Financial Modeling Using ANN Technologies : Result Analysis with Different Network Architectures and Parameters

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Abstract

The future is always uncertain and uncertainty leads to risk. The elaborate exercise of forecasting and making predictions is a course of action to which organizations take recourse in order to minimize this uncertainty and the risks arising therefrom. Business decisions, and that too financial business decisions, depend heavily on future predictions. Financial forecasting is a management technique that refers to the estimation of information for the future based on the availability of past financial conditions. Neural networks have been a popular choice among researchers when it comes to modeling financial forecasting. However, the factors like learning rate, momentum, and architectural configuration affect a lot if not selected properly. The selection of an effective architecture and parameter combination improves the accuracy and acceptability of the results by many folds. In this paper, an analysis was made to measure the impact of various combinations of neural architecture and parameters through the application of artificial neural networks (ANN) as a forecasting tool using Zaitun Statistical Package. It was observed that the architecture with 12 neurons in hidden layer and learning rate of 0.03 produced the minimum error.

Keywords : time series analysis, ANN, financial forecasting

JEL Classification: C45, C53, G17

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Forecasting is all about making an intelligent estimate about the future based on some logical conclusion. Much of the human activities are oriented around one or another kind of forecasting. The same pattern or phenomenon is also applied in organizations, especially for the purpose of decision making. Business decisions, especially financial decisions, depend a lot on prediction of future trends and patterns. For this purpose, experts rely on a number of financial decision making tools or forecasting tools. It is the business function that is responsible for assessing current internal business information, external economic information, and analyzing & processing this information through valid financial tools. It is used for the purpose of determining the profitability

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of business, business expansion, new business opportunities, understanding stock markets, etc. Some of the commonly used tools for financial forecasting are financial cost analysis, break even analysis, ratio analysis, trend analysis, and so on and so forth.

With the advancement in computer and information technology, organizations are relying more heavily on computerized statistical models for better prediction and analysis of information. Artificial neural networking is one such tool that enables us to develop the right kind of model to make an assessment about some financial situation based on the available data. ANN has been known to establish distinctions between hidden and unknown patterns in data and it is one of the most useful features for the prediction and forecasting of the share market. It is considered parallel to non - linear, non - parametric regression models.

A number of models have been proposed by a number of researchers using various parametric, non-parametric, linear, non-linear, fundamental, and analytical techniques to come up with more or less accurate predictions. Fundamental analysis is mainly based on thorough analysis of the share price dynamism in terms of those macroeconomic variables which are exogenous in nature. It considers that the share prices depend on their intrinsic values and probable return on investment (RoI) of the investors. RoI is subject to change on the basis of the availability of any new information, which in turn will change the share price. Not only this, the analysis of the economic variable is highly subjective and since share prices are greatly governed by these variables, they are also highly subjective. The outcome greatly depends on the individual intellect of the researcher/analyst (Majumder & Hussian, 2011).

Sometimes, technical analysis methods are also used, which in turn depend on volume, price, and interest rates to make an estimated guess about the stock prices. This technique takes into account all the internal as well as external factors affecting the share market at any point of time (Mendelsohn, 2000).

Not only these, but many a times, traditional forecasting tools like time series analysis are also used for share price prediction. In this method, the past data is taken into consideration and models are prepared to create patterns in the historical data and similar patterns are applied in forecasting the future prices. Time series forecasting takes into account a series of existing data like $at - n, \ldots, at - 2, at - 1, at$, and forecasts the $at + 1, at + 2\ldots$ data values. The idea is to observe and analyze the existing data series to make as accurate as possible a forecast about unknown future data values. Financial data series could be stocks, indices, interest rates, etc. ; physically observed data series could be weather reports, rainfall, temperature etc. ; and examples of mathematical data series could be Fibonacci sequence, integrals of differential equations, etc. (Desikan & Srivastava, 2013). Nowadays, many organizations are making use of information technology tools to store data over a period of time. They set the parameters criteria and data is stored accordingly. Later on, this data is used to analyze or predict the outcomes of a number of unforeseen situations. This whole scenario points out toward reaching the level where uncertainties could be minimized to the minimum possible levels by combining the advantages of information technology and statistics (time series). Making plans by estimating trends in the future is one way to apply statistical knowledge to analyze data of the past and using the results that are related to the present event. Time series is generally the historical data that resembles the collection of a group or a set of observations of the data that have been collected over a continuous period of time. That collected data may be in the form of daily data, weekly data, monthly data, quarterly data, or yearly data, depending upon the nature of the source of collection. Time series data consists of four components : trend, seasonal effect, cyclical, and irregular effect (Bowerman, Richard, & Koehler, 2005).

