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# Stock Market Prediction using Financial Cybernetics

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***Abstract:***
Research on stock markets is unusual because of random walk performance of stock time series. Forecasting in stock market returns is a significant problem in finance. Currently, the essentials of stock market cannot be isolated from human life because of the frequent investment done in the stock market by people worldwide. While making investments in stock market, traders not only purchase a stock whose value is likely to increase in the future but also, they are likely to refrain from purchasing those stocks whose value is expected to drop in the future. Therefore, a precise estimation of the movement of stock price in the market in order to make maximum profit and curtail loss is urgently required.At large, it is tough to explore specific training algorithm that works best under all conditions at all time therefore, revolutionizing strategies and optimization protocols to develop stochastic methods for training artificial neural networks. A complete study of evolutionary algorithms in developing artificial neural networks can be found. Very recently, an analytical analysis for the stock price movement prediction was reported during the demonetization period in India. Recently, our group has shown the capabilities of artificial neural network in the field of atmospheric physics by the prediction of the ozone hole area. In this paper, comprehensive working of multi-layered neural network along with brief report of various activation function is presented. Using the given information, neural network is skilled, and predictions are stated for Reliance Industries listed in National Stock Exchange, India.

***Keywords****: Stock Markets, returns, investment, price.*

## Introduction

Research on stock markets is unusualbecause of random walk performance of stock time series. Forecasting in stock market returns is asignificantproblem in finance. Currently, the essentials of stock market cannot be isolated from human life because of the frequent investment done in the stock market by people worldwide (Guresen et al., 2011). They capitalize their income by investing in stock market to makeextra profit. While making investments in stock market, traders not only purchase a stock whose value is likely to increase in the future but also, they are likely to refrain from purchasing those stocks whose value is expected to drop in the future. Therefore, apreciseestimationof themovement of stock price in the market in order to make maximum profit and curtail loss is urgently required. Also, stock market calculation is still problematicdue to factors effecting the stock market price like economy,investor's emotion, company and industry performances, social media, etc. According to Fama's efficient market hypothesis it is difficult for investors to get benefit by buying undervalued stocks or trading stocks for inflated price (Malkiel and Fema, 1970).Gradually several machine learning algorithms have established torealise problems that are particular to random walk character of stock exchange. Several researches stated thatthe development of a mathematical model for stimulation of non-linear relations among input and output factors is a tough task because of itscomplex nature. The dynamics of stock markets display wide disparity, non-linear nature and

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complex dimensionality thus making the prediction of the stock market anextremelydifficult task (Allen and Jagtiani, 1997).

The significance of neural network modelling techniques in executionof complex pattern recognition and nonlinear foretelling tasks has shown wide applications. Presently, artificial neural networks (ANNs) have been used in financial prediction related to stock exchange index, bankruptcy and corporate bond classification. An ANN model is a computer-basedmodelling who mimics the learning ability of the human brain. The processing unit of an ANN is similar to the biological and structural unit of human brain *i.e.* neurons wherenumerous simple well connected linear or nonlinear computational elements are working in parallel processing at multiple layers. In 1948 Turing reportedvisionary survey of creating machines capable of intelligent behaviour (Webster, 2012). This report acted as foundation of ANN with endless future promises. Artificial intelligent systems like hybrid algorithms, ANN and Particle Swarm Optimization (PSO) have properties of both ANN and evolutionary intelligence and are applied to solve ample problems in science and engineering. ANN is proven worthy in bankruptcy prediction, credit risk assessment and security markets than conventional statistical methods such as discriminant analysis and logistic regression due to complex relation between financial and other input variables (Lee et al., 2005). Other applications of ANN includes thin film deposition techniques where by smart learning mechanism of NN, assessment of controlling parameters like layer thickness and refractive index can be achieved(Shen et al., 2016), calculation of nanostructured zinc oxide (ZnO) thin film electrical properties (Corcione, 2011) and investigation of thermal conductivity and viscosity of several nanofluids related to heat transfer facilities have also been examined (Yoe, 2019). At large, it is tough to explorespecific training algorithm that works best under all conditions at all time therefore, revolutionizing strategies and optimization protocols to develop stochastic methods for training artificial neural networks. A complete study of evolutionary algorithms in developing artificial neural networks can be found. Very recently, an analytical analysis for the stock price movement prediction was reported during the demonetization period in India. Recently, our group has shown the capabilities of artificial neural network in the field of atmospheric physics by the prediction of the ozone hole area.

In this paper, comprehensive working of multi-layered neural network along with brief report of various activation function is presented. Using the given information, neural network is skilled, and predictions are statedfor Reliance Industries listed in National Stock Exchange, India.

