuron 1-50
65-15-20	1-1-1 to 1-50-1	Neuron 1-50
65-20-15	1-1-1 to 1-50-1	Neuron 1-50
70-10-20	1-1-1 to 1-50-1	Neuron 1-50
70-15-15	1-1-1 to 1-50-1	Neuron 1-50
70-20-10	1-1-1 to 1-50-1	Neuron 1-50
75-05-20	1-1-1 to 1-50-1	Neuron 1-50
75-10-15	1-1-1 to 1-50-1	Neuron 1-50
75-15-10	1-1-1 to 1-50-1	Neuron 1-50
75-20-05	1-1-1 to 1-50-1	Neuron 1-50
80-05-15	1-1-1 to 1-50-1	Neuron 1-50
80-15-05	1-1-1 to 1-50-1	Neuron 1-50
80-10-10	1-1-1 to 1-50-1	Neuron 1-50
85-10-05	1-1-1 to 1-50-1	Neuron 1-50
85-05-10	1-1-1 to 1-50-1	Neuron 1-50
90-05-10	1-1-1 to 1-50-1	Neuron 1-50

Source: Author Calculation

TABLE 3.4: Distribution of Dataset in Training, Validation, and Testing for FF3F Model

Dataset Distribution	**Network Architecture**	**Hidden Layer Neurons**
60-20-20	3-1-1 to 3-50-1	Neuron 1-50
65-15-20	3-1-1 to 3-50-1	Neuron 1-50
65-20-15	3-1-1 to 3-50-1	Neuron 1-50
70-10-20	3-1-1 to 3-50-1	Neuron 1-50
70-15-15	3-1-1 to 3-50-1	Neuron 1-50
70-20-10	3-1-1 to 3-50-1	Neuron 1-50
75-05-20	3-1-1 to 3-50-1	Neuron 1-50
75-10-15	3-1-1 to 3-50-1	Neuron 1-50
75-15-10	3-1-1 to 3-50-1	Neuron 1-50
75-20-05	3-1-1 to 3-50-1	Neuron 1-50
80-05-15	3-1-1 to 3-50-1	Neuron 1-50
80-15-05	3-1-1 to 3-50-1	Neuron 1-50
80-10-10	3-1-1 to 3-50-1	Neuron 1-50
85-10-05	3-1-1 to 3-50-1	Neuron 1-50
85-05-10	3-1-1 to 3-50-1	Neuron 1-50
90-05-10	3-1-1 to 3-50-1	Neuron 1-50

Source: Author Calculation

Table 3.5: Distribution of Dataset in Training, Validation, and Testing for FF5F Model

Dataset Distribution	**Network Architecture**	**Hidden Layer Neurons**
60-20-20	5-1-1 to 5-50-1	Neuron 1-50
65-15-20	5-1-1 to 5-50-1	Neuron 1-50
65-20-15	5-1-1 to 5-50-1	Neuron 1-50
70-10-20	5-1-1 to 5-50-1	Neuron 1-50
70-15-15	5-1-1 to 5-50-1	Neuron 1-50
70-20-10	5-1-1 to 5-50-1	Neuron 1-50
75-05-20	5-1-1 to 5-50-1	Neuron 1-50
75-10-15	5-1-1 to 5-50-1	Neuron 1-50
75-15-10	5-1-1 to 5-50-1	Neuron 1-50
75-20-05	5-1-1 to 5-50-1	Neuron 1-50
80-05-15	5-1-1 to 5-50-1	Neuron 1-50
80-15-05	5-1-1 to 5-50-1	Neuron 1-50
80-10-10	5-1-1 to 5-50-1	Neuron 1-50
85-10-05	5-1-1 to 5-50-1	Neuron 1-50
85-05-10	5-1-1 to 5-50-1	Neuron 1-50
90-05-10	5-1-1 to 5-50-1	Neuron 1-50

Source: Author Calculation

Annexure - B

Tables from Chapter 4

TABLE 4.1: Descriptive Statistics of High Beta Portfolios Returns (180 Monthly Counts)

Sr.No	Mean	Median	Minimum	Maximum	St.dev	Sample Var.	Kurtosis	Skewness
P1	0.0038	0.0072	-0.4884	0.1971	0.0788	0.0062	8.1284	-1.4872
P2	0.0032	0.0061	-0.4979	0.2156	0.0814	0.0066	7.8277	-1.4427
P3	0.0032	0.0061	-0.4979	0.2156	0.0814	0.0066	7.8277	-1.4427
P4	0.0032	0.0061	-0.4979	0.2156	0.0814	0.0066	7.8277	-1.4427
P5	0.0019	0.0045	-0.5001	0.2185	0.0859	0.0074	6.6515	-1.3876
P6	0.0015	0.0032	-0.4606	0.2192	0.0836	0.007	5.3412	-1.1849
P7	0.0012	-0.0003	-0.4442	0.2245	0.0846	0.0072	4.5281	-1.0488
P8	0.001	0.0012	-0.4506	0.2271	0.0843	0.0071	4.8468	-1.1086
P9	0.0007	0.0032	-0.4438	0.2226	0.0841	0.0071	4.5452	-1.1013
P10	0.0014	0.0018	-0.468	0.2241	0.0863	0.0074	4.8837	-1.1418
Average	0.0021	0.0039	-0.4749	0.218	0.0831	0.0069	6.2407	-1.2788

TABLE 4.2: Descriptive Statistics of Mid Beta Portfolios Returns (180 Monthly Counts)

Sr.No	Mean	Median	Minimum	Maximum	St.dev	Sample Var.	Kurtosis	Skewness
P11	0.0025	0.0063	-0.4721	0.2295	0.0887	0.0079	4.48	-1.0697
P12	0.0015	0.0075	-0.5253	0.2383	0.0904	0.0082	6.2193	-1.2694
P13	0.0011	0.007	-0.4876	0.2503	0.0896	0.008	4.6725	-1.0253
P14	0.0017	0.005	-0.4976	0.2527	0.0898	0.0081	4.9919	-1.0351
P15	0.003	0.0067	-0.4892	0.2601	0.0914	0.0083	4.4734	-0.9261
P16	0.0032	0.0047	-0.5021	0.2538	0.0926	0.0086	4.6678	-0.9791
P17	0.0036	0.0023	-0.4545	0.2719	0.0913	0.0083	3.4643	-0.7156
P18	0.0042	0.0002	-0.4082	0.2927	0.0909	0.0083	2.6969	-0.5663
P19	0.0041	-0.002	-0.4159	0.326	0.0939	0.0088	2.7308	-0.4866
P20	0.0046	0	-0.4078	0.3215	0.094	0.0088	2.5234	-0.4765
Average	0.0029	0.0038	-0.466	0.2697	0.0913	0.0083	4.092	-0.855

TABLE 4.3: Descriptive Statistics of Low Beta Portfolios Returns (180 Monthly Counts)

Sr.No	Mean	Median	Minimum	Maximum	St.dev	Sample Var.	Kurtosis	Skewness
P21	0.004	0.0014	-0.3916	0.3146	0.096	0.0092	2.2096	-0.5164
P22	0.0044	0.0075	-0.3096	0.3388	0.0957	0.0092	1.6513	-0.3237
P23	0.0049	0.0067	-0.3187	0.3462	0.097	0.0094	1.6114	-0.2425
P24	0.0055	0.0077	-0.3128	0.3536	0.0968	0.0094	1.6765	-0.2562
P25	0.0052	0.0076	-0.317	0.3424	0.0955	0.0091	1.7197	-0.3044
P26	0.0046	0.007	-0.3054	0.343	0.0939	0.0088	1.5829	-0.2369
P27	0.0055	0.0072	-0.2934	0.3448	0.0945	0.0089	1.5444	-0.2253
P28	0.0054	0.0012	-0.2825	0.3273	0.0916	0.0084	1.4666	-0.1707
P29	0.0067	0.0052	-0.2918	0.3302	0.0903	0.0082	1.4141	-0.0854
P30	0.0062	0.0009	-0.2586	0.2649	0.0768	0.0059	0.9455	0.0703
Average	0.0052	0.0052	-0.3081	0.3306	0.0928	0.0086	1.5822	-0.2291

TABLE 4.4: CAPM based MSE Score of All Portfolios

CAPM	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13
60-20-20	0.72%	0.70%	0.67%	0.66%	0.65%	0.64%	0.64%	1.95%	1.63%	0.64%	0.85%	0.63%	2.53%
65-15-20	0.72%	0.71%	0.68%	0.66%	0.65%	0.65%	0.64%	2.00%	1.67%	0.64%	0.83%	0.64%	2.55%
60-20-15	0.72%	0.70%	0.67%	0.66%	0.65%	0.64%	0.64%	1.99%	1.66%	0.63%	0.82%	0.63%	2.55%
70-10-20	0.72%	0.70%	0.67%	0.66%	0.65%	0.64%	0.64%	1.99%	1.66%	0.63%	0.82%	0.64%	2.55%
70-15-15	0.73%	0.71%	0.69%	0.69%	0.67%	0.66%	0.65%	2.00%	1.67%	0.65%	0.84%	0.66%	2.56%
70-20-10	0.72%	0.71%	0.68%	0.66%	0.65%	0.65%	0.64%	2.00%	1.67%	0.64%	0.83%	0.64%	2.55%
75-05-20	0.72%	0.71%	0.68%	0.66%	0.65%	0.64%	0.64%	1.99%	1.66%	0.64%	0.83%	0.64%	2.55%
75-10-15	0.74%	0.73%	0.72%	0.69%	0.70%	0.68%	0.67%	2.01%	1.70%	0.68%	0.87%	0.62%	2.58%
75-15-10	0.73%	0.71%	0.69%	0.67%	0.67%	0.66%	0.65%	2.00%	1.68%	0.66%	0.85%	0.66%	2.56%
75-20-05	0.72%	0.71%	0.68%	0.66%	0.65%	0.65%	0.64%	2.00%	1.67%	0.64%	0.83%	0.65%	2.55%
80-05-15	0.72%	0.71%	0.68%	0.66%	0.65%	0.65%	0.64%	1.99%	1.66%	0.64%	0.83%	0.64%	2.55%
80-10-10	0.74%	0.73%	0.72%	0.71%	0.70%	0.69%	0.68%	2.02%	1.71%	0.70%	0.88%	0.70%	2.60%
80-15-05	0.73%	0.71%	0.85%	0.68%	0.67%	0.66%	0.66%	2.00%	1.68%	0.66%	0.85%	0.66%	2.56%
85-05-10	0.72%	0.71%	2.09%	0.67%	0.66%	0.65%	0.65%	2.00%	1.67%	0.65%	0.84%	0.65%	2.56%
85-10-05	0.73%	0.74%	0.72%	0.72%	0.71%	0.71%	2.08%	2.99%	0.72%	0.90%	0.72%	2.61%	2.96%
90-05-05	0.74%	0.72%	0.70%	0.68%	0.69%	0.67%	0.66%	2.01%	1.68%	0.67%	0.85%	0.69%	2.57%