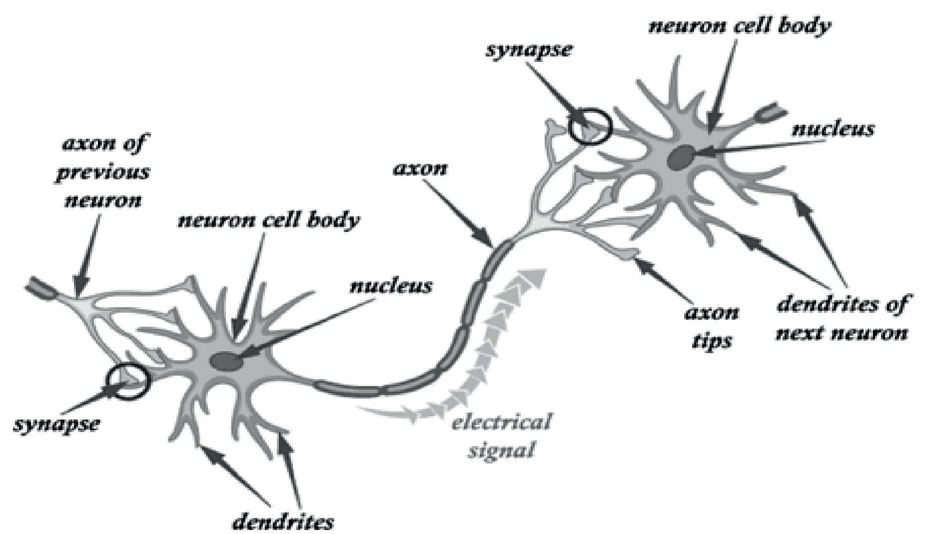
Artificial neural network (ANN) is a technique based on the processing of the brain (Figure 1). In this technique, data are analyzed, checked, and cross - checked in a similar manner in which the brain processes information. Working on a similar pattern, ANN develops algorithms and models to sort out and generalize complex problems. It can be used for the purpose of forecasting and making intelligent estimates.

In our brain, millions and millions of neurons process the information in the form of electric signals. The stimuli is received by the neurons present in the sensory organs (dendrites of the neurons), processed by neurons, converted into output, and then passed on to the next neuron. Depending upon the strength of the signal, the next neuron can either accept it or reject it.

In ANN, all this process is conducted using computer and information technology tools. Innumerably large data sets, oriented around thousands of parameters, requiring a number of checks and cross checks are analyzed and the final result is presented depending upon the strength of the input (weightage associated with it, Figure 2).

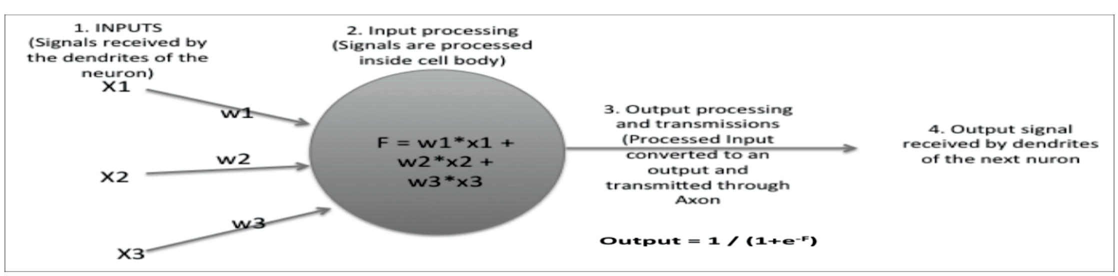
Neural networks these days are preferred over the traditional linear models as most of the things in the real world are non - linear in nature. Due credit is given to neural network systems as linear models fail to analyze hidden and non - obvious data patterns. Other than neural networks, some other non-parametric tools like autoregressive conditional heteroskedasticity (Engle,1982) and general autoregressive conditional heteroskedasticity have also been used for the purpose of financial estimations. These kinds of non - linear statistical techniques require a pre-specified non-linear model before the forecasting is done. It may happen that

Figure 1. Processing of Information Inside the Brain (Working of Neurons)



Source : From *"Introduction to neural networks, advantages and applications,"* by J. Mahanta, 2017 (https://towardsdatascience.com/introduction-to-neural-networks-advantages-and-applications-96851bd1a207). In the public domain.