## Literature Review

### Neural Networks

Neural network had been coined to discuss a network or circuit of biological neurons. The currentpractice of this term refers to artificial neural networks (ANN), which consists of artificial neurons or nodes. Thus the term has two diversepractises:

- Biological neural networks are composed of actual biological neurons that are linked or functionally associated in the central nervous system of an organism. In neuroscience, they are frequentlyknown as groups of neurons that are responsible fordefinite physiological function in laboratory study (Miikkulainen et al., 2019).
- ANN are compiled of artificial neurons which are interlinked. ANN may either be used to increasethe knowledge of biological neural networks, or for unravelling artificial intelligence difficulties without generating a model of a real biological system, which is complexed and contains some characteristics that may not be useful

based on the knowledge of artificial networks (Morris et al, 2019).

A neural network can be defined as a parallel, dispensed information processing assemblycontaining processing elements which are interrelated together through unidirectional signal channels known as connections. Each processing element consists of single output connection along branches ("fans out") into ample desired collateral connections. The processing element output signal can be of any mathematical type desired. Each and every processing that runs within each processing element must be entirely local, *i.e.* it must be determined only upon the existing values of the input signals arriving at the processing element throughinterrupting connections and upon values kept in the processing element's local memory (Aihara, 1990).

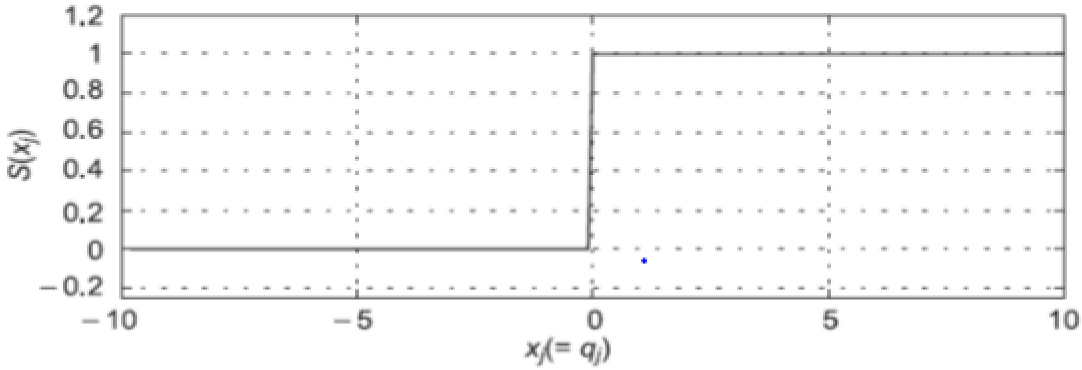
**Neuron Signal Functions**

**Binary Threshold Signal Function**

Neurons with binary signal functions are loosely referred to as binary neurons or threshold logic neurons (TLNs) and they find their origin in the 1943 publication of McCulloch and Pitts (Guan, 2019). As before, a binary neuron computes its activation, xj = STWj , and generates a +1 or a 0 signal depending upon whether this activity is positive or negative:

$$\mathcal{S}(x_j) = \begin{cases} 1 & x_j \geq 0 \\ 0 & x_j < 0 \end{cases}$$

As Fig.(1) shows, this translates to saying that net positive activations



(a) Binary threshold function: $\theta_j = 0$

**Figure 1: Neuron Signal Function**

Binary threshold neuron signal function with different neuronal thresholds as indicated translate to a +1 signal value, and net negative activations translate to a0 signal value. The threshold logic function is a two state machine, i.e. $s_j = \mathrm{S}(x_j) \in \{0, 1\}$. Notice that to get around the discontinuity at 0, Eq. employs the “greater than or equal to” condition. An alternative solution to handling the discontinuity is to assume that the activation xj = 0 is ambiguous and cannot be suitably translated to any value. In such a situation we might be justified in leaving the neuron signal unchanged. To model such a situation we assume that a neuron updates its signal at discrete instants of time, k, by sampling its instantaneous activation $x_j^k$. In discrete time, we may therefore write this modified binary threshold signal function as:

$$\mathcal{S}(x_j^{k+1}) = \begin{cases} 1 & x_j^{k+1} > 0 \\ \mathcal{S}(x_j^k) & x_j^{k+1} = 0 \\ 0 & x_j^{k+1} < 0 \end{cases}$$

**Linear Threshold (Ramp) Signal Function**

The McCulloch–Pitts model for binary threshold neurons has been generalized in various ways. One obvious generalization is to use signal functions other than the threshold function. The simplest function is the linear function (Eq.) where we have

$$\mathcal{S}(x_j) = x_j$$

This amounts to saying that the signal is equal to the activation untransformed in any way. However, such a signal function is unbounded. The bounded version of the linear signal function is the linear threshold function shown in following Fig.

