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An Efficient Approach to Forecasting the NIFTY-50 Indian Stock Market's Daily Closing Price with Artificial Neural Networks

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Abstract: The most lucrative area of the financial industry is stock market trend forecasting. The incorporation of machine learning has improved the accuracy, accessibility, and dependability of stock market forecasts. This study compares and contrasts several machine learning methods, including Support Vector Machine (SVM), Random Base Pairing (RBF), Multi-Layer Perceptron (MLP), and Single Layer Perceptron (SLP). The unique features of each method are also examined separately. Of these methods, the MLP algorithm produced better results. The inquiry explores the relationship between changes in the dollar exchange rate, the performance of NIFTY 50, Foreign Institution Investors' Gross Purchase (FII inflow), and Foreign Institution Investors' Gross Sale (FII outflow). For the study, daily average closing prices for the NIFTY 50, FII inflow, FII outflow, and Dollar are taken into account. The study covers a period of 5 years from April 1, 2018, to March 31, 2023. The NN Toolbox in Matlab is used in the analysis to evaluate the correlation between NIFTY 50, FII inflow, FII outflow, and Dollar exchange rates. A strong correlation has been found by the data analysis between Dollar values, FII inflow, FII outflow, and NIFTY 50.

Keywords— ANN, NARX, Stock market, NSE, machine learning, forecast, prediction, finance. Exchange Rate, Dollar, FII inflow, FII outflow and NIFTY 50.

I. INTRODUCTION

The ability to predict stock market returns is a critical aspect of the financial domain. If a participant in the market, whether an individual or institutional investor, can accurately foresee market behavior, they stand the chance to consistently outperform the market in terms of returns adjusted for risk. This serves as a catalyst for developing precise models for stock market prediction, utilizing machine learning and computational intelligence techniques. However, over time, there has been a growing array of challenges. It is not surprising that many market players form their expectations about future stock prices based on historical market prices, company-specific data such as past earnings and profits, and other relevant factors, acknowledging the potential existence of market anomalies.

Artificial neural networks (ANNs) have become widely employed in addressing financial challenges, such as forecasting stock market indices, predicting bankruptcies, and categorizing corporate bonds. An ANN model is a computer-based model designed with an architecture closely mirroring the learning capabilities of the human brain. The internal workings of a human brain and the biological structure of neurons bear similarities to the processing components within an ANN. The model involves multiple layers executing simple, interconnected linear or nonlinear computations concurrently. It has been observed that ANNs may encounter limitations in learning data patterns, especially when dealing with complex financial data, leading to inconsistent and unpredictable performance. Adequate data abundance can also pose challenges for effective learning. While numerous predictive techniques exist, machine learning methods are deemed more efficient as they offer a broader perspective on potential solutions. Global attention is drawn to stock markets, which often reflect economic fluctuations, with millions of investors closely monitoring them. Given the stock market's inherent high risk and high yield, investors are keen on research and prediction efforts to anticipate its trends.

Numerous prediction algorithms and models have been presented in the literature to successfully anticipate the stock market. The aim for the likely stock market prediction could be the price of the stock in the future, price volatility, or market trend. There are two kinds of predictions: dummy and real-time, which are utilized in stock market prediction systems. In

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dummy prediction, a set of rules is defined, and the average price is used to forecast the future price of shares. During the required real-time prediction, its looked up the company's share price on the Internet. Most often, regression analysis is employed to create predictions. Research examines a well-known, effective regression technique for predicting stock market price based on stock market data. Future iterations of the multiple regression technique may employ additional variables to enhance the results.

The stock market holds significant allure for investors as it provides an opportunity for financial gain through investments in shares and derivatives of various companies[2]. Given its inherently tumultuous nature, the behavior of stock prices is unpredictable and chaotic. In response to this uncertainty, researchers have sought to devise a method capable of quantifying the impact of such unpredictability on stock price movements, aiming to bring clarity to this chaotic behavior. Evaluations of different statistical models allow for a comparison between artificial neural networks and nonparametric, nonlinear regression models. Artificial neural networks (ANN) excel in recognizing unknown and concealed patterns within data, proving particularly effective in forecasting stock market trends.

In the contemporary era, the capital market is essential to a nation's economic growth. Primary market and secondary market are two ways to partition the capital market. The secondary market, also referred to as stock exchanges, deals with publicly traded assets that have already been issued in the primary market, which is where financial instruments are initially made available for trading. One of the key elements of the capital market and seen as an indicator of an economy's economic health is the stock exchange. The unrestricted movement of surplus funds to industry in the form of capital is made possible by the stock market, which will promote economic growth. In [3] the benchmark stock market for the National Stock Exchange of India is the NIFTY 50 Index. Investment managers have access to the Indian market through NIFTY 50, which includes 13 sectors of the Indian economy. 65% of the free float market capitalization of the equities is represented by the Nifty 50 Index. The RBI's monetary policy has an impact on the volatility of the NIFTY.

Numerous foreign investors actively engage in the Indian capital market, reducing our reliance solely on domestic resources. However, sustaining the current rate of cash flow to the industry over an extended period faces challenges due to various macroeconomic factors. Macroeconomic considerations, encompassing monetary and fiscal policy, inflation, deflation, exchange rates, the balance of payments, among others, significantly influence the movement of capital and the performance of capital markets.Foreign exchange, also known as forex, involves the exchange of one currency[4] for another. In a free economy, a nation's currency value is determined by supply and demand. This value may be pegged to another currency, such as the dollar, or even a basket of currencies. Alternatively, a government