Figure 2. Processing Through ANN (Very Similar to Working of Brain)



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the pre-specified model might fail to take into account specific critical and complex features of the system under study and may not be able to generate very accurate forecasts. Neural network models are driven by data. The uniqueness of these models lies in the fact that they are able to identify the non-linear relationship in the input data set without any pre-specified assumption about the relation between the input data set and the output. By using special activation function, it squashes and transforms the input data set to map it to the output. These models independently identify and learn the relationship inherent in the variables on the basis of the data set that is used for training.

Stock markets across the world are dependent upon the determination of the future value of the share prices of a company. Success or failure of dealing in the share business depends largely upon the accuracy of the prediction. Prediction of stock market trends is the act of trying to determine the likely value of company shares or other financial instruments traded on stock exchanges in the future. The successful prediction of a stock's future price could yield a significant profit. The stock prices reveal the current prices of the stock of any company, but the prediction of future prices of the stock that is dependent upon a number of market forces is highly unpredictable. People dealing with such uncertainties everyday apply myriad methods and technologies, which purportedly allow them to gain future price information. Stock markets are full of chaos, and any form of linear model will not work in prediction of a chaotic system which can only be attempted to explain through non-linear deterministic model because of its randomness and irregular fluctuations. These systems are highly dynamic and are sensitive to the initial conditions of the system (like opening position of the stocks). Systems with such characteristics are difficult to deal with normal analytical tools. ANN is considered to be one of the effective solutions to handle such uncertainties. It makes only a few assumptions about the functional form of ever-changing dependencies and is not much driven by the initial conditions of the system.

For the purpose of the study, secondary data were collected from the official website of NSE (https://www.nseindia.com) from January - December 2017. It took us about three months from January - March 2018 to apply various neural architecture models on the given data and to come up with the present results. Zaitun statistical software package was used for the purpose of data analysis.

Literature Review

A number of studies have already been conducted using various architectures of ANN model to assess its usability in making the closest predictions. It is an emerging field; hence, research is still going on, and each of these studies has been found to make some contribution to this field.

The study by Simutis, Dilijonas, Bastina, and Friman (2008) demonstrated the forecasting of the daily cash demand for automatic teller machines (ATM). The first implementation by the authors was artificial neural network (ANN). The second forecasting method implemented by the authors was the support vector regression (SPR) algorithm. The authors reported that forecasting method based on flexible ANN could produce better results compared to other methods.

In neural networks, some approaches might be problem-specific and cannot be accepted universally. Different researchers tend to prefer different methodologies. One such approach could be the adaptation of network training using the genetic algorithm (GA). This implies the extraction of ANN weight matrix using the genetic algorithm. Sarangi, Singh, Swain, Chauhan, and Singh (2009) examined and analyzed a hybrid approach combining the use of artificial neural networks (ANN) and genetic algorithm (GA) as a forecasting tool for predicting the future load demand. The weight matrix for ANN was extracted through genetic algorithm. The authors reported that the results produced by GA based ANN network was more accurate than the simple ANN implementation. Another work by Sarangi, Singh, Chauhan, and Singh (2009) examined the use of genetic algorithm (GA) techniques for the determination of weights matrix for a back propagation network (BPN). The authors implemented four different architectures such as 3-2-1, 3-3-1, 3-2-2-1, and 3-3-3-1. The error obtained was in between 0.01 to 0.02, which was quite appreciable. The authors reported that the architecture 3-2-1 produced a better result than the architecture 3-3-1, and the architecture 3-2-2-1 produced a better result than the architecture 3-3-3-1. Also, the authors observed that factors like structure of the network and selection of parameters such as learning rate and momentum also affected the results. The authors concluded that architecture with two hidden layers having two neurons in each hidden layer performed better than that of other architectures.

Prediction of bank insolvency using neural networks was undertaken by Al - Shayea, El - Refae, and El - Itter (2010). The authors predicted bank insolvency to avert bankruptcy. The results showed that SOM gave better results than feed-forward back propagation network. In another work by Dagmar and Trešl (2011), the application of neural networks was applied for financial forecasting. The results produced by the authors reflected that artificial neural networks were more effective and reliable tool for financial forecasting. Use of artificial neural networks on estimating financial failure of the Turkish banks was executed by Mumtaz, Ufuk, and Emin (2011). The authors in their study developed two models for estimating the probable financial failure. The first model was the logistic regression method, and the second one was the artificial neural network model. The authors reported that the performance of the artificial neural network model was better than that of the logistic regression model for estimating the financial failures of the banks. Khan, Alin, and Hussain (2011) concluded that more data set for the input always generated better training and closer results. It implied that the stock market predictions could be more accurate if we used ANN on a large amount of data.