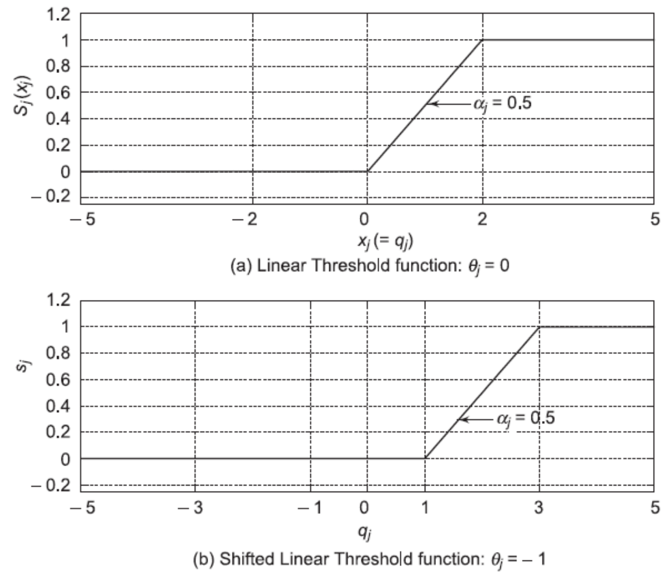



**Figure 2: Linear Threshold Signal Function**

Linear threshold neuron signal function with different neuronal thresholds as indicated for a piecewise linear threshold signal function for above Figure 2.

$$\mathcal{S}_j(x_j) = \begin{cases} 0 & x_j \leq 0 \\ \alpha_j\, x_j & 0 < x_j < x_m \\ 1 & x_j \geq x_m \end{cases}$$

## Sigmoidal Signal Function

The sigmoid function is undoubtedly the most repeatedly used signal function in neural networks. A common example is the logistic signal function:

$$\mathcal{S}_j(x_j) = \frac{1}{1 + e^{-\lambda_j x_j}}$$

where$\lambda j$ is a gain scale factor In the limit, as $\lambda j \to \infty$ the smooth logistic function approaches the non-smooth binary threshold function. This should be clear from Fig. 3.5(a). Figure 3.5(b) shows the shifted version of the signal on the qj axis, once again for $\theta j = -1$. The 0.5 signal crossing point has shifted right to the point qj = 1. The sigmoidal signal function has some important mathematical properties. These properties are its monotonicity and continuity. In general, monotonicity signify that the function y either always increases or always decreases as x increases.

$$\mathcal{S}_j(x_j) = k \tanh(\lambda_j x_j)$$

Continuity state there are no breaks or gaps in the function, it is smooth. These essential properties gives neurons the power to estimate and generalize on functions by learning from data. In some neural network applications, the logistic function is replaced by the hyperbolic tangent form,for some constant k > 0, that scales the signal range, and a slope factor, $\lambda j$ . The figure in the margin shows this signal function for $\lambda j = 1$. The hyperbolic tangent signal function is an example of a bipolar signal function since the signal values can become both positive and negative, though continuously. Interestingly, one can generate a bipolar sigmoidal signal from the logistic signal function. The selection of the sigmoid as a neuron signal function is frequentlyvalidated by the biological argument that it mimics the biological function of the firing rate of action potentials, averaged over a population of neurons.

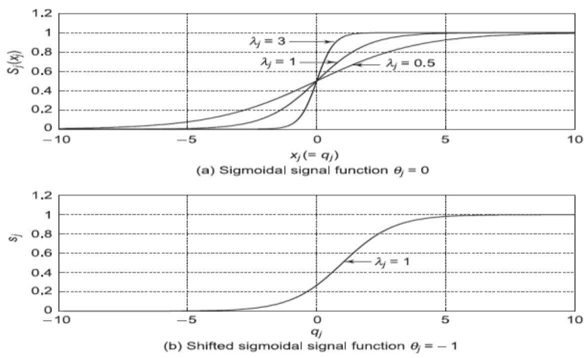



**Figure 3: Sigmoidal Signal Function**

## Back propagation Algorithm

Presently many researches have stated that back propagation is the vastly applied neural network architecture. Theacceptanceof back propagation networks chiefly revolves around itscapability to studycomplexed multidimensional mapping. One aspect of understanding this ability as described by Werbos (1990), back propagation goes “Beyond

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Regression”. Back propagation is classified under“mapping neural network architectures and hence the information processing function that it transports is the estimation of a bounded mapping or function f as f: A belongs to Rn-Rm, from a compact subset A of n dimensional Euclidean space to a bounded subset f[A] of m dimensional Euclidean space, by means of training on examples (x1, y1), (x2, y2)., . . . , (xk, yk), of the mapping, where yk=f (xk)” . Nielsen[24].In Figure 2, the architecture comprises of “k number of layers, each layer consists of n number of neurons or processing units beginning from 1. Here, first layer consists of three neurons (depends on number of input variables)”. This layer receivesinformation from outside environment called input layer and distribute them, without any change to the first hidden layer or the I$^{st}$ intermediate layer. Intermediate layers are also termed as hidden layers due to their indirect connection to outside world. Transmission of every values to second hidden layer is completed through hidden layer transfer function. Lastly, every individual values from second hidden layer are altogether added, compiled and distributed to output layer via output layer transfer function.