TABLE 4.4 CONTINUED: CAPM based MSE Score of All Portfolios

CAPM	N14	N15	N16	N17	N18	N19	N20	N25	N30	N35	N40	N45	N50
60-20-20	2.75%	1.60%	4.04%	8.96%	10.30%	7.66%	3.43%	25.37%	22.18%	35.96%	77.12%	71.66%	72.77%
65-15-20	2.76%	1.56%	4.08%	9.13%	10.39%	7.76%	3.21%	29.10%	22.08%	35.97%	77.30%	71.77%	72.62%
60-20-15	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.96%	77.30%	71.56%	72.62%
70-10-20	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.96%	77.30%	71.56%	72.62%
70-15-15	2.82%	1.57%	4.11%	9.14%	10.39%	7.76%	3.22%	28.95%	22.08%	36.04%	77.30%	71.77%	72.62%
70-20-10	2.81%	1.57%	4.08%	9.13%	10.39%	7.76%	3.21%	28.94%	22.08%	35.97%	77.30%	71.77%	72.62%
75-05-20	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.97%	77.30%	71.77%	72.62%
75-10-15	2.85%	1.61%	4.15%	9.16%	10.43%	7.80%	3.28%	28.99%	22.10%	36.06%	77.30%	71.77%	72.62%
75-15-10	2.82%	1.58%	4.11%	9.14%	10.40%	7.77%	3.23%	28.97%	22.08%	36.04%	77.30%	71.77%	72.62%
75-20-05	2.82%	1.57%	4.10%	9.13%	10.39%	7.76%	3.21%	28.93%	22.08%	35.97%	77.30%	71.77%	72.62%
80-05-15	2.76%	1.56%	4.07%	9.13%	10.39%	7.76%	3.21%	25.48%	25.48%	35.97%	77.30%	71.77%	72.62%
80-10-10	2.95%	1.62%	4.17%	9.17%	10.44%	7.83%	3.29%	29.00%	22.12%	36.17%	77.71%	71.90%	72.62%
80-15-05	2.82%	1.58%	4.12%	9.14%	10.40%	7.77%	3.23%	28.98%	22.09%	36.06%	77.31%	71.77%	72.62%
85-05-10	2.82%	1.57%	4.10%	9.14%	10.39%	7.76%	3.22%	28.94%	22.08%	35.98%	77.30%	71.77%	72.62%
85-10-05	1.64%	4.20%	9.16%	10.47%	7.86%	3.35%	30.78%	22.34%	36.19%	77.76%	71.91%	72.62%	71.91%
90-05-05	2.83%	1.58%	4.13%	9.14%	10.41%	7.78%	3.24%	28.98%	22.09%	36.06%	77.31%	71.77%	72.62%

Table 4.5: FF3F based MSE Score of All Portfolios

CAPM	N14	N15	N16	N17	N18	N19	N20	N25	N30	N35	N40	N45	N50
60-20-20	2.75%	1.60%	4.04%	8.96%	10.30%	7.66%	3.43%	25.37%	22.18%	35.96%	77.12%	71.66%	72.77%
65-15-20	2.76%	1.56%	4.08%	9.13%	10.39%	7.76%	3.21%	29.10%	22.08%	35.97%	77.30%	71.77%	72.62%
60-20-15	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.96%	77.30%	71.56%	72.62%
70-10-20	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.96%	77.30%	71.56%	72.62%
70-15-15	2.82%	1.57%	4.11%	9.14%	10.39%	7.76%	3.22%	28.95%	22.08%	36.04%	77.30%	71.77%	72.62%
70-20-10	2.81%	1.57%	4.08%	9.13%	10.39%	7.76%	3.21%	28.94%	22.08%	35.97%	77.30%	71.77%	72.62%
75-05-20	2.76%	1.56%	4.07%	9.11%	10.39%	7.66%	3.21%	25.48%	22.07%	35.97%	77.30%	71.77%	72.62%
75-10-15	2.85%	1.61%	4.15%	9.16%	10.43%	7.80%	3.28%	28.99%	22.10%	36.06%	77.30%	71.77%	72.62%
75-15-10	2.82%	1.58%	4.11%	9.14%	10.40%	7.77%	3.23%	28.97%	22.08%	36.04%	77.30%	71.77%	72.62%
75-20-05	2.82%	1.57%	4.10%	9.13%	10.39%	7.76%	3.21%	28.93%	22.08%	35.97%	77.30%	71.77%	72.62%
80-05-15	2.76%	1.56%	4.07%	9.13%	10.39%	7.76%	3.21%	25.48%	25.48%	35.97%	77.30%	71.77%	72.62%
80-10-10	2.95%	1.62%	4.17%	9.17%	10.44%	7.83%	3.29%	29.00%	22.12%	36.17%	77.71%	71.90%	72.62%
80-15-05	2.82%	1.58%	4.12%	9.14%	10.40%	7.77%	3.23%	28.98%	22.09%	36.06%	77.31%	71.77%	72.62%
85-05-10	2.82%	1.57%	4.10%	9.14%	10.39%	7.76%	3.22%	28.94%	22.08%	35.98%	77.30%	71.77%	72.62%
85-10-05	1.64%	4.20%	9.16%	10.47%	7.86%	3.35%	30.78%	22.34%	36.19%	77.76%	71.91%	72.62%	71.91%
90-05-05	2.83%	1.58%	4.13%	9.14%	10.41%	7.78%	3.24%	28.98%	22.09%	36.06%	77.31%	71.77%	72.62%

TABLE 4.5 CONTINUED: FF3F based MSE Score of All Portfolios

FF3F	N14	N15	N16	N17	N18	N19	N20	N25	N30	N35	N40	N45	N50
60-20-20	0.43%	0.39%	0.42%	0.39%	0.40%	0.39%	0.41%	0.38%	0.36%	0.37%	0.37%	0.41%	0.35%
65-15-20	0.43	0.39	0.43	0.39	0.4	0.4	0.41	0.38	0.37	0.39	0.38	0.43	0.36
60-20-15	0.42	0.39	0.42	0.39	0.4	0.4	0.41	0.38	0.36	0.37	0.37	0.41	0.35
70-10-20	0.44	0.4	0.43	0.4	0.4	0.41	0.41	0.39	0.38	0.4	0.39	0.44	0.37
70-15-15	0.43	0.39	0.43	0.39	0.4	0.4	0.41	0.38	0.37	0.39	0.38	0.43	0.36
70-20-10	0.42	0.39	0.42	0.39	0.4	0.4	0.41	0.38	0.36	0.37	0.38	0.41	0.35
75-05-20	0.43	0.39	0.43	0.39	0.4	0.4	0.41	0.38	0.36	0.38	0.38	0.41	0.36
75-10-15	0.43	0.39	0.43	0.39	0.4	0.4	0.41	0.38	0.37	0.39	0.39	0.43	0.36
75-15-10	0.44	0.4	0.44	0.42	0.4	0.42	0.41	0.39	0.38	0.4	0.4	0.4	0.38
75-20-05	0.46	0.44	0.48	0.44	0.41	0.44	0.43	0.42	0.42	0.44	0.44	0.49	0.41
80-05-15	0.43	0.4	0.43	0.4	0.4	0.4	0.41	0.38	0.37	0.4	0.39	0.44	0.36
80-10-10	0.44	0.41	0.44	0.43	0.4	0.43	0.41	0.4	0.39	0.41	0.4	0.45	0.39
80-15-05	0.49	0.48	0.5	0.45	0.42	0.47	0.44	0.44	0.44	0.49	0.45	0.5	0.45
85-05-10	0.44	0.42	0.45	0.43	0.41	0.44	0.42	0.41	0.41	0.43	0.4	0.46	0.39
85-10-05	0.51	0.5	0.53	0.5	0.45	0.52	0.48	0.48	0.53	0.52	0.5	0.54	0.44
90-05-05	0.68	0.65	0.63	0.65	0.64	0.68	0.58	0.67	0.81	0.79	0.72	0.83	0.6

Table 4.6: FF5F based MSE Score of All Portfolios

FF5F	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13
60-20-20	0.70%	0.67%	0.65%	0.58%	0.58%	0.56%	0.57%	0.50%	0.54%	0.53%	0.57%	0.53%	0.52%
65-15-20	0.51	0.51	0.52	0.52	0.52	0.53	0.53	0.53	0.53	0.53	0.53	0.54	0.55
60-20-15	0.5	0.51	0.51	0.51	0.51	0.52	0.52	0.52	0.53	0.53	0.53	0.53	0.54
70-10-20	0.52	0.52	0.53	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.55	0.55	0.55
70-15-15	0.51	0.51	0.52	0.52	0.53	0.53	0.53	0.53	0.53	0.54	0.54	0.54	0.55
70-20-10	0.5	0.51	0.51	0.51	0.52	0.52	0.53	0.53	0.53	0.53	0.53	0.54	0.54
75-05-20	0.56	0.57	0.57	0.58	0.58	0.58	0.59	0.59	0.59	0.59	0.6	0.61	0.61
75-10-15	0.53	0.53	0.54	0.54	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.56	0.58
75-15-10	0.52	0.52	0.52	0.53	0.53	0.53	0.54	0.54	0.54	0.55	0.55	0.55	0.56
75-20-05	0.51	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.54	0.5
80-05-15	0.58	0.59	0.6	0.6	0.6	0.6	0.6	0.61	0.62	0.62	0.62	0.62	0.63
80-10-10	0.53	0.53	0.55	0.55	0.55	0.55	0.56	0.56	0.56	0.57	0.57	0.57	0.58
80-15-05	0.52	0.52	0.52	0.53	0.53	0.54	0.54	0.54	0.54	0.55	0.55	0.55	0.57
85-05-10	0.61	0.62	0.63	0.63	0.63	0.63	0.64	0.64	0.64	0.65	0.65	0.65	0.66
85-10-05	0.53	0.55	0.55	0.56	0.56	0.56	0.56	0.57	0.57	0.57	0.58	0.58	0.58
90-05-05	0.67	0.68	0.68	0.7	0.71	0.71	0.71	0.72	0.72	0.72	0.73	0.73	0.74

TABLE 4.6 CONTINUED: FF5F based MSE Score of All Portfolios

FF5F	N14	N15	N16	N17	N18	N19	N20	N28	N30	N35	N40	N45	N50
60-20-20	0.53%	0.52%	0.53%	0.54%	0.51%	0.51%	0.53%	0.38%	1.60%	2.00%	15.87%	8.67%	4.21%
65-15-20	0.56	0.57	0.57	0.58	0.59	0.66	0.68	0.39	1.61	2	4.55	8.69	15.88
60-20-15	0.54	0.55	0.57	0.57	0.58	0.58	0.65	0.38	0.7	2	4.21	8.68	15.87
70-10-20	0.58	0.58	0.58	0.6	0.6	0.66	0.69	0.4	1.64	2.02	4.55	8.86	15.9
70-15-15	0.56	0.57	0.57	0.58	0.6	0.66	0.68	0.38	1.62	2	4.54	15.88	15.88
70-20-10	0.56	0.57	0.57	0.58	0.58	0.65	0.68	0.38	1.61	2	4.22	8.69	15.88
75-05-20	0.62	0.62	0.62	0.65	0.69	0.69	0.73	0.39	2.03	5.49	8.92	15.91	15.91
75-10-15	0.58	0.58	0.6	0.61	0.67	0.68	0.71	0.39	2.02	5.35	8.86	15.9	15.9
75-15-10	0.57	0.57	0.58	0.6	0.66	0.68	0.71	0.4	2.01	2.01	4.54	8.68	8.68
75-20-05	0.57	0.57	0.58	0.58	0.66	0.68	0.7	0.35	2	8.69	8.69	15.88	15.88
80-05-15	0.63	0.63	0.65	0.67	0.69	0.71	0.74	0.4	2.04	5.5	8.94	15.96	15.96
80-10-10	0.59	0.6	0.6	0.62	0.67	0.67	0.71	0.41	2.02	5.41	8.88	15.9	15.9
80-15-05	0.57	0.58	0.58	0.6	0.66	0.69	0.71	0.46	2.01	4.54	8.69	15.89	15.89
85-05-10	0.67	0.67	0.68	0.68	0.7	0.71	0.74	0.52	2.2	5.74	9.27	16.09	16.09
85-10-05	0.59	0.6	0.6	0.61	0.64	0.68	0.68	0.42	1.65	2.03	5.41	8.91	15.91
90-05-05	0.75	0.76	0.76	0.77	0.79	0.8	0.81	0.76	1.8	2.28	5.82	9.39	16.5