In yet another work by Gupta and Sarangi (2012), the authors again used the GA - BPN model for extracting the best weight matrices for different layers of BPN. For this reason, this work introduced evaluation of connection weights in ANN using GA as means of improving adaptability of the forecasting.

A study conducted by Anyaeche and Ighravwe (2013) reported the use of artificial neural network trained by back propagation algorithm (BP-ANN). The authors used ANN as an alternative tool in place of multi-linear regression for ascertaining the interrelationships among dependent and independent variables. The authors used a four layered network having two hidden layers with 20 neurons each. Productivity and price recovery were used as independent variables and profitability was used as the dependent variable. The authors reported that BP-ANN model had a mean square error (MSE) of 0.02, while the multiple linear regression (MLR) model had MSE of 0.036. Finally, the authors concluded that ANN was a more efficient tool for modeling interrelationships among productivity, price recovery, and profitability. In another work by Darwish (2013), a methodology for improving the cash demand forecasting for ATM networks was presented. The author reported that the results from ATM cash forecasting using ANN had high feasibility and effectiveness. Mortezapour and Afzali (2013) in their work implemented a combination of genetics algorithm, Bayesian probabilities, and neural network on assessment of customer credit through combined clustering. The authors assessed the customer credit using ANN and GA and then compared with the methods such as clustering - launched classification (CLC), support vector machine (SVM), and GA + SVM.

Sarangi, Sinha, Sinha and Sharma (2018) in their latest work used various architectures of neural networks to forecast the consumer price index (CPI), and it was compared with the actual fluctuations in the CPI. It was found that the forecast values generated through ANN were very close to the corresponding actual values. The error factor was very negligible, which signified that this network could be used as a forecasting model for the CPI forecasting.

Ranjan, Singh, Dua, and Sood (2018) proposed a model based on semantic analysis of social network communities for predicting stock day end closing prices using the wisdom of crowds. Their prediction model was based on correlation between blog sentiments and stock day end closing prices for predicting the stock trends. The authors achieved a prediction accuracy of 84%.

Besides these, many other experiments were found where the authors implemented neural network models for forecasting the future trends. However, a common agreement was seen in all works regarding the selection of neural network architecture, learning rate, and parameters. Also, most of the authors agreed on the point that no

ANN model can be generalized. Mostly, it was problem specific and depended on the nature of the input. Care had to be taken to construct a suitable model and related parameters. This also required some level of technical expertise. In this situation, a readymade package helped a lot where many technical parts were automatically addressed by the package.

ANN Model and Parameters

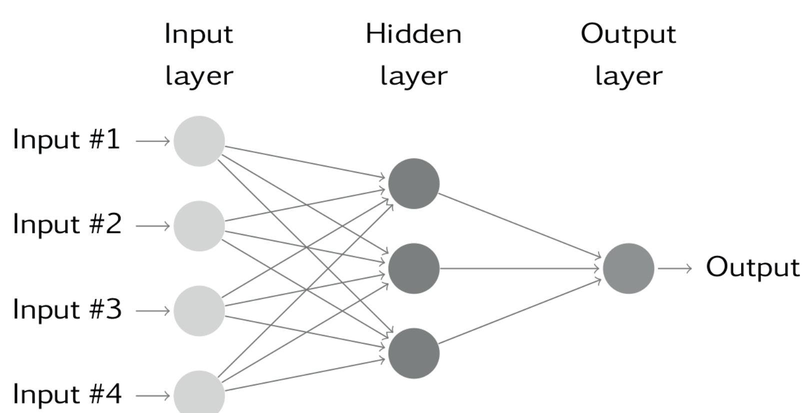
The Figure 3 represents a simple structure of an ANN model. This model has three layers namely, input layer, hidden layer, and output layer. The circles represent the neurons, and arrow lines represent the connections which are also called connections weights. The following model has four neurons in the input layer, three neurons in the hidden layer, and one neuron in the output layer. The four neurons in the input layer represent the four independent variables in the input pattern and the single neuron in the output layer represents the only dependent variable in the input pattern. This model is called a 4-3-1 model where there is only one hidden layer having three neurons.