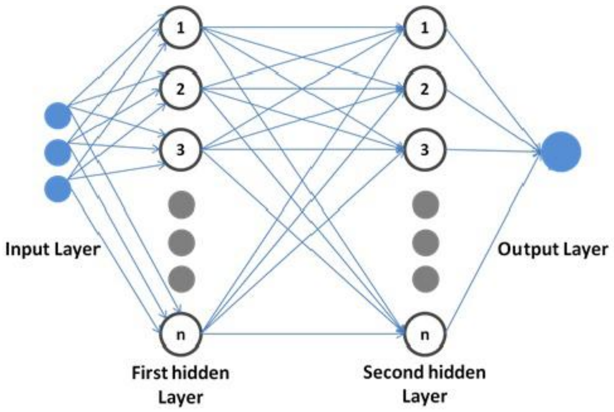


**Figure 4: Network Architecture**

If the output is precise to definite error level then it accepted else it is passed back to the input layer for further update in the values of weights and biases. It should be noted that there is no connection in between the neurons within the same layer. This series keeps on going till all the limitations are gratified and correct output is achieved.

## Model Development and Training of Network

### Selection Criteria for sample observation (Reliance Industries)

We have followed two major measures:

- **Highest Market Capitalization**: Reliance industries has market capitalization of over 100 billion US$ which is largest in amongst all companies listed
- **Maximum Weight in the Index:** Reliance industries have highest weight in the BSE Sensex and NSE Nifty and have .93 correlations with indices.

### Prediction Mechanism

The prediction is done on the basis of each day returns on the particular security using Backpropagation Algorithm. Following are the main reasons for predicting the returns:

- **More Abstract Measure**: Returns are more abstract measure than the Stock price because it is the difference of Opening and Closing price so it is independent to intraday fluctuations
- **Better Predictability**: The fluctuations are based on the opening and closing difference which is less uncertain in comparison to the closing price
- **More Useful for Investors**: Investors are more interested in returns and this will give them the future trend of returns on the particular security

### Return Calculation

Returns are calculated form the following formula:

Returns = Opening Price – Closing Price

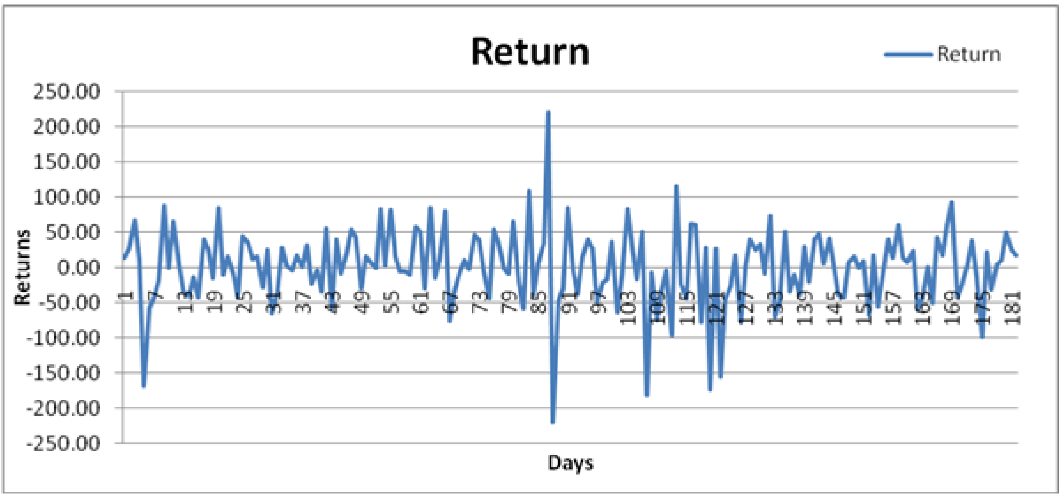


**Figure 5: Reliance Returns**

### Prediction

Predictions are based on the daily basis and we are making an attempt to predict the returns for Reliance for a particular month. The prediction is based on Historical Data only. We are using data from 1st January 2019 to 30th September 2019 for training and on that basis the Data is predicted for October month and results are validated. Following are the key preambles:

- The prediction is based on the Historical Data from 1st January to 30th September
- October data is predicted and validated with comparison from real data
- Predictions are on the daily basis and the monthly trend is predicted

### Normalization and clipping of Data

The use of normalization in statistics is to remove statistical error in repetitive measured data. Occasionally normalization is based on a property. For example, Quintile normalization is normalization created on the magnitude of the measures. In additional statistics application, normalization may be used to divide multiple sets of data by a common variable in order to contradict variable's outcome on the data, thus permittingcomparison of primary characteristics of the data sets. This allows data on different scales to be compared, by adjusting them to a common scale. In terms of levels of measurement, these ratios are only sensitive for ratio measurements and not interval measurements. Parametric normalization oftenpractices pivotal quantities functions whose sampling distribution are not dependent on the parameters and chiefly ancillary statistics – pivotal quantities that can be calculated from observations, without knowing parameters.