Table 4.7: CAPM Based Actual Vs. Predicted Returns (Annualized) of High Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	30.09	29.1	1	70-15-15	16
2005	22.93	22.14	0.8	70-15-15	16
2006	-1.9	-2.68	0.77	70-15-15	16
2007	16.83	16.18	0.65	70-15-15	16
2009	-54.44	-55.85	1.41	70-15-15	16
2010	-15.95	-17.25	1.3	70-15-15	16
2011	-19.19	-20.8	1.61	70-15-15	16
2012	-11	-12.07	1.08	70-15-15	16
2013	12.03	10.86	1.17	70-15-15	16
2014	20.35	19.8	0.55	70-15-15	16
2015	21.04	20.67	0.37	70-15-15	16

TABLE 4.8: CAPM Based Actual Vs. Predicted Returns (Annualized) of Mid Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	32.26	31.39	0.87	70-15-15	16
2005	22.24	21.33	0.9	70-15-15	16
2006	-14.2	-15.08	0.88	70-15-15	16
2007	29.95	28.85	1.1	70-15-15	16
2009	-51.85	-52.53	0.68	70-15-15	16
2010	-25.04	-26.29	1.26	70-15-15	16
2011	-15.67	-17.3	1.63	70-15-15	16
2012	-35.03	-36.36	1.33	70-15-15	16
2013	55.68	54.33	1.35	70-15-15	16
2014	15.29	14.68	0.61	70-15-15	16
2015	40.56	39.84	0.72	70-15-15	16

TABLE 4.9: CAPM Based Actual Vs. Predicted Returns (Annualized) of Low Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	32.26	31.39	0.87	70-15-15	16
2005	22.24	21.33	0.9	70-15-15	16
2006	-14.2	-15.08	0.88	70-15-15	16
2007	29.95	28.85	1.1	70-15-15	16
2009	-51.85	-52.53	0.68	70-15-15	16
2010	-25.04	-26.29	1.26	70-15-15	16
2011	-15.67	-17.3	1.63	70-15-15	16
2012	-35.03	-36.36	1.33	70-15-15	16
2013	55.68	54.33	1.35	70-15-15	16
2014	15.29	14.68	0.61	70-15-15	16
2015	40.56	39.84	0.72	70-15-15	16

Table 4.10: In sample and Out sample Results of CAPM (High Beta Portfolios)

Sr.No	Avg.Return%	MSE Training%	MSE Validation%	MSE Testing%	Dataset	No.of Neurons
P1	0.08	0.22	0.29	0.08	70-15-15	16 Neurons
P2	0.01	1.08	0.51	0.1	70-15-15	16 Neurons
P3	-0.05	1.01	0.17	0.1	70-15-15	16 Neurons
P4	-0.05	0.43	0.45	0.14	70-15-15	16 Neurons
P5	-0.15	0.25	0.26	0.12	70-15-15	16 Neurons
P6	-0.21	0.15	0.22	0.17	70-15-15	16 Neurons
P7	-0.22	0.3	0.17	0.04	70-15-15	16 Neurons
P8	-0.24	0.41	0.24	0.11	70-15-15	16 Neurons
P9	-0.27	0.33	0.31	0.05	70-15-15	16 Neurons
P10	-0.19	0.28	0.19	0.09	70-15-15	16 Neurons

Table 4.11: In sample and Out sample Results of CAPM (Mid Beta Portfolios)

Sr.No	Avg.Return%	MSE Training%	MSE Validation%	MSE Testing%	Dataset	No.of Neurons
P11	-0.02	0.52	0.62	0.09	70-15-15	16 Neurons
P12	-0.15	0.35	0.31	0.21	70-15-15	16 Neurons
P13	-0.22	1.87	0.18	0.04	70-15-15	16 Neurons
P14	-0.18	0.6	0.67	0.11	70-15-15	16 Neurons
P15	0.01	1.03	1.04	0.12	70-15-15	16 Neurons
P16	0.01	1.87	1.65	0.05	70-15-15	16 Neurons
P17	0.05	0.62	0.29	0.16	70-15-15	16 Neurons
P18	0.1	0.95	1.35	0.13	70-15-15	16 Neurons
P19	0.07	0.6	0.28	0.15	70-15-15	16 Neurons
P20	0.16	1.19	0.48	0.11	70-15-15	16 Neurons

Table 4.12: In sample and Out sample Results of CAPM (Low Beta Portfolios)

Sr.No	Avg.Return%	MSE Training%	MSE Validation%	MSE Testing%	Dataset	No.of Neurons
P21	0.1	0.93	0.41	0.11	70-15-15	16 Neurons
P22	0.15	0.96	2.66	0.2	70-15-15	16 Neurons
P23	0.18	0.44	0.72	0.62	70-15-15	16 Neurons
P24	0.21	0.58	0.94	0.11	70-15-15	16 Neurons
P25	0.12	0.46	1.8	0.12	70-15-15	16 Neurons
P26	0.04	0.16	0.84	0.19	70-15-15	16 Neurons
P27	0.19	0.51	0.77	0.16	70-15-15	16 Neurons
P28	0.13	1.14	0.6	0.12	70-15-15	16 Neurons
P29	0.34	0.12	1.1	0.22	70-15-15	16 Neurons
P30	0.31	0.69	1.09	0.05	70-15-15	16 Neurons

TABLE 4.13: FF3F Based Actual Vs. Predicted Returns (Annualized) of High Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	30.09	29.34	0.75	60-20-20	27
2005	22.93	21.83	1.1	60-20-20	27
2006	-1.9	-2.63	0.73	60-20-20	27
2007	16.83	16.15	0.68	60-20-20	27
2009	-54.44	-55.18	0.74	60-20-20	27
2010	-15.95	-17.31	1.36	60-20-20	27
2011	-19.19	-20.89	1.7	60-20-20	27
2012	-11	-12.33	1.33	60-20-20	27
2013	12.03	10.59	1.44	60-20-20	27
2014	20.35	19.89	0.45	60-20-20	27
2015	21.04	20.48	0.56	60-20-20	27

Table 4.14: FF3F Based Actual Vs. Predicted Returns (Annualized) of Mid Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	32.26	31.3	0.96	60-20-20	27
2005	22.24	21.18	1.06	60-20-20	27
2006	-14.2	-14.94	0.74	60-20-20	27
2007	29.95	29.19	0.76	60-20-20	27
2009	-51.85	-52.75	0.91	60-20-20	27
2010	-25.04	-26.56	1.52	60-20-20	27
2011	-15.67	-17.95	2.28	60-20-20	27
2012	-35.03	-36.73	1.71	60-20-20	27
2013	55.68	54.26	1.42	60-20-20	27
2014	15.29	14.65	0.64	60-20-20	27
2015	40.56	39.96	0.6	60-20-20	27

Table 4.15: FF3F Based Actual Vs. Predicted Returns (Annualized) of Low Beta Portfolios

Year	Actual Returns%	Predicted Returns%	MSE%	Dataset	Neurons
2004	55.52	53.73	1.79	60-20-20	27
2005	23.75	22.25	1.51	60-20-20	27
2006	-18.05	-18.96	0.91	60-20-20	27
2007	41.37	40.79	0.58	60-20-20	27
2009	-49.03	-49.79	0.75	60-20-20	27
2010	-28.37	-29.95	1.58	60-20-20	27
2011	-22.17	-23.66	1.49	60-20-20	27
2012	-25.45	-26.55	1.10	60-20-20	27
2013	70.56	69.55	1.01	60-20-20	27
2014	12.09	11.35	0.74	60-20-20	27
2015	30.53	29.74	0.79	60-20-20	27

Table 4.16: In sample and Out sample Results of FF3F Model (High Beta Portfolios)

Sr.No	Avg.Return%	MSE Training%	MSE Validation%	MSE Testing%	Dataset	No.of Neurons
P1	0.08	0.07	0.35	0.17	60-20-20	27
P2	0.01	0.13	0.83	0.16	60-20-20	27
P3	-0.05	0.44	0.82	0.25	60-20-20	27
P4	-0.05	0.7	1.19	0.24	60-20-20	27
P5	-0.15	0.29	0.73	0.23	60-20-20	27
P6	-0.21	0.04	0.19	0.14	60-20-20	27
P7	-0.22	0.2	1.17	0.16	60-20-20	27
P8	-0.24	0.11	2.19	0.16	60-20-20	27
P9	-0.27	0.89	0.45	0.23	60-20-20	27
P10	-0.19	0.15	0.64	0.13	60-20-20	27

TABLE 4.17: In sample and Out sample Results of FF3F Model (Mid. Beta Portfolios)

Sr. No	Avg.Return	MSE Training%	MSE Validation%	MSE Testing%	Dataset	No.of Neurons
P11	-0.02	0.27	0.12	0.25	60-20-20	27
P12	-0.15	1.34	1.69	0.19	60-20-20	27
P13	-0.22	0.53	0.28	0.31	60-20-20	27
P14	-0.18	0.2	1.6	0.25	60-20-20	27
P15	0.01	0.71	0.82	0.26	60-20-20	27
P16	0.01	0.16	1.13	0.22	60-20-20	27
P17	0.05	0.06	0.33	0.14	60-20-20	27
P18	0.1	0.02	2.11	0.24	60-20-20	27
P19	0.07	0.59	0.97	0.27	60-20-20	27
P20	0.16	0.05	0.26	0.22	60-20-20	27

TABLE 4.18: In sample and Out sample Results of FF3F Model (Low Beta Portfolios)

Sr.No	Avg.Return	MSE Training%	MSE Validation	MSE Testing	Dataset	No.of Neurons
P21	0.1	0.15	0.31%	0.20%	60-20-20	27
P22	0.15	0.02	0.59	0.23	60-20-20	27
P23	0.18	0.33	0.82	0.29	60-20-20	27
P24	0.21	0.11	0.94	0.18	60-20-20	27
P25	0.12	0.42	0.58	0.43	60-20-20	27
P26	0.04	0.33	0.44	0.11	60-20-20	27
P27	0.19	0.1	1.52	0.05	60-20-20	27
P28	0.13	0.44	0.41	0.14	60-20-20	27
P29	0.34	0.14	0.22	0.23	60-20-20	27
P30	0.31	0.92	0.51	0.13	60-20-20	27

Table 4.19: FF5F Based Actual Vs. Predicted Returns (Annualized) of High Beta Portfolios

Year	Actual Returns	Predicted Returns	MSE	Dataset	Neurons
2004	30.09%	29.30%	0.79%	75-20-05	28
2005	22.93	22.2	0.73	75-20-05	28
2006	-1.9	-2.48	0.58	75-20-05	28
2007	16.83	16.08	0.75	75-20-05	28
2009	-54.44	-55.34	0.9	75-20-05	28
2010	-15.95	-17.44	1.49	75-20-05	28
2011	-19.19	-22.84	3.65	75-20-05	28
2012	-11	-12.34	1.34	75-20-05	28
2013	12.03	11.14	0.89	75-20-05	28
2014	20.35	19.92	0.42	75-20-05	28
2015	21.04	20.58	0.46	75-20-05	28

TABLE 4.20: FF5F Based Actual Vs. Predicted Returns (Annualized) of Mid Beta Portfolios

Year	Actual Returns	Predicted Returns	MSE	Dataset	Neurons
2004	32.26%	31.26%	1.00%	75-20-05	28
2005	22.24	21.55	0.69	75-20-05	28
2006	-14.2	-14.73	0.53	75-20-05	28
2007	29.95	29.45	0.5	75-20-05	28
2009	-51.85	-52.85	1	75-20-05	28
2010	-25.04	-26.18	1.14	75-20-05	28
2011	-15.67	-16.55	0.88	75-20-05	28
2012	-35.03	-36.66	1.63	75-20-05	28
2013	55.68	54.73	0.95	75-20-05	28
2014	15.29	14.85	0.44	75-20-05	28
2015	40.56	40.12	0.44	75-20-05	28