The major problem with applying expert systems to the stock market is the difficultly in formulating knowledge of the markets because we ourselves do not completely understand them. Neural fuzzy networks have an advantage over expert systems because they can extract rules without having them explicitly formalized. In a highly dynamic, uncertain, and chaotic environment such as that of the stock market, only very less is understood clearly. It is hard to extract information from experts and formalize it in a way usable by expert systems. Expert systems are only good within their domain of knowledge and do not work well when there is missing or incomplete information. Neural networks handle dynamic data better and can generalize and make 'educated guesses'. Thus, neural networks are more suited to the stock market environment than expert systems. In a wide variety of different models presented so far, each model has its own benefits and shortcomings. The best way is that these methods work best when employed together. The major benefit of using a fuzzy neural network then is for the network to learn how to use these methods in combination effectively, and hopefully learn how the market behaves as a factor of our collective consciousness.

➩ **Factors Influencing Performance :** There are many factors that affect the performance of ANN. Some of these factors are :

(i) The Number of Neurons Within the First Layer : This issue is one among the foremost effective parameters in performance of ANN. Though additional neurons need additional computation, their implementation would possibly result in more efficiency for determination of advanced issues.

Figure 3. ANN Model



(ii) The Number of Neurons Within the Second Layer : This issue determines the quantity of neurons within the second layer, and what is more helps us to see whether or not the network is one layered or not. In different words, for instance, if the parameter level is taken as zero, it implies that the network has only one hidden layer. Though additional layers need additional computation, their implementation would possibly result in more efficiency for figuring out complicated issues.

(iii) The Percentage of Training Data : Data plays an important role in the training of an ANN model. More training data means chance of better training. While using ANN, the data are divided into three parts: training, validation, and testing set. The training set is used to train the network and obtain a stable weight matrix. The validation set is used to validate the trained network, and the testing set is used for forecasting the future values.

In neural networks, gradient descent optimization algorithm is used to minimize the error function and to reach a global minima. If all parameters are not selected properly, then the network can easily get stuck in a local minima, and the algorithm may produce incorrect results. This situation can be avoided by using a momentum factor which is a value between 0 and 1 that increases the size of the steps taken towards the minimum by trying to jump from a local minima. Care has to be taken that if the value of the momentum is large, then the value of learning rate should be smaller. A large value of momentum may lead to a faster convergence. If both the momentum and learning rate have large values, then the training might skip the minimum with a huge step. A right value of momentum can be either learned by hit and trial or through cross - validation.

Research Objectives

The specific objectives of this research work are :

(1) To propose a neural network model for predicting the future stock values.

(2) Training of the models using back propagation algorithm.

(3) Testing of the trained models to get the future stock value.

Implementation Design

The most important part of implementing a neural network model is the selection of the appropriate architecture and training parameters. Three different architectures (Table 1) have been considered for implementation :

- Architecture - 1 : 12-12-1
- Architecture - 2 : 12-8-1
- Architecture - 3 : 12-6-1

The input layer has 12 neurons in each architecture and the output layer has one neuron in each architecture. However, the hidden layer has different number of neurons, that is, 12, 8, and 6, respectively. The momentum factor has been kept constant (0.5) for all executions. The learning rate "η" has been taken from 0.05. Various parameters used are depicted in the Table 1.

Analysis and Results

The data used in this work is the secondary data collected from the website of National Stock Exchange (NSE) for the period from January - December 2017. All inputs have been normalized to a standard form to make it usable in

ANN networks. The networks were trained with the above parameters (Table 1) and forecast values for each network were observed. The training screen - shots are given in the Figures 4 - 7. After the training was over, the network was asked to produce the forecast values for the next 5 periods based on the training of the network. The results from different implementations are shown in the Table 2.

From the Table 2, it is observed that the architecture with 12 neurons in hidden layer and learning rate of 0.03 produces the minimum error. This implies that for the given input patterns, 12-12-1 architecture with learning rate 0.03 could be the best model for forecasting. This has been concluded by experimenting various ANN architectures using the available time - series data. The findings are comparable to the study findings obtained by Anyaeche and Ighravwe (2013) where the authors used a four layered network having two hidden layers with 20

Table 1. Different Architectures

Parameters	Architecture - 1	Architecture - 2	Architecture - 3
No. of Neurons in Input Layer	12	12	12
No. of Neurons in Hidden Layer	12	8	6
No. of Neurons in Output Layer	1	1	1
Transfer Function	Bipolar Sigmoid	Bipolar Sigmoid	Bipolar Sigmoid
Momentum	0.5	0.5	0.5
Learning Rate	0.03, 0.05, 0.07	0.03, 0.05, 0.07	0.03, 0.05, 0.07
Max Iterations	50000	50000	50000