There are numerous normalizations in statistics as described by Miller (1995)that "non dimensional ratios of errors, residuals, means and standard deviations, which are hence scale invariant while some of which may be summarized as follows". We have used following formula to normalise the data in the series

Scaled = (((A-DMin)*(.95-.05))/(DMax-DMin))+.05

### Purpose of Normalization & Clipping

Neural Networks only take values from 0 to 1 as it works in the Binary process. We have classified the returns from .05 to .95. The extreme values disturb the arrangement of the series that is why the extreme values are clipped from the data.

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## Normalised results

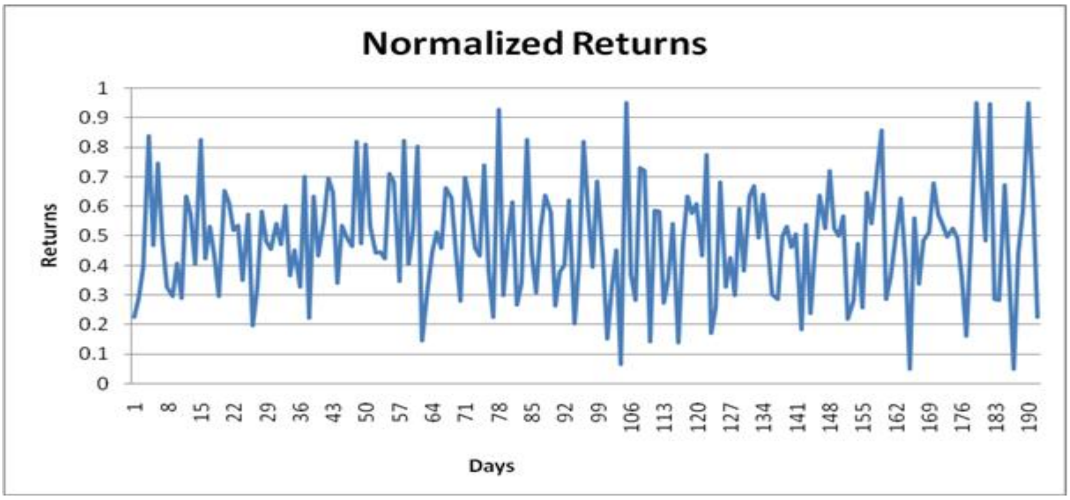


**Figure 6: Reliance Returns Normalised**

## Backpropagation Training

Everyneuron comprises of 2 units. The products of weights coefficients and input signals were sum up by I[st]unit, whereasthe 2[nd]unit analyse nonlinear function, known as neuron activation function. Signal *e* is "adder output signal", and $y = f(e)$ is "output signal of nonlinear element". Signal *y* is also output signal of neuron.

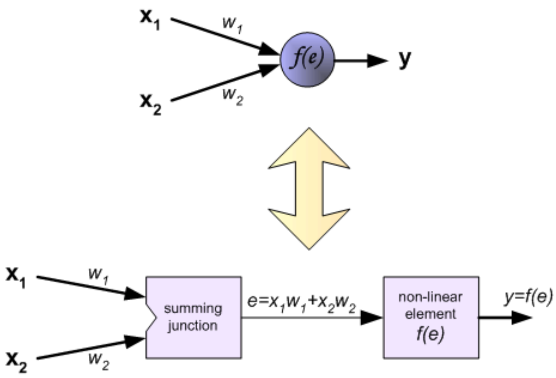


**Figure 7: Backpropagation Function**

The training data set contains of input signals ($x_1$ and $x_2$) assigned with consistent target (desired output) *z*. The network training is an iterative procedure. In each iteration weights, coefficients of nodes are alteredby new data from training data set. Modification is calculated using algorithm described below:

"Each teaching step starts with forcing both input signals from training set. After this stage determination of output signals values for each neuron in each network layer were made. Pictures below shows how signal is propagating through the network, Symbols $w_{(xm)n}$ represent weights of connections between network input $x_m$ and neuron *n* in input layer. Symbols $y_n$ represents output signal of neuron *n*".

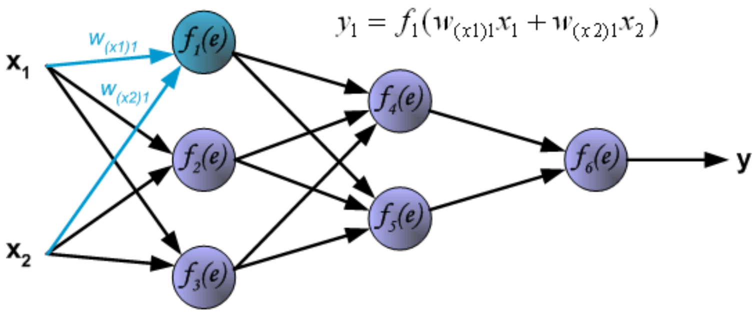


**Figure 8: Neuron Interaction**

Spreading of signals through the hidden layer. Symbols $w_{mn}$ signify weights of connections among output of neuron *m* and input of neuron *n* in the next layer.