TABLE 4.21: FF5F Based Actual Vs. Predicted Returns (Annualized) of Low Beta Portfolios

Year	Actual Returns	Predicted Returns	MSE	Dataset	Neurons
2004	55.52%	54.37%	1.15%	75-20-05	28
2005	23.75	22.57	1.18	75-20-05	28
2006	-18.05	-18.6	0.55	75-20-05	28
2007	41.37	40.66	0.71	75-20-05	28
2009	-49.03	-49.72	0.68	75-20-05	28
2010	-28.37	-29.47	1.09	75-20-05	28
2011	-22.17	-23.37	1.2	75-20-05	28
2012	-25.45	-26.41	0.97	75-20-05	28
2013	70.56	69.41	1.15	75-20-05	28
2014	12.09	11.54	0.55	75-20-05	28
2015	30.53	29.45	1.08	75-20-05	28

Table 4.22: In sample and Out sample Results of FF5F Model (High Beta Portfolios)

Sr.No	Avg.Return	MSE Training	MSE Validation	MSE Testing	Dataset	No.of Neurons
P1	0.08	0.11%	0.78%	0.06%	75-20-05	28
P2	0.01	0.19	0.48	0.2	75-20-05	28
P3	-0.05	0.18	0.41	0.1	75-20-05	28
P4	-0.05	0.13	0.47	0.12	75-20-05	28
P5	-0.15	0.16	0.35	0.05	75-20-05	28
P6	-0.21	0.13	1.09	0.08	75-20-05	28
P7	-0.22	0.07	0.13	0.18	75-20-05	28
P8	-0.24	0.02	0.22	0.23	75-20-05	28
P9	-0.27	1.12	0.12	0.08	75-20-05	28
P10	-0.19	0.17	0.42	0.12	75-20-05	28

TABLE 4.23: In sample and Out sample Results of FF5F Model (Mid Beta Portfolios)

Sr.No	Avg.Return	MSE Training	MSE Validation	MSE Testing	Dataset	No.of Neurons
P11	-0.02	0.38%	0.33%	0.22%	75-20-05	28
P12	-0.15	0.53	1.34	0.08	75-20-05	28
P13	-0.22	0.38	0.17	0.3	75-20-05	28
P14	-0.18	0.31	1.39	0.14	75-20-05	28
P15	0.01	0.32	2.35	0.17	75-20-05	28
P16	0.01	0.22	0.85	4.22	75-20-05	28
P17	0.05	0.17	0.9	0.11	75-20-05	28
P18	0.1	0.35	0.31	0.14	75-20-05	28
P19	0.07	0.11	0.63	0.22	75-20-05	28
P20	0.16	0.21	0.37	0.2	75-20-05	28

TABLE 4.24: In sample and Out sample Results of FF5F Model (Low Beta Portfolios)

Sr.No	Avg.Return	MSE Training	MSE Validation	MSE Testing	Dataset	No.of Neurons
P21	0.1	0.26%	0.35%	0.32%	75-20-05	28
P22	0.15	0.29	0.75	0.17	75-20-05	28
P23	0.18	0.04	0.17	0.33	75-20-05	28
P24	0.21	1.04	2.59	0.1	75-20-05	28
P25	0.12	0.27	0.63	0.33	75-20-05	28
P26	0.04	0.04	1.63	0.24	75-20-05	28
P27	0.19	0.35	0.62	0.15	75-20-05	28
P28	0.13	0.17	0.79	0.2	75-20-05	28
P29	0.34	0.53	0.47	0.12	75-20-05	28
P30	0.31	0.1	0.33	0.1	75-20-05	28

TABLE 4.25: MSE Score of All portfolios (Average) based on Bayesian Regularization Method.)

Dataset	N1%	N2%	N3%	N4%	N5%	N6%	N7%	N8%	N9%	N10%	N11%	N12%	N13%
60-20-20	0.69	0.68	0.67	0.68	0.67	0.66	0.66	0.66	0.64	0.64	0.66	0.65	0.8
65-15-20	0.69	0.68	0.68	0.68	0.67	0.67	0.67	0.66	0.64	0.65	0.66	0.66	0.83
65-20-15	0.69	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.64	0.65	0.65	0.65	0.8
70-10-20	0.7	0.69	0.68	0.68	0.67	0.67	0.67	0.67	0.65	0.66	0.66	0.66	0.89
70-15-15	0.69	0.68	0.68	0.68	0.67	0.67	0.67	0.66	0.64	0.65	0.66	0.66	0.83
70-20-10	0.69	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.64	0.65	0.66	0.66	0.83
75-05-20	0.7	0.71	0.7	0.69	0.69	0.69	0.69	0.7	0.67	0.67	0.68	0.68	2.3
75-10-15	0.7	0.69	0.68	0.68	0.68	0.67	0.67	0.67	0.65	0.66	0.67	0.66	0.89
75-15-10	0.7	0.69	1.45	1.44	0.68	0.67	1.47	1.42	0.65	0.65	0.66	0.66	0.84
75-20-05	0.69	0.68	0.67	0.68	0.67	0.66	0.67	0.66	0.64	0.65	0.66	0.66	0.83
80-05-15	0.71	0.72	0.71	0.7	0.7	0.69	0.69	0.7	0.67	0.69	0.69	0.69	2.41
80-15-05	0.69	0.69	0.68	0.68	0.67	0.67	0.67	0.67	0.65	0.66	0.66	0.66	0.84
80-10-10	0.7	0.69	0.69	0.68	0.68	0.68	0.67	0.67	0.65	0.67	0.67	0.67	0.9
85-10-05	0.7	0.7	0.69	0.69	0.68	0.68	0.68	0.68	0.66	0.67	0.68	0.67	0.91
85-05-10	0.71	0.74	0.73	0.7	0.72	0.71	0.71	0.75	0.69	0.74	0.74	0.73	2.46
90-05-05	0.74	0.76	0.83	0.78	0.84	0.79	0.79	0.91	0.79	1.18	0.88	0.85	2.55

TABLE 4.25 CONTINUED: MSE Score of All portfolios (Average) based on Bayesian Regularization Method.)

Dataset	N14	N15	N16	N17	N18	N19	N20	N25	N30	N35	N40	N45	N50
60-20-20	6.83	3.22	0.66	3.75	3.56	1.92	8.85	11.78	12.96	23.32	16.28	58.48	52.17
65-15-20	6.95	3.24	0.66	2.16	1.9	3.58	7.48	9.96	12.35	24.38	17.33	57.59	57.7
65-20-15	6.94	3.22	0.66	2.15	1.9	3.57	7.47	9.72	12.23	24.11	17.17	56.87	55.9
70-10-20	6.89	3.27	0.68	2.18	1.92	3.82	7.53	10.38	13.57	24.55	18.21	58.48	59.68
70-15-15	6.94	3.25	0.66	2.16	1.91	3.57	8.6	11.5	12.37	24.38	17.3	52.71	55.04
70-20-10	6.94	3.24	0.66	2.16	1.9	3.58	7.48	9.76	12.25	24.23	17.17	56.74	52.66
75-05-20	6.95	3.3	0.72	2.22	2.02	4.03	8.41	11.9	16.49	29.85	19.22	60.71	65.25
75-10-15	6.89	3.27	0.69	2.19	1.98	3.85	7.54	10.4	13.78	27.32	18.27	59.15	60.22
75-15-10	6.88	3.25	0.64	2.17	1.92	3.96	8.41	10.96	12.19	23.29	23.37	47.7	59.34
75-20-05	6.94	3.24	0.66	2.15	1.9	3.58	7.48	9.78	12.25	24.37	17.21	57.34	56.74
80-05-15	6.94	3.32	0.74	2.37	3.69	4.05	7.69	15.27	18.5	31.25	24.51	63.4	63.8
80-15-05	6.88	3.25	0.66	2.16	1.91	3.72	7.52	10.24	12.38	24.48	17.65	58.39	59.4
80-10-10	6.9	3.28	0.69	0.64	1.99	4.01	6.09	11.57	13.2	27.61	20.35	56.6	62.37
85-10-05	6.92	3.29	0.69	2.2	2.01	4.02	7.64	11.77	13.95	27.87	18.98	60.14	63.54
85-05-10	7.23	4.62	0.79	2.42	2.12	6.25	14.43	12.72	20.52	31.87	26.42	57.53	63.92
90-05-05	7.97	5.83	2.34	4.48	2.31	7.49	14.8	16.44	23.86	41.46	29.27	107.87	78.54

Table 4.26: ANN Results of All the Models on various Parameters and (60-20-20) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.27%	6.87%	3–1—1	0.70%	9.10%	6.67%	5–1–1	0.64%	9.56%	7.15%
1–2–1	0.7	9.43	6.96	3–2—1	0.67	9.31	6.67	5–2–1	0.56	9.88	7.35
1–3–1	0.67	9.56	7	3–3—1	0.65	9.27	6.8	5–3–1	0.54	10.14	7.65
1–4–1	0.66	9.72	7.14	3–4—1	0.58	9.83	7.15	5–4–1	0.54	10.11	7.57
1–5–1	0.65	9.63	7.08	3–5—1	0.58	9.73	7.1	5–5–1	0.52	10.03	7.57
1–6–1	0.64	9.73	7.19	3–6—1	0.56	9.85	7.22	5–6–1	0.49	10.38	7.79
1–7–1	0.64	9.81	7.26	3–7—1	0.57	9.82	7.19	5–7–1	0.48	10.35	7.74
1–8–1	1.99	12.37	9.46	3–8—1	0.5	10.12	7.46	5–8–1	0.5	10.19	7.7
1–9–1	1.66	11.32	8.46	3–9—1	0.54	10.12	7.3	5–9–1	0.47	9.59	7.8
1–10–1	0.63	9.6	7.08	3–10—1	0.53	9.81	7.23	5–10–1	0.45	10.4	7.87
1–11–1	0.82	10.32	7.71	3–11—1	0.57	9.57	6.95	5–11–1	0.42	10.51	7.99
1–12–1	0.64	9.65	7.11	3–12—1	0.53	9.91	7.29	5–12–1	0.45	10.37	7.79
1–13–1	2.55	12.86	10	3–13—1	0.52	9.92	7.3	5–13–1	0.39	10.6	8
1–14–1	2.76	13.26	10.29	3–14—1	0.53	9.94	7.29	5–14–1	0.43	10.49	7.92
1–15–1	1.56	11.92	9.1	3–15—1	0.52	9.95	7.32	5–15–1	0.39	10.59	8
1–16–1	4.06	15.99	12.58	3–16—1	0.53	9.84	7.23	5–16–1	0.42	10.42	7.87
1–17–1	9.11	18.98	15.35	3–17—1	0.54	9.79	7.23	5–17–1	0.39	10.69	8.1
1–18–1	10.39	22.63	18.07	3–18—1	0.51	9.97	7.31	5–18–1	0.4	10.52	7.95
1–19–1	7.61	18.29	14.54	3–19—1	0.51	10.03	7.38	5–19–1	0.39	10.66	8.07
1–20–1	3.21	14.74	11.24	3–20—1	0.53	9.96	7.32	5–20–1	0.41	10.58	7.97

TABLE 4.26 CONTINUED: ANN Results of All the Models on various Parameters and (60-20-20) Dataset