Figure 4. Architecture 1 : 12-12-1

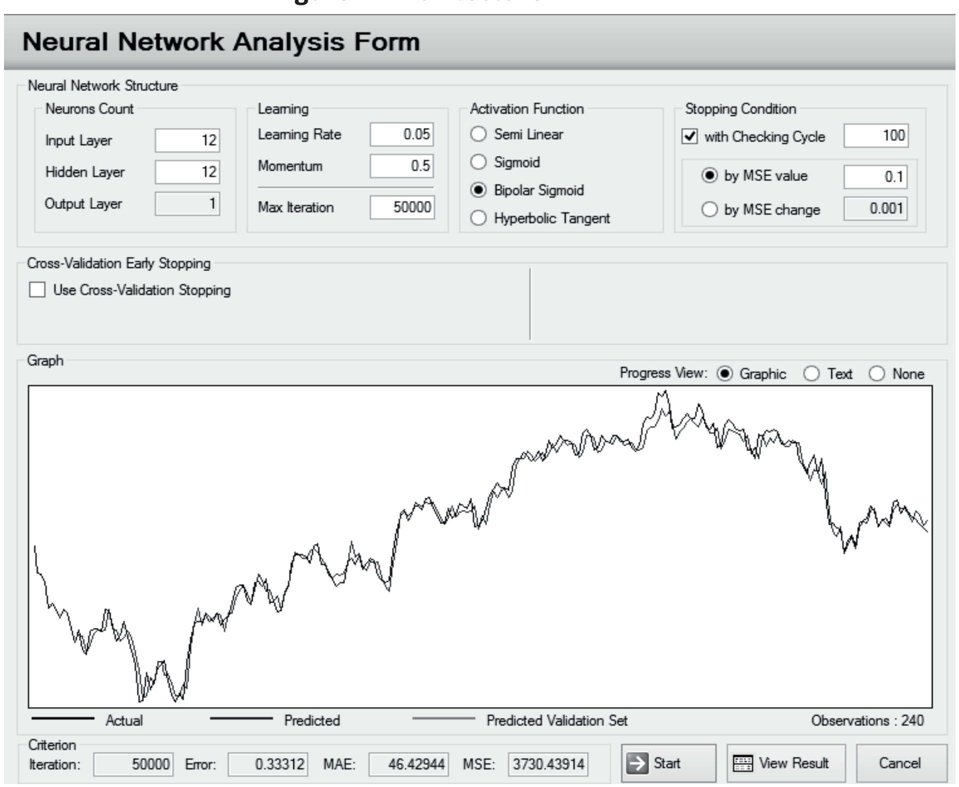


Figure 5. Architecture 2: 12-8-1

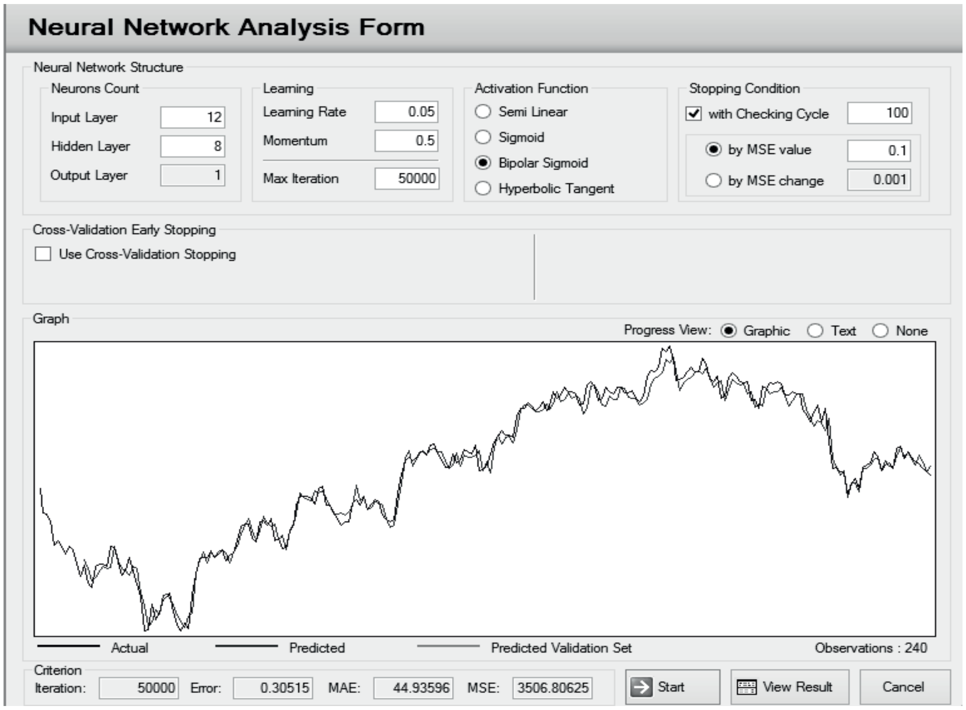


Figure 6. Architecture 3: 12-6-1

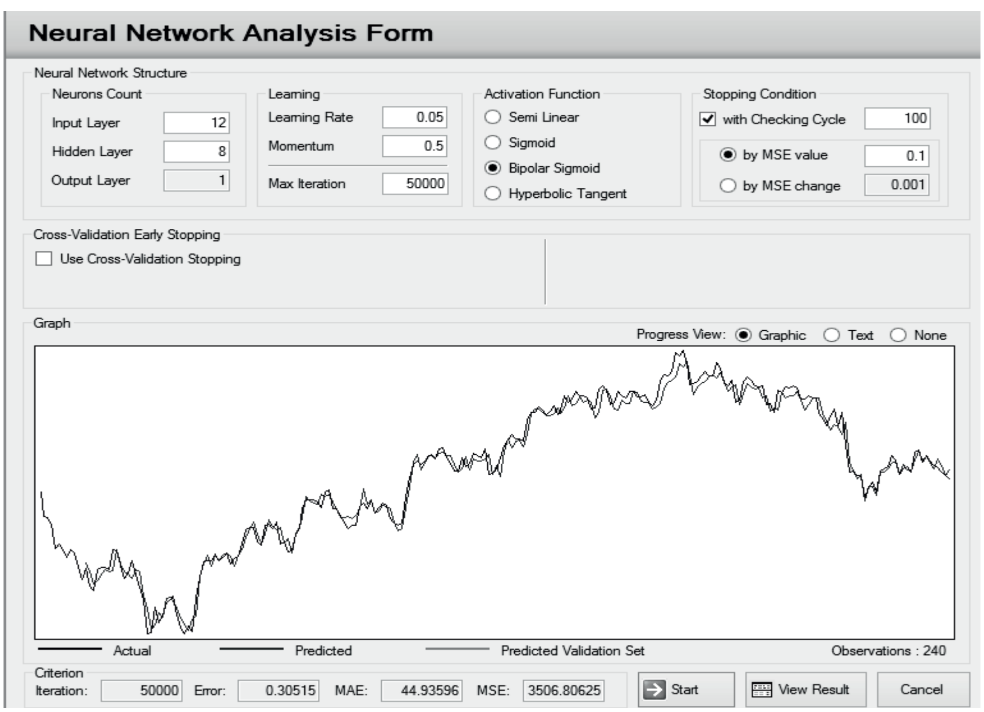


Figure 7. Neural Network Result

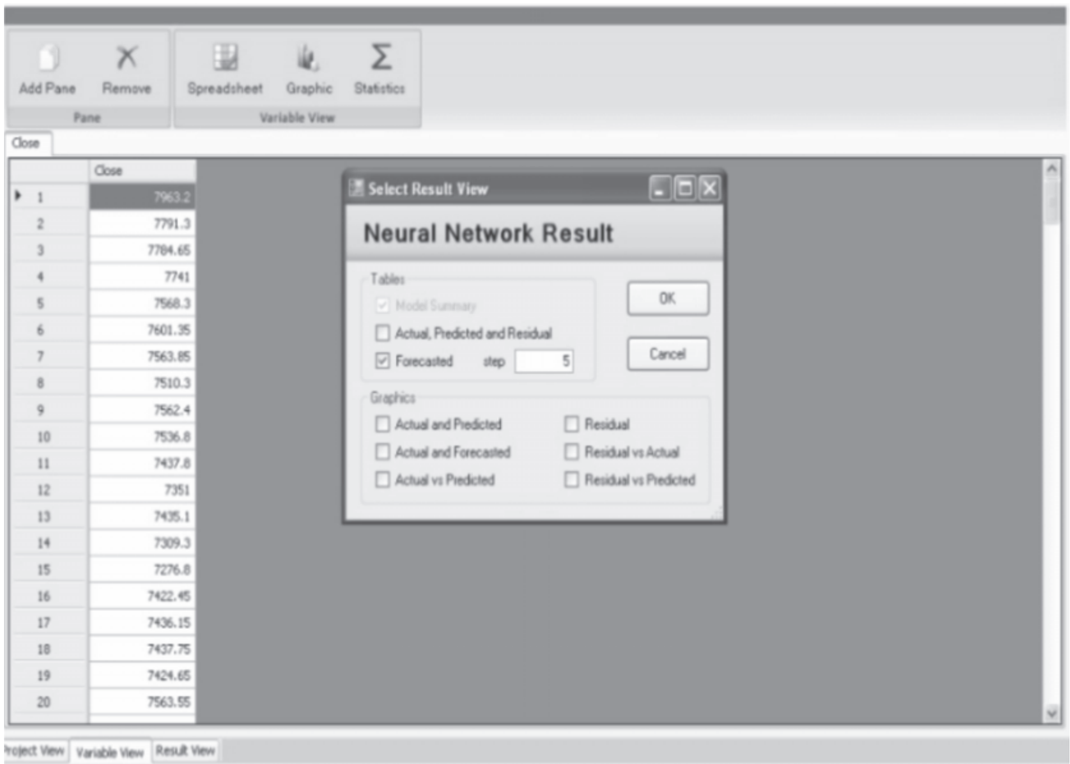


Table 2. Forecasted Values Through Different Architectures

Sl. No	Architecture	Training Error			Forecasting Error (%)
		Error	MSE	MAE	
1	Structure : 12-12-1 ; Learning Rate : 0.05	0.33312	46.42944	3730.43914	0.23
2	Structure : 12-12-1 ; Learning Rate : 0.03	0.34899	45.57132	3752.23513	0.20
3	Structure : 12-12-1; Learning Rate : 0.07	0.30033	49.90008	4228.15902	1.02
4	Structure : 12-8-1 ; Learning Rate : 0.05	0.30515	44.93596	3506.80625	0.26
5	Structure : 12-8-1 ; Learning Rate : 0.03	0.38543	47.95578	4063.53480	0.32
6	Structure : 12-8-1 ; Learning Rate : 0.07	0.30747	44.50891	3432.55476	1.0
7	Structure : 12-6-1 ; Learning Rate : 0.05	0.377734	49.37599	4149.58398	0.06
8	Structure : 12-6-1 ; Learning Rate : 0.03	0.37921	48.59755	4098.88107	0.18
9	Structure : 12-6-1 ; Learning Rate : 0.07	0.37862	50.78396	4210.60271	0.70

neurons each. The methodology is also similar to the one used by Sarangi et al. (2009), where the authors examined the use of genetic algorithm (GA) techniques for the determination of weights matrix for a back propagation network (BPN).