## Predictions and Analysis of Results

The results have been achieved by keeping the following setting of neurons architecture;

**Single Layer with 7 Neurons**

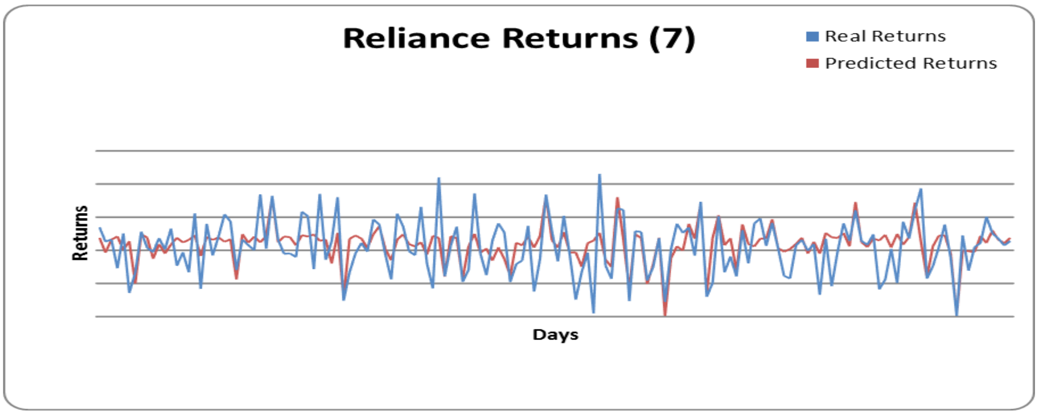


**Figure 9: Prediction Results A**

The prediction was having Mean square Error of **561.0123.**

**Double Layer Architecture t=6 with 4 Neurons (15-15)**

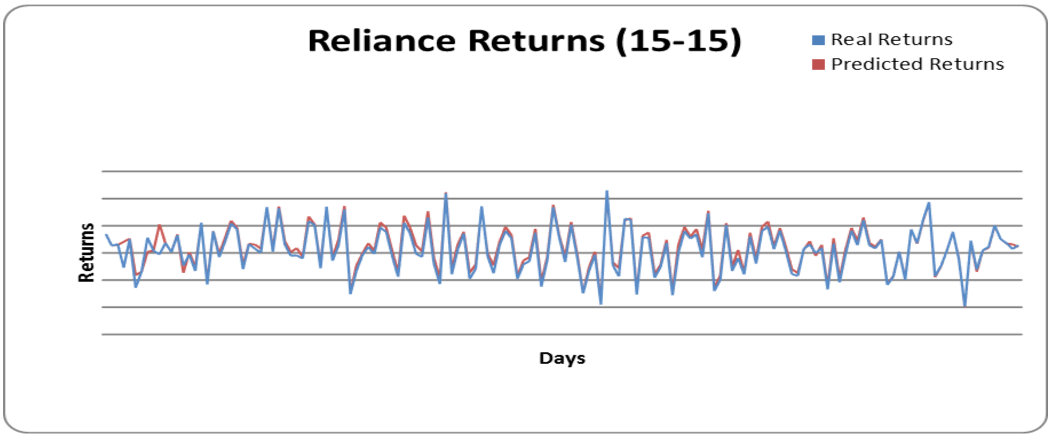


**Figure 10: Prediction Results B**

The prediction was having Mean square Error of 48.4316.