Dataset	N14	N15	N16	N17	N18	N19	N20	N25	N30	N35	N40	N45	N50
60-20-20	6.83	3.22	0.66	3.75	3.56	1.92	8.85	11.78	12.96	23.32	16.28	58.48	52.17
65-15-20	6.95	3.24	0.66	2.16	1.9	3.58	7.48	9.96	12.35	24.38	17.33	57.59	57.7
65-20-15	6.94	3.22	0.66	2.15	1.9	3.57	7.47	9.72	12.23	24.11	17.17	56.87	55.9
70-10-20	6.89	3.27	0.68	2.18	1.92	3.82	7.53	10.38	13.57	24.55	18.21	58.48	59.68
70-15-15	6.94	3.25	0.66	2.16	1.91	3.57	8.6	11.5	12.37	24.38	17.3	52.71	55.04
70-20-10	6.94	3.24	0.66	2.16	1.9	3.58	7.48	9.76	12.25	24.23	17.17	56.74	52.66
75-05-20	6.95	3.3	0.72	2.22	2.02	4.03	8.41	11.9	16.49	29.85	19.22	60.71	65.25
75-10-15	6.89	3.27	0.69	2.19	1.98	3.85	7.54	10.4	13.78	27.32	18.27	59.15	60.22
75-15-10	6.88	3.25	0.64	2.17	1.92	3.96	8.41	10.96	12.19	23.29	23.37	47.7	59.34
75-20-05	6.94	3.24	0.66	2.15	1.9	3.58	7.48	9.78	12.25	24.37	17.21	57.34	56.74
80-05-15	6.94	3.32	0.74	2.37	3.69	4.05	7.69	15.27	18.5	31.25	24.51	63.4	63.8
80-15-05	6.88	3.25	0.66	2.16	1.91	3.72	7.52	10.24	12.38	24.48	17.65	58.39	59.4
80-10-10	6.9	3.28	0.69	0.64	1.99	4.01	6.09	11.57	13.2	27.61	20.35	56.6	62.37
85-10-05	6.92	3.29	0.69	2.2	2.01	4.02	7.64	11.77	13.95	27.87	18.98	60.14	63.54
85-05-10	7.23	4.62	0.79	2.42	2.12	6.25	14.43	12.72	20.52	31.87	26.42	57.53	63.92
90-05-05	7.97	5.83	2.34	4.48	2.31	7.49	14.8	16.44	23.86	41.46	29.27	107.87	78.54

Table 4.27: ANN Results of All the Models on Various Parameters and (65-15-20) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.30%	6.89%	3–1–1	0.7%1	9.03%	6.63%	5–1–1	0.65%	9.57%	7.17%
1–2–1	0.71	9.37	6.91	3–2–1	0.68	9.31	6.73	5–2–1	0.57	9.86	7.33
1–3–1	0.68	9.55	6.99	3–3–1	0.66	9.21	6.75	5–3–1	0.55	10.22	7.66
1–4–1	0.66	9.66	7.1	3–4–1	0.58	9.83	7.15	5–4–1	0.55	10.01	7.5
1–5–1	0.65	9.6	7.07	3–5–1	0.59	9.67	7.05	5–5–1	0.52	10.05	7.57
1–6–1	0.65	9.71	7.17	3–6–1	0.56	9.73	7.13	5–6–1	0.5	10.36	7.78
1–7–1	0.64	9.76	7.24	3–7–1	0.57	9.82	7.18	5–7–1	0.48	10.35	7.74
1–8–1	2	12.33	9.42	3–8–1	0.51	10.13	7.47	5–8–1	0.51	10.12	7.67
1–9–1	1.67	11.28	8.41	3–9–1	0.55	9.92	7.28	5–9–1	0.47	10.27	7.76
1–10–1	0.64	9.58	7.08	3–10–1	0.53	9.79	7.22	5–10–1	0.46	10.36	7.83
1–11–1	0.83	10.31	7.72	3–11–1	0.57	9.6	6.97	5–11–1	0.42	10.51	7.99
1–12–1	0.64	9.71	7.16	3–12–1	0.53	9.91	7.3	5–12–1	0.45	10.36	7.79
1–13–1	2.55	12.8	9.96	3–13–1	0.53	9.91	7.3	5–13–1	0.4	10.66	8.05
1–14–1	2.76	13.3	10.3	3–14–1	0.52	9.93	7.29	5–14–1	0.43	10.4	7.84
1–15–1	1.56	11.92	9.08	3–15–1	0.53	9.94	7.31	5–15–1	0.39	10.6	8
1–16–1	4.08	15.97	12.55	3–16–1	0.53	9.8	7.2	5–16–1	0.43	10.44	7.88
1–17–1	9.13	18.98	15.35	3–17–1	0.54	9.79	7.22	5–17–1	0.39	10.69	8.1
1–18–1	10.39	22.65	18.06	3–18–1	0.51	9.96	7.31	5–18–1	0.4	10.53	7.95
1–19–1	7.76	18.37	14.64	3–19–1	0.52	10.03	7.39	5–19–1	0.4	10.63	8.04
1–20–1	3.21	14.73	11.23	3–20–1	0.53	9.89	7.25	5–20–1	0.41	10.58	7.97

Table 4.28: ANN Results of All the Models on Various Parameters and (65-15-20) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.30%	6.89%	3–1–1	0.7%1	9.03%	6.63%	5–1–1	0.65%	9.57%	7.17%
1–2–1	0.71	9.37	6.91	3–2–1	0.68	9.31	6.73	5–2–1	0.57	9.86	7.33
1–3–1	0.68	9.55	6.99	3–3–1	0.66	9.21	6.75	5–3–1	0.55	10.22	7.66
1–4–1	0.66	9.66	7.1	3–4–1	0.58	9.83	7.15	5–4–1	0.55	10.01	7.5
1–5–1	0.65	9.6	7.07	3–5–1	0.59	9.67	7.05	5–5–1	0.52	10.05	7.57
1–6–1	0.65	9.71	7.17	3–6–1	0.56	9.73	7.13	5–6–1	0.5	10.36	7.78
1–7–1	0.64	9.76	7.24	3–7–1	0.57	9.82	7.18	5–7–1	0.48	10.35	7.74
1–8–1	2	12.33	9.42	3–8–1	0.51	10.13	7.47	5–8–1	0.51	10.12	7.67
1–9–1	1.67	11.28	8.41	3–9–1	0.55	9.92	7.28	5–9–1	0.47	10.27	7.76
1–10–1	0.64	9.58	7.08	3–10–1	0.53	9.79	7.22	5–10–1	0.46	10.36	7.83
1–11–1	0.83	10.31	7.72	3–11–1	0.57	9.6	6.97	5–11–1	0.42	10.51	7.99
1–12–1	0.64	9.71	7.16	3–12–1	0.53	9.91	7.3	5–12–1	0.45	10.36	7.79
1–13–1	2.55	12.8	9.96	3–13–1	0.53	9.91	7.3	5–13–1	0.4	10.66	8.05
1–14–1	2.76	13.3	10.3	3–14–1	0.52	9.93	7.29	5–14–1	0.43	10.4	7.84
1–15–1	1.56	11.92	9.08	3–15–1	0.53	9.94	7.31	5–15–1	0.39	10.6	8
1–16–1	4.08	15.97	12.55	3–16–1	0.53	9.8	7.2	5–16–1	0.43	10.44	7.88
1–17–1	9.13	18.98	15.35	3–17–1	0.54	9.79	7.22	5–17–1	0.39	10.69	8.1
1–18–1	10.39	22.65	18.06	3–18–1	0.51	9.96	7.31	5–18–1	0.4	10.53	7.95
1–19–1	7.76	18.37	14.64	3–19–1	0.52	10.03	7.39	5–19–1	0.4	10.63	8.04
1–20–1	3.21	14.73	11.23	3–20–1	0.53	9.89	7.25	5–20–1	0.41	10.58	7.97

Table 4.29: ANN Results of All the Models on Various Parameters and (65-20-15) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.29%	62.44%	3–1–1	0.70%	9.11%	6.68%	5–1–1	0.64%	9.56%	7.1%6
1–2–1	0.7	9.38	6.93	3–2–1	0.68	9.33	6.73	5–2–1	0.57	9.84	7.33
1–3–1	0.67	9.55	7	3–3–1	0.65	9.23	6.76	5–3–1	0.54	10.11	7.63
1–4–1	0.66	9.72	7.14	3–4–1	0.58	9.83	7.15	5–4–1	0.55	10.04	7.52
1–5–1	0.65	9.63	7.08	3–5–1	0.58	9.73	7.1	5–5–1	0.52	10.03	7.57
1–6–1	0.64	9.74	7.19	3–6–1	0.55	9.83	7.22	5–6–1	0.49	10.36	7.78
1–7–1	0.64	9.79	7.25	3–7–1	0.57	9.82	7.19	5–7–1	0.48	10.35	7.74
1–8–1	1.99	12.35	9.44	3–8–1	0.5	10.13	7.46	5–8–1	0.51	10.15	7.68
1–9–1	1.66	11.27	8.42	3–9–1	0.54	9.92	7.29	5–9–1	0.47	10.35	7.8
1–10–1	0.63	9.6	7.08	3–10–1	0.53	9.81	7.23	5–10–1	0.45	10.4	7.87
1–11–1	0.82	10.32	7.71	3–11–1	0.57	9.62	6.99	5–11–1	0.42	10.51	7.99
1–12–1	0.64	9.64	7.11	3–12–1	0.53	9.92	7.29	5–12–1	0.45	10.36	7.79
1–13–1	2.55	12.81	9.96	3–13–1	0.52	9.91	7.31	5–13–1	0.39	10.6	8
1–14–1	2.76	13.26	10.28	3–14–1	0.52	9.94	7.29	5–14–1	0.42	10.45	7.88
1–15–1	1.56	11.91	9.09	3–15–1	0.52	9.95	7.32	5–15–1	0.39	10.59	8
1–16–1	4.07	15.96	12.55	3–16–1	0.53	9.83	7.21	5–16–1	0.42	10.42	7.87
1–17–1	9.11	18.98	15.34	3–17–1	0.54	9.78	7.21	5–17–1	0.39	10.7	8.11
1–18–1	10.39	22.64	18.07	3–18–1	0.51	9.97	7.31	5–18–1	0.4	10.52	7.95
1–19–1	7.66	18.32	14.58	3–19–1	0.51	10.02	7.38	5–19–1	0.4	10.66	8.07
1–20–1	3.21	14.73	11.24	3–20–1	0.53	9.9	7.27	5–20–1	0.41	10.58	7.97