Conclusion

Financial decision making plays an important role in the business performance. Prior information of the future trend helps the managers in making a right business decision. Neural network has become a very popular tool for researchers and analysts due to its capability of analyzing time - series data. However, care has to be taken while selecting the network architecture and learning parameters. There are no mathematically proven rules to determine the network structure. All depends on the nature of data and applying the thumb rule to decide the structure and parameters. Parameters like learning rate and momentum affect the accuracy of the network. Selection of dependent and independent variables also affect the accuracy and acceptability of the results. However, if proper architecture and parameter combination is selected, then neural networks can produce better results for time series forecasting. Zaitun statistical package is also found to be a suitable option for implementing ANN.

Research Implications, Limitations of the Study, and Scope for Further Research

The main objective of this research was to analyze the impact of architecture and parameter selection in time series forecasting. The study will help researchers to make a suitable choice of architecture and parameters (learning rate) while designing a forecasting model. The study has great implications in making predictions about day to day life situations like budgeting, return on investment, political predictions, performance of movies on the box-office, etc.

The study has been carried out on secondary data, and the architecture and parameters are purely associated with the data set used in this study. This research was carried out under a controlled environment and also has some constraints. The results have been obtained as the output of the program used for this purpose. The results and analysis are based on the network and parameters selected for this experiment. If the combination of architecture and parameter is changed, a different result may come into picture.

In order to pursue further research on this, more combinations of architecture and parameters may be explored. This model and methodology will have larger and more accurate outcomes if applied on large data sets. In future, researchers may apply it on making predictions about day to day happenings of life using primary data.

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