**Double Layer Architecture t=6 with 4 Neurons (10-10)**

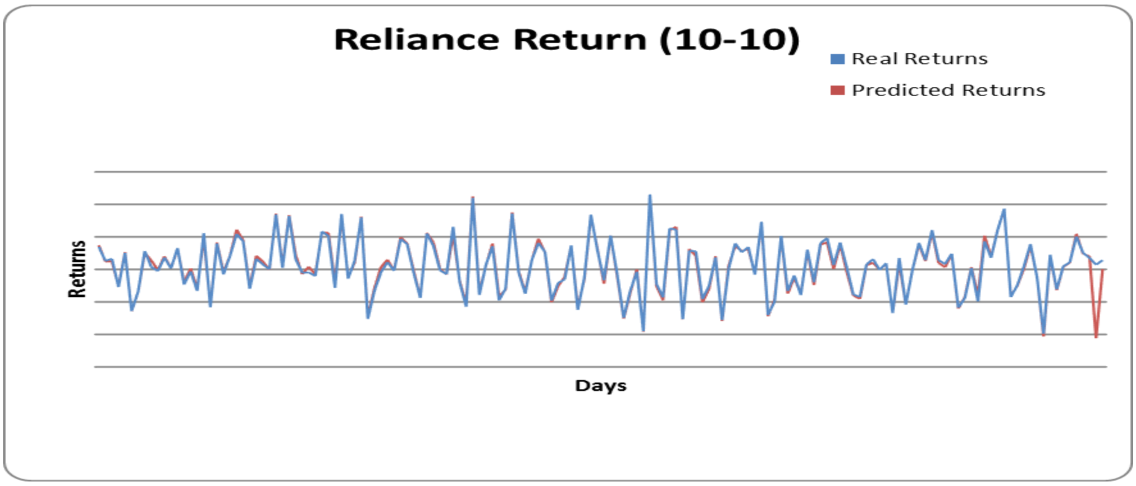


**Figure 11: Prediction Results C**

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The prediction was having Mean square Error of 88.63. In the same way the prediction was tried on various combinations such as 5-10, 11-10 etc. which were failed and the t=6 mechanism for 4 neurons architecture was not able to provide best predictions. Further, t=1 architecture has been designed

**Double Layer Architecture t=1 with 4 Neurons (12-10)**

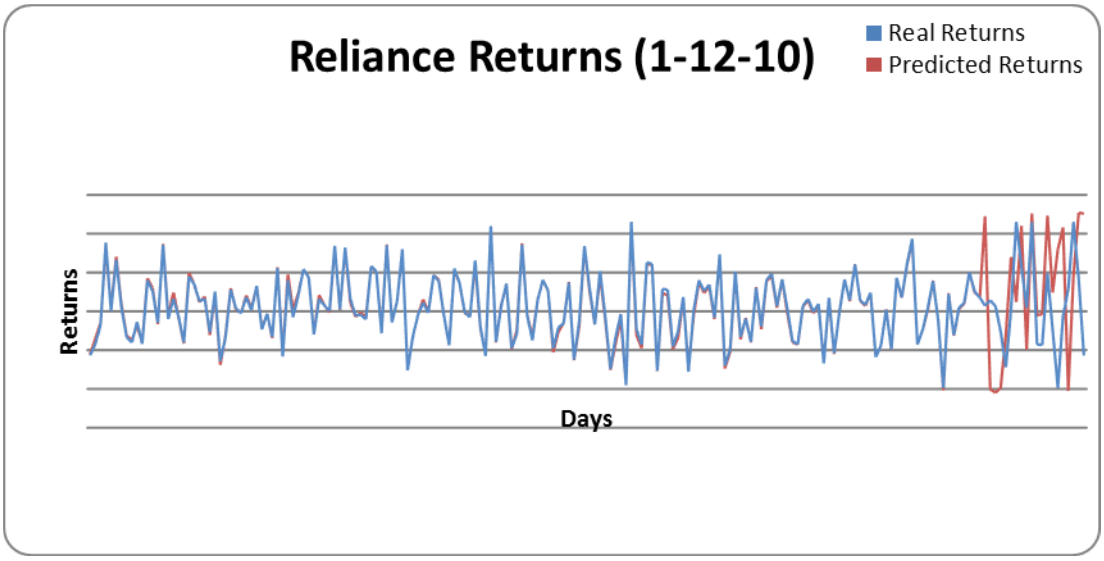


**Figure 12: Prediction Results D**

The prediction was having Mean square Error of 726.4.