Table 4.30: ANN Results of All the Models on Various Parameters and (70-10-20) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.73%	9.28%	6.86%	3–1–1	0.71%	9.03%	6.63%	5–1–1	0.65%	9.44%	7.08%
1–2–1	0.71	9.41	6.92	3–2–1	0.69	9.3	6.71	5–2–1	0.58	9.84	7.34
1–3–1	0.69	9.55	6.99	3–3–1	0.66	9.19	6.75	5–3–1	0.56	10.12	7.61
1–4–1	0.69	9.65	7.1	3–4–1	0.6	9.65	7.02	5–4–1	0.56	10	7.51
1–5–1	0.67	9.55	7.02	3–5–1	0.6	9.67	7.03	5–5–1	0.53	10.01	7.55
1–6–1	0.66	9.78	7.2	3–6–1	0.58	9.69	7.07	5–6–1	0.52	10.3	7.73
1–7–1	0.65	9.74	7.23	3–7–1	0.58	9.8	7.19	5–7–1	0.49	10.3	7.7
1–8–1	2	12.35	9.43	3–8–1	0.52	10.09	7.43	5–8–1	0.52	10.05	7.61
1–9–1	1.67	11.28	8.42	3–9–1	0.55	9.95	7.31	5–9–1	0.48	10.34	7.79
1–10–1	0.65	9.5	7.03	3–10–1	0.54	9.8	7.24	5–10–1	0.48	10.29	7.8
1–11–1	0.84	10.18	7.64	3–11–1	0.58	9.62	6.98	5–11–1	0.42	10.52	7.99
1–12–1	0.66	9.66	7.11	3–12–1	0.54	9.91	7.28	5–12–1	0.46	10.38	7.8
1–13–1	2.56	12.84	9.98	3–13–1	0.55	9.81	7.22	5–13–1	0.41	10.56	8
1–14–1	2.82	13.35	10.35	3–14–1	0.54	9.92	7.27	5–14–1	0.44	10.46	7.9
1–15–1	1.57	11.91	9.06	3–15–1	0.54	9.91	7.29	5–15–1	0.4	10.61	8.02
1–16–1	4.11	16.02	12.57	3–16–1	0.54	9.74	7.15	5–16–1	0.43	10.46	7.89
1–17–1	9.14	18.98	15.34	3–17–1	0.55	9.75	7.2	5–17–1	0.4	10.7	8.11
1–18–1	10.39	22.64	18.05	3–18–1	0.52	9.9	7.26	5–18–1	0.4	10.53	7.96
1–19–1	7.76	18.31	14.59	3–19–1	0.54	9.98	7.34	5–19–1	0.41	10.6	8.03
1–20–1	3.22	14.71	11.2	3–20–1	0.54	9.87	7.23	5–20–1	0.41	10.6	7.98

Table 4.31: ANN Results of All the Models on Various Parameters and (70-15-15) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE%	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.28%	6.86%	3–1–1	0.71%	9.04%	6.64	5–1–1	0.6%4	9.54%	7.14%
1–2–1	0.71	9.38	6.91	3–2–1	0.68	9.29	6.71	5–2–1	0.57	9.85	7.32
1–3–1	0.68	9.55	6.99	3–3–1	0.66	9.2	6.75	5–3–1	0.54	10.12	7.63
1–4–1	0.66	9.62	7.09	3–4–1	0.58	9.75	7.09	5–4–1	0.55	9.99	7.49
1–5–1	0.65	9.59	7.06	3–5–1	0.6	9.65	7.04	5–5–1	0.52	10.04	7.56
1–6–1	0.65	9.73	7.17	3–6–1	0.56	9.74	7.14	5–6–1	0.5	10.36	7.78
1–7–1	0.64	9.78	7.25	3–7–1	0.57	9.86	7.21	5–7–1	0.48	10.35	7.74
1–8–1	2	12.33	9.42	3–8–1	0.51	10.13	7.47	5–8–1	0.51	10.11	7.66
1–9–1	1.67	11.28	8.42	3–9–1	0.55	9.94	7.3	5–9–1	0.47	10.27	7.76
1–10–1	0.64	9.56	7.07	3–10–1	0.54	9.79	7.23	5–10–1	0.46	10.37	7.84
1–11–1	0.83	10.29	7.7	3–11–1	0.57	9.6	6.97	5–11–1	0.42	10.51	7.98
1–12–1	0.65	9.67	7.13	3–12–1	0.53	9.93	7.3	5–12–1	0.45	10.37	7.79
1–13–1	2.55	12.84	9.98	3–13–1	0.54	9.88	7.27	5–13–1	0.4	10.62	8.01
1–14–1	2.81	13.38	10.36	3–14–1	0.53	9.93	7.28	5–14–1	0.43	10.44	7.87
1–15–1	1.57	11.94	9.08	3–15–1	0.53	9.96	7.32	5–15–1	0.39	10.6	8
1–16–1	4.08	16.02	12.58	3–16–1	0.53	9.79	7.19	5–16–1	0.43	10.43	7.87
1–17–1	9.13	18.98	15.35	3–17–1	0.54	9.77	7.21	5–17–1	0.39	10.69	8.1
1–18–1	10.39	22.64	18.06	3–18–1	0.51	9.93	7.3	5–18–1	0.4	10.52	7.95
1–19–1	7.76	18.35	14.61	3–19–1	0.52	10.03	7.39	5–19–1	0.4	10.66	8.07
1–20–1	3.21	14.73	11.22	3–20–1	0.53	9.88	7.24	5–20–1	0.41	10.58	7.97

TABLE 4.32: ANN Results of All the Models on Various Parameters and (70-20-10) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.29%	6.88%	3–1–1	0.70%	9.1%1	6.68%	5–1–1	0.64%	9.57%	7.16%
1–2–1	0.71	9.37	6.91	3–2–1	0.68	9.33	6.74	5–2–1	0.57	9.85	7.33
1–3–1	0.68	9.57	7	3–3–1	0.65	9.21	6.75	5–3–1	0.54	10.1	7.64
1–4–1	0.66	9.69	7.13	3–4–1	0.58	9.83	7.15	5–4–1	0.55	10.01	7.5
1–5–1	0.65	9.63	7.08	3–5–1	0.58	9.72	7.09	5–5–1	0.52	10.05	7.57
1–6–1	0.64	9.75	7.2	3–6–1	0.56	9.74	7.15	5–6–1	0.49	10.37	7.79
1–7–1	0.64	9.79	7.25	3–7–1	0.57	9.74	7.18	5–7–1	0.48	10.35	7.74
1–8–1	1.99	12.32	9.41	3–8–1	0.5	10.13	7.46	5–8–1	0.51	10.14	7.68
1–9–1	1.66	11.27	8.42	3–9–1	0.54	10.13	7.3	5–9–1	0.47	10.33	7.8
1–10–1	0.64	9.61	7.09	3–10–1	0.53	9.79	7.22	5–10–1	0.45	10.4	7.87
1–11–1	0.83	10.29	7.69	3–11–1	0.57	9.61	6.98	5–11–1	0.42	10.51	7.98
1–12–1	0.64	9.64	7.11	3–12–1	0.53	9.91	7.29	5–12–1	0.45	10.36	7.79
1–13–1	2.55	12.79	9.96	3–13–1	0.52	9.91	7.3	5–13–1	0.39	10.6	8
1–14–1	2.76	13.27	10.28	3–14–1	0.52	9.94	7.29	5–14–1	0.42	10.6	7.88
1–15–1	1.56	11.88	9.07	3–15–1	0.53	9.93	7.3	5–15–1	0.39	10.59	8
1–16–1	4.07	15.96	12.55	3–16–1	0.53	9.83	7.21	5–16–1	0.42	10.43	7.87
1–17–1	9.11	18.96	15.33	3–17–1	0.54	9.79	7.22	5–17–1	0.39	10.7	8.11
1–18–1	10.39	22.65	18.08	3–18–1	0.51	9.98	7.31	5–18–1	0.4	10.52	7.95
1–19–1	7.66	18.3	14.57	3–19–1	0.51	10.02	7.37	5–19–1	0.4	10.52	8.05
1–20–1	3.21	14.72	11.23	3–20–1	0.53	9.89	7.26	5–20–1	0.41	10.58	7.97

TABLE 4.33: ANN Results of All the Models on Various Parameters and (70-05-20) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.74%	9.12%	6.74%	3–1–1	0.73%	8.97%	0.73%	5–1–1	0.67%	9.41%	7.05%
1–2–1	0.73	9.42	6.93	3–2–1	0.69	9.18	0.69	5–2–1	0.62	9.78	7.26
1–3–1	0.72	9.51	6.97	3–3–1	0.69	9.17	0.69	5–3–1	0.59	10.01	7.55
1–4–1	0.69	9.41	6.92	3–4–1	0.62	9.56	0.62	5–4–1	0.59	9.89	7.43
1–5–1	0.7	9.45	6.9	3–5–1	0.65	9.65	0.65	5–5–1	0.56	9.99	7.51
1–6–1	0.68	9.82	7.26	3–6–1	0.62	9.47	0.62	5–6–1	0.54	10.29	7.73
1–7–1	0.67	9.7	7.17	3–7–1	0.61	9.63	0.61	5–7–1	0.53	10.31	7.75
1–8–1	2.01	12.27	9.38	3–8–1	0.59	9.79	0.59	5–8–1	0.56	9.91	7.51
1–9–1	1.7	11.11	8.31	3–9–1	0.58	9.71	0.58	5–9–1	0.52	10.12	7.61
1–10–1	0.68	9.24	6.83	3–10–1	0.57	9.65	0.57	5–10–1	0.51	10.17	7.73
1–11–1	0.87	10.06	7.54	3–11–1	0.62	9.65	0.62	5–11–1	0.44	10.5	7.97
1–12–1	0.69	9.59	7.07	3–12–1	0.59	9.84	0.59	5–12–1	0.49	10.37	7.79
1–13–1	2.58	12.82	9.95	3–13–1	0.59	9.67	0.59	5–13–1	0.44	10.5	7.95
1–14–1	2.85	13.33	10.33	3–14–1	0.56	9.77	0.56	5–14–1	0.46	10.46	7.88
1–15–1	1.61	11.79	9.01	3–15–1	0.59	9.74	0.59	5–15–1	0.44	10.52	7.95
1–16–1	4.15	15.78	12.43	3–16–1	0.56	9.65	0.56	5–16–1	0.48	10.14	7.65
1–17–1	9.16	18.86	15.29	3–17–1	0.6	9.61	0.6	5–17–1	0.44	10.6	8.02
1–18–1	10.43	22.64	18.05	3–18–1	0.58	9.77	0.58	5–18–1	0.41	10.55	7.96
1–19–1	7.8	18.28	14.57	3–19–1	0.61	9.76	0.61	5–19–1	0.44	10.61	8.02
1–20–1	3.28	14.7	11.24	3–20–1	0.58	9.81	0.58	5–20–1	0.43	10.68	8.03

Table 4.34: ANN Results of All the Models on Various Parameters and (75-10-15) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.73%	9.29%	6.86%	3–1–1	0.71%	9.04%	0.71%	5–1–1	0.65%	9.42%	7.07%
1–2–1	0.71	9.39	6.91	3–2–1	0.68	9.2	0.68	5–2–1	0.59	9.84	7.32
1–3–1	0.69	9.56	6.99	3–3–1	0.67	9.15	0.67	5–3–1	0.56	10.06	7.57
1–4–1	0.67	9.55	7.04	3–4–1	0.6	9.67	0.6	5–4–1	0.57	9.87	7.42
1–5–1	0.67	9.55	7.02	3–5–1	0.61	9.59	0.61	5–5–1	0.53	9.96	7.52
1–6–1	0.66	9.81	7.22	3–6–1	0.58	9.71	0.58	5–6–1	0.52	10.27	7.73
1–7–1	0.65	9.73	7.22	3–7–1	0.58	9.66	0.58	5–7–1	0.5	10.31	7.7
1–8–1	2	12.3	9.39	3–8–1	0.52	10.06	0.52	5–8–1	0.53	10.04	7.6
1–9–1	1.68	11.2	8.37	3–9–1	0.55	9.85	0.55	5–9–1	0.49	10.31	7.77
1–10–1	0.66	9.44	6.96	3–10–1	0.55	9.71	0.55	5–10–1	0.49	10.26	7.78
1–11–1	0.85	10.15	7.61	3–11–1	0.58	9.61	0.58	5–11–1	0.42	10.52	7.98
1–12–1	0.66	9.61	7.09	3–12–1	0.55	9.89	0.55	5–12–1	0.46	10.36	7.78
1–13–1	2.56	12.82	9.98	3–13–1	0.55	9.8	0.55	5–13–1	0.41	10.55	7.98
1–14–1	2.82	13.33	10.34	3–14–1	0.54	9.92	0.54	5–14–1	0.44	10.42	7.87
1–15–1	1.58	11.83	9.03	3–15–1	0.54	9.9	0.54	5–15–1	0.4	10.6	8.02
1–16–1	4.11	16.03	12.57	3–16–1	0.54	9.74	0.54	5–16–1	0.44	10.35	7.8
1–17–1	9.14	18.99	15.36	3–17–1	0.55	9.75	0.55	5–17–1	0.42	10.69	8.07
1–18–1	10.4	22.65	18.06	3–18–1	0.53	9.85	0.53	5–18–1	0.4	10.53	7.96
1–19–1	7.77	18.28	14.57	3–19–1	0.56	9.93	0.56	5–19–1	0.42	10.55	7.98
1–20–1	3.23	14.72	11.23	3–20–1	0.55	9.84	0.55	5–20–1	0.41	10.61	7.99

Table 4.35: ANN Results of All the Models on Various Parameters and (75-15-10) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.01%	0.09%	0.07%	3–1—1	0.01%	0.0902	0.01%	5–1–1	0.01%	0.10%	0.07%
1–2–1	0.0071	0.0936	0.069	3–2—1	0.0068	0.0927	0.0068	5–2–1	0.0057	0.0987	0.0734
1–3–1	0.0068	0.0955	0.07	3–3—1	0.0066	0.092	0.0066	5–3–1	0.0055	0.1013	0.0764
1–4–1	0.0066	0.0963	0.0709	3–4—1	0.0058	0.0972	0.0058	5–4–1	0.0055	0.0998	0.0747
1–5–1	0.0065	0.0961	0.0707	3–5—1	0.006	0.0962	0.006	5–5–1	0.0052	0.1002	0.0756
1–6–1	0.0065	0.0971	0.0716	3–6—1	0.0056	0.0974	0.0056	5–6–1	0.005	0.1033	0.0776
1–7–1	0.0064	0.0978	0.0725	3–7—1	0.0057	0.0981	0.0057	5–7–1	0.0049	0.103	0.077
1–8–1	0.02	0.1235	0.0944	3–8—1	0.0051	0.1012	0.0051	5–8–1	0.0052	0.1013	0.0766
1–9–1	0.0167	0.1124	0.084	3–9—1	0.0055	0.0995	0.0055	5–9–1	0.0048	0.103	0.0777
1–10–1	0.0064	0.0955	0.0706	3–10—1	0.0054	0.0981	0.0054	5–10–1	0.0047	0.1034	0.0783
1–11–1	0.0083	0.1024	0.0768	3–11—1	0.0057	0.096	0.0057	5–11–1	0.0042	0.1052	0.0799
1–12–1	0.0065	0.0963	0.0709	3–12—1	0.0054	0.0988	0.0054	5–12–1	0.0045	0.1038	0.078
1–13–1	0.0255	0.1284	0.0999	3–13—1	0.0055	0.0983	0.0055	5–13–1	0.0041	0.1059	0.08
1–14–1	0.0282	0.1335	0.1034	3–14—1	0.0053	0.0993	0.0053	5–14–1	0.0043	0.1044	0.0787
1–15–1	0.0157	0.1196	0.0909	3–15—1	0.0053	0.0992	0.0053	5–15–1	0.0039	0.106	0.08
1–16–1	0.041	0.1603	0.1259	3–16—1	0.0054	0.0975	0.0054	5–16–1	0.0043	0.1045	0.0789
1–17–1	0.0913	0.1898	0.1534	3–17—1	0.0055	0.0978	0.0055	5–17–1	0.0039	0.1069	0.0811
1–18–1	0.1039	0.2263	0.1805	3–18—1	0.0052	0.0993	0.0052	5–18–1	0.004	0.1052	0.0795
1–19–1	0.0776	0.1836	0.1461	3–19—1	0.0052	0.1004	0.0052	5–19–1	0.004	0.1063	0.0804
1–20–1	0.0321	0.1473	0.1122	3–20—1	0.0053	0.0985	0.0053	5–20–1	0.0041	0.1058	0.0797

Table 4.36: ANN Results of All the Models on Various Parameters and (75-20-05) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.01%	0.092%7	0.07%	3–1—1	0.01%	0.090%9	0.01%	5–1–1	0.01%	0.10%	0.07%
1–2–1	0.0071	0.0938	0.0692	3–2—1	0.0068	0.093	0.0068	5–2–1	0.0057	0.0986	0.0733
1–3–1	0.0068	0.0956	0.07	3–3—1	0.0066	0.0919	0.0066	5–3–1	0.0054	0.1011	0.0764
1–4–1	0.0066	0.0968	0.0712	3–4—1	0.0058	0.0982	0.0058	5–4–1	0.0054	0.1001	0.075
1–5–1	0.0065	0.0961	0.0707	3–5—1	0.0058	0.0972	0.0058	5–5–1	0.0052	0.1005	0.0757
1–6–1	0.0065	0.0972	0.0718	3–6—1	0.0056	0.0973	0.0056	5–6–1	0.0049	0.1037	0.0779
1–7–1	0.0064	0.0977	0.0724	3–7—1	0.0057	0.0982	0.0057	5–7–1	0.0048	0.1035	0.0774
1–8–1	0.0199	0.1233	0.0941	3–8—1	0.0051	0.1013	0.0051	5–8–1	0.0051	0.1014	0.0768
1–9–1	0.0166	0.1128	0.0842	3–9—1	0.0054	0.0993	0.0054	5–9–1	0.0047	0.1027	0.0776
1–10–1	0.0064	0.0961	0.071	3–10—1	0.0053	0.0979	0.0053	5–10–1	0.0045	0.1041	0.0787
1–11–1	0.0083	0.103	0.0771	3–11—1	0.0057	0.0961	0.0057	5–11–1	0.0042	0.1051	0.0799
1–12–1	0.0064	0.0965	0.0712	3–12—1	0.0053	0.0992	0.0053	5–12–1	0.0045	0.1036	0.0779
1–13–1	0.0255	0.1279	0.0996	3–13—1	0.0053	0.099	0.0053	5–13–1	0.0039	0.1062	0.0801
1–14–1	0.0276	0.1328	0.1029	3–14—1	0.0053	0.0993	0.0053	5–14–1	0.0043	0.1042	0.0785
1–15–1	0.0156	0.1188	0.0906	3–15—1	0.0053	0.0995	0.0053	5–15–1	0.0039	0.106	0.0801
1–16–1	0.0407	0.1595	0.1254	3–16—1	0.0053	0.0979	0.0053	5–16–1	0.0043	0.1044	0.0787
1–17–1	0.0913	0.1896	0.1533	3–17—1	0.0053	0.0979	0.0053	5–17–1	0.0039	0.107	0.0811
1–18–1	0.1039	0.2266	0.1808	3–18—1	0.0053	0.0997	0.0053	5–18–1	0.004	0.1053	0.0796
1–19–1	0.0776	0.1835	0.1463	3–19—1	0.0053	0.1003	0.0053	5–19–1	0.004	0.1063	0.0804
1–20–1	0.0321	0.1473	0.1123	3–20—1	0.0053	0.0989	0.0053	5–20–1	0.0041	0.1058	0.0797

Table 4.37: ANN Results of All the Models on Various Parameters and (80-10-10) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.73%	9.27%	6.8%5	3–1–1	0.71%	8.98%	0.7%1	5–1–1	0.65%	9.40%	7.05%
1–2–1	0.71	9.39	6.91	3–2–1	0.67	9.24	0.67	5–2–1	0.6	9.81	7.27
1–3–1	0.69	9.51	6.95	3–3–1	0.67	9.15	0.67	5–3–1	0.56	10.07	7.58
1–4–1	0.68	9.48	6.99	3–4–1	0.6	9.67	0.6	5–4–1	0.58	9.9	7.44
1–5–1	0.67	9.49	6.98	3–5–1	0.62	9.57	0.62	5–5–1	0.55	9.99	7.52
1–6–1	0.66	9.84	7.25	3–6–1	0.58	9.65	0.58	5–6–1	0.52	10.21	7.7
1–7–1	0.66	9.71	7.21	3–7–1	0.59	9.66	0.59	5–7–1	0.51	10.29	7.69
1–8–1	2	12.28	9.4	3–8–1	0.52	10.07	0.52	5–8–1	0.53	10.02	7.59
1–9–1	1.68	11.18	8.37	3–9–1	0.56	9.78	0.56	5–9–1	0.5	10.24	7.71
1–10–1	0.66	9.4	6.95	3–10–1	0.55	9.68	0.55	5–10–1	0.5	10.26	7.79
1–11–1	0.85	10.15	7.61	3–11–1	0.6	9.65	0.6	5–11–1	0.43	10.54	8
1–12–1	0.66	9.55	7.05	3–12–1	0.56	9.81	0.56	5–12–1	0.46	10.36	7.78
1–13–1	2.56	12.86	0.02	3–13–1	0.57	9.73	0.57	5–13–1	0.42	10.51	7.96
1–14–1	2.82	13.35	10.34	3–14–1	0.55	9.87	0.55	5–14–1	0.44	10.42	7.87
1–15–1	1.58	11.81	9.02	3–15–1	0.55	9.9	0.55	5–15–1	0.41	10.65	8.05
1–16–1	4.12	15.93	12.54	3–16–1	0.55	9.69	0.55	5–16–1	0.44	10.34	7.8
1–17–1	9.14	18.92	15.32	3–17–1	0.57	9.71	0.57	5–17–1	0.43	10.63	8.03
1–18–1	10.4	22.64	18.06	3–18–1	0.53	9.85	0.53	5–18–1	0.4	10.53	7.96
1–19–1	7.77	18.26	14.54	3–19–1	0.57	9.85	0.57	5–19–1	0.43	10.61	8.02
1–20–1	3.23	14.7	11.2	3–20–1	0.56	9.78	0.56	5–20–1	0.41	10.61	7.99

TABLE 4.38: ANN Results of All the Models on Various Parameters and (80-15-05) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.72%	9.25%	6.85%	3–1–1	0.71%	9.02%	0.71%	5–1–1	0.65%	9.44%	7.09%
1–2–1	0.71	9.36	6.9	3–2–1	0.69	9.32	0.69	5–2–1	0.58	9.84	7.32
1–3–1	0.68	9.54	6.99	3–3–1	0.66	9.2	0.66	5–3–1	0.55	10.11	7.63
1–4–1	0.67	9.65	7.1	3–4–1	0.58	9.71	0.58	5–4–1	0.56	9.99	7.49
1–5–1	0.66	9.56	7.03	3–5–1	0.6	9.65	0.6	5–5–1	0.53	10.01	7.55
1–6–1	0.65	9.77	7.2	3–6–1	0.57	9.73	0.57	5–6–1	0.5	10.27	7.72
1–7–1	0.65	9.73	7.22	3–7–1	0.58	9.8	0.58	5–7–1	0.49	10.3	7.7
1–8–1	2	12.35	9.44	3–8–1	0.52	10.08	0.52	5–8–1	0.52	10.09	7.63
1–9–1	1.67	11.24	8.4	3–9–1	0.55	9.97	0.55	5–9–1	0.48	10.32	7.77
1–10–1	0.65	9.5	7.03	3–10–1	0.54	9.79	0.54	5–10–1	0.48	10.31	7.81
1–11–1	0.84	10.2	7.65	3–11–1	0.57	9.59	0.57	5–11–1	0.42	10.52	7.99
1–12–1	0.65	9.62	7.09	3–12–1	0.54	9.89	0.54	5–12–1	0.45	10.38	7.8
1–13–1	2.56	12.83	9.99	3–13–1	0.55	9.81	0.55	5–13–1	0.41	10.55	7.99
1–14–1	2.82	13.34	10.34	3–14–1	0.53	9.93	0.53	5–14–1	0.43	10.45	7.88
1–15–1	1.57	11.95	9.1	3–15–1	0.54	9.9	0.54	5–15–1	0.4	10.62	8.03
1–16–1	4.1	16.03	12.57	3–16–1	0.54	9.75	0.54	5–16–1	0.43	10.46	7.89
1–17–1	9.14	18.99	15.34	3–17–1	0.55	9.78	0.55	5–17–1	0.4	10.7	8.11
1–18–1	10.39	22.63	18.05	3–18–1	0.52	9.92	0.52	5–18–1	0.4	10.53	7.96
1–19–1	7.76	18.34	14.61	3–19–1	0.52	10.02	0.52	5–19–1	0.4	10.62	8.03
1–20–1	3.22	14.73	11.23	3–20–1	0.53	9.85	0.53	5–20–1	0.41	10.6	7.97