**ouble Layer Architecture t=1 with 4 Neurons (5-10)**

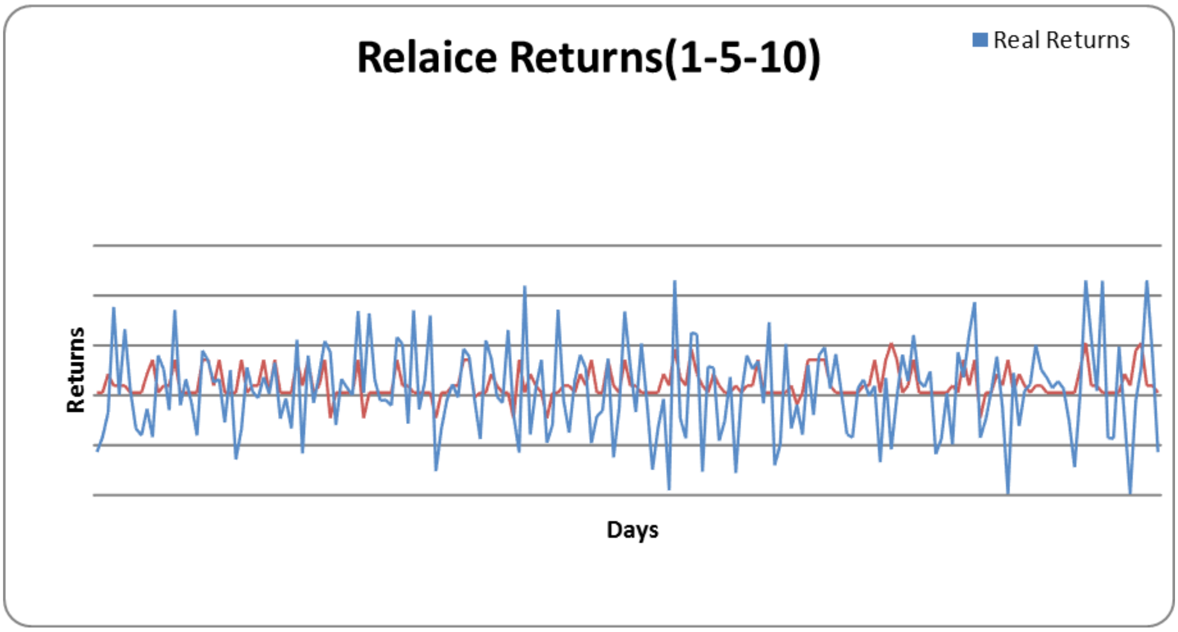


**Figure 13: Prediction Results E**

The prediction is having Mean square Error of 947.4725. In the same way we have tried other combinations such as 10-5, 6-8, 9-11 etc. None of the architecture was able to predict the returns and trend properly.

**Double Layer Architecture t=6 with 6 Neurons (10-9)**

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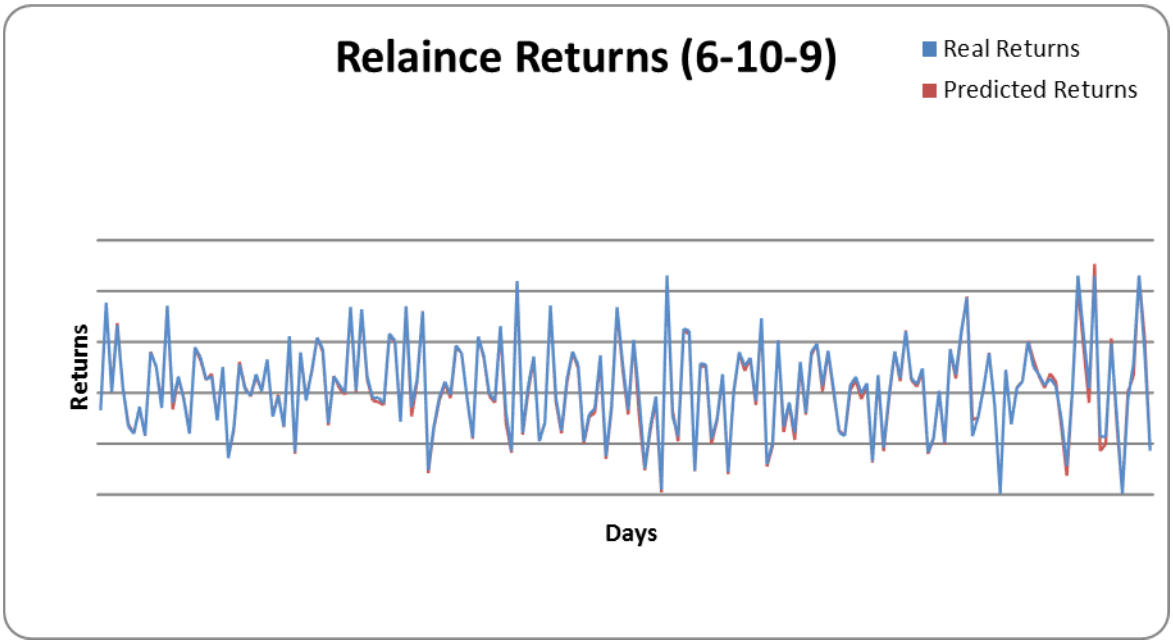


**Figure 14: Prediction Results F**

The prediction is having Mean square Error of 4.223. The best prediction model is made with 6 Neurons and with 10-9 architecture.

## Limitation of the Study

The study has the following limitations:

- **Continuity Assumption:** The data must be continuous and should maintain same time dimension
- **Normal Economic Conditions**: The architecture proposed will only work if the normal economic conditions are prevailing. In case of some fundamental change the prediction model may not work with the same accuracy
- Careful balance must be made between the approximation and generalization capabilities of the model

## Conclusions and Directions for Future Research

Artificial Neural Networks (ANN) are adaptive networks. Adaptive nature of ANN enables them to make connections between input and output values in such a way that the generated network becomes capable to predict the expected trend of future. This model can be used as a tool to use the interest rates volatility to benefit and generate better returns through debt instruments/interest rates swaps. The investments can be done on daily as well as on weekly and monthly basis according to the predicted values. It can be used for portfolio construction as the security selection can be done with the help of this architecture. It can be used in Derivatives as the trend can help in selection of Call and Put options. It can be used for prediction of Indices and can be used in portfolio construction.The true versatility of the model has been brought out by predicting the series for time points in the future. This prediction on unseen data that we call good generalization. Neural Networks can be one of the most efficient techniques for prediction.

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