Table 4.39: ANN Results of All the Models on Various Parameters and (85-05-10) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.75%	9.05%	6.69%	3–1–1	0.74%	9.01%	0.74%	5–1–1	0.68%	9.32%	6.97%
1–2–1	0.73	9.34	6.89	3–2–1	0.7	9.05	0.7	5–2–1	0.64	9.59	7.17
1–3–1	0.74	9.22	6.8	3–3–1	0.71	9.09	0.71	5–3–1	0.63	9.6	7.23
1–4–1	0.72	9.17	6.78	3–4–1	0.65	9.36	0.65	5–4–1	0.64	9.6	7.2
1–5–1	0.72	9.29	6.86	3–5–1	0.68	9.35	0.68	5–5–1	0.61	9.78	7.35
1–6–1	0.71	9.52	6.99	3–6–1	0.67	9.14	0.67	5–6–1	0.61	9.75	7.31
1–7–1	0.71	9.42	6.95	3–7–1	0.65	9.4	0.65	5–7–1	0.61	10.12	7.65
1–8–1	2.08	12.23	9.36	3–8–1	0.67	9.51	0.67	5–8–1	0.58	9.83	7.44
1–9–1	2.99	12.79	9.86	3–9–1	0.63	9.52	0.63	5–9–1	0.54	9.99	7.55
1–10–1	0.72	9.29	6.87	3–10–1	0.63	9.53	0.63	5–10–1	0.59	10.18	7.73
1–11–1	0.9	9.9	7.43	3–11–1	0.65	9.5	0.65	5–11–1	0.5	10.36	7.86
1–12–1	0.72	9.41	6.96	3–12–1	0.66	9.56	0.66	5–12–1	0.54	10.15	7.62
1–13–1	2.61	12.74	9.9	3–13–1	0.68	9.78	0.68	5–13–1	0.5	10.44	7.91
1–14–1	2.96	13.38	10.37	3–14–1	0.6	9.61	0.6	5–14–1	0.51	10.2	7.71
1–15–1	1.64	11.68	8.89	3–15–1	0.64	9.64	0.64	5–15–1	0.5	10.41	7.88
1–16–1	4.2	15.72	12.38	3–16–1	0.63	9.52	0.63	5–16–1	0.53	10.14	7.65
1–17–1	9.16	18.8	15.21	3–17–1	0.62	9.53	0.62	5–17–1	0.5	10.46	7.95
1–18–1	10.47	22.74	18.11	3–18–1	0.63	9.44	0.63	5–18–1	0.45	10.44	7.89
1–19–1	7.86	18.25	14.53	3–19–1	0.64	9.57	0.64	5–19–1	0.52	10.34	7.85
1–20–1	3.35	14.71	11.23	3–20–1	0.61	9.57	0.61	5–20–1	0.48	10.41	7.82

Table 4.40: ANN Results of All the Models on Various Parameters and (90-05-05) Dataset

CAPM	MSE	RMSE	MAE	FF3F	MSE	RMSE	MAE	FF5F	MSE	RMSE	MAE
1–1–1	0.78%	9.08%	6.73%	3–1–1	0.80%	9.16%	0.80%	5–1–1	0.72%	9.35%	6.97%
1–2–1	0.76	9.31	6.9	3–2–1	0.74	8.93	0.74	5–2–1	0.7	9.41	7.01
1–3–1	0.77	9.18	6.76	3–3–1	0.73	8.97	0.73	5–3–1	0.69	9.48	7.14
1–4–1	0.81	9.32	6.93	3–4–1	0.75	9.37	0.75	5–4–1	0.67	9.46	7.09
1–5–1	0.81	9.3	6.91	3–5–1	0.73	9.46	0.73	5–5–1	0.69	9.97	7.52
1–6–1	0.79	9.79	7.25	3–6–1	0.72	9.27	0.72	5–6–1	0.72	9.81	7.4
1–7–1	0.81	9.51	7.05	3–7–1	0.68	9.4	0.68	5–7–1	0.7	10.14	7.67
1–8–1	2.14	12.22	9.33	3–8–1	0.95	9.92	0.95	5–8–1	0.64	9.96	7.53
1–9–1	3.1	13.11	10.19	3–9–1	0.67	9.52	0.67	5–9–1	0.6	9.96	7.52
1–10–1	0.79	9.33	6.88	3–10–1	0.7	9.67	0.7	5–10–1	0.7	10.36	7.84
1–11–1	0.93	9.96	7.45	3–11–1	0.72	9.5	0.72	5–11–1	0.61	10.15	7.95
1–12–1	0.83	9.79	7.26	3–12–1	0.81	10.02	0.81	5–12–1	0.64	10.72	7.65
1–13–1	3.57	14.29	11.29	3–13–1	0.76	9.95	0.76	5–13–1	0.63	10.45	8.15
1–14–1	3.99	14.84	11.74	3–14–1	0.68	9.68	0.68	5–14–1	0.68	10.45	7.95
1–15–1	1.86	12.24	9.38	3–15–1	0.72	9.7	0.72	5–15–1	0.65	10.45	7.95
1–16–1	5.45	16.86	13.36	3–16–1	0.71	9.69	0.71	5–16–1	0.63	10.28	7.79
1–17–1	9.29	18.98	15.4	3–17–1	0.76	9.88	0.76	5–17–1	0.65	10.67	8.07
1–18–1	11.17	23.68	18.97	3–18–1	0.79	9.88	0.79	5–18–1	0.64	10.46	7.96
1–19–1	7.99	18.52	14.77	3–19–1	0.77	10.1	0.77	5–19–1	0.68	10.81	8.26
1–20–1	3.59	15.33	11.86	3–20–1	0.71	9.61	0.71	5–20–1	0.58	10.47	7.88

Annexure - C

MatLab Code

close all

clc

load datacompany

for company=1:30

company;

data=datacompanycompany;

per=1;

TT=data(:,1);

for i=1:size(TT,1)

T1,i=TT(i);

end

for var=1:3 var;

if(var==1)

XX=data(:,2);

for i=1:size(XX,1)

X1,i=XX(i); end

elseif(var==2)

D=data(:,1:3);

X=multiinput$_{p}repare(D)$;

$else$

$D = data(:, 2 : 6)$;

$X = multiinput_{p}repare(D)$;

end

$inputSeries = X;$

$targetSeries = T;$

$forhiddenlayer = 1 : 1$

$if(hiddenlayer == 1)$

$forh1 = 1 : 1 : 50$

$inputDelays = 1 : 2;$

$feedbackDelays = 1 : 2;$

$hiddenLayerSize = h1;$

$net = narxnet(inputDelays, feedbackDelays, hiddenLayerSize);$

$net = closeloop(net);$

$net.trainFcn = trainscg;$

$net.trainFcn = traingda;$

$net.trainFcn = trainlm;$

$net.trainFcn = traingd;$

$net.trainFcn = traingdx;$

$net.trainFcn = trainbfg;$

$view(net)$

$PreparetheDataforTrainingandSimulation$

$inputs, inputStates, layerStates, targets = ...$

$preparets(net, inputSeries, , targetSeries);$

$\%SetupDivisionofDataforTraining, Validation, Testing$

$forvalidR = 5 : 5 : 20$

$fortestR = 5 : 5 : 20$

$-----------------------testrationet.divideParam.trainRatio =$

$(100 - (validR + testR))/100;$

$net.divideParam.valRatio = validR/100;$

$net.divideParam.testRatio = testR/100;$
net,tr

$= train(net, inputs, targets, inputStates, layerStates);$

$outputs = net(inputs, inputStates, layerStates);$

$errors = gsubtract(targets, outputs);$

$performance = perform(net, targets, outputs);$

$Trg = cell2mat(T(:, 1 : 178));$

$yclosed = cell2mat(outputs);$

$MAE = errperf(Trg, yclosed, mae);$

$RMSE = errperf(Trg, yclosed, rmse);$

$generated_output(:, per) = cell2mat(outputs);$

$generated_output_error(:, per) = errors;$

$net_arrayper = net;$

$performance_tr(per) = tr;$

$results(per, 1) = var;$

$results(per, 2) = 1;$

$results(per, 3) = h1;$

$results(per, 4) = 0;$

$results(per, 5) = net.divideParam.trainRatio;$

$results(per, 6) = net.divideParam.valRatio;$

$results(per, 7) = net.divideParam.testRatio;$

$results(per, 8) = performance;$

$results(per, 9) = MAE;$

$results(per, 10) = RMSE;$

$results(per, 11) = tr.best_perf;$

$results(per, 12) = tr.best_vperf;$

$results(per, 13) = tr.best_tperf;$

$per = per + 1;$

$end - - - - - - - - endlooptestratio$

$end - - - - - - -endloopvalidationratio$

$end - - - - - - -endloopifhiddenlayerisone$

$else$

$forh1 = 1 : 1 : 50$

$forh2 = 1 : 1 : 50$

$inputDelays = 1 : 2;$

$feedbackDelays = 1 : 2;$

$hiddenLayerSize = [h1h2];$

$net = narxnet(inputDelays, feedbackDelays, hiddenLayerSize);$

$net = closeloop(net);$

$net.trainFcn = trainscg;$

$\%net.trainFcn = traingda;$

$\%net.trainFcn = traingd;$

$\%net.trainFcn = traingdx;$

$\%view(net)$

$\%PreparetheDataforTrainingandSimulation$

$inputs, inputStates, layerStates, targets = ...$

$preparets(net, inputSeries, , targetSeries);$

$\%SetupDivisionofDataforTraining, Validation, Testing$

$forvalidR = 5 : 5 : 20$

$fortestR = 5 : 5 : 20$

$net.divideParam.trainRatio = (100 - (validR + testR))/100;$

$net.divideParam.valRatio = validR/100;$

$net.divideParam.testRatio = testR/100;$

$\%TraintheNetwork$
net,tr

$= train(net, inputs, targets, inputStates, layerStates);$

$\%TesttheNetwork$

$outputs = net(inputs, inputStates, layerStates);$

$errors = gsubtract(targets, outputs);$

$performance = perform(net, targets, outputs);$

$Trg = cell2mat(T(1, 1 : 178));$

$yclosed = cell2mat(outputs);$

$MAE = errperf(Trg, yclosed, mae);$

$RMSE = errperf(Trg, yclosed, rmse);$

$generated_output(:, per) = cell2mat(outputs);$

$generated_output_error(:, per) = errors;$

$net_arrayper = net;$

$performance_tr(per) = tr;$

$results(per, 1) = var;$

$results(per, 2) = 2;$

$results(per, 3) = h1;$

$results(per, 4) = h2;$

$results(per, 5) = net.divideParam.trainRatio;$

$results(per, 6) = net.divideParam.valRatio;$

$results(per, 7) = net.divideParam.testRatio;$

$results(per, 8) = performance;$

$results(per, 9) = MAE;$

$results(per, 10) = RMSE;$

$results(per, 11) = tr.best_perf;$

$results(per, 12) = tr.best_vperf;$

$results(per, 13) = tr.best_tperf;$

$per = per + 1;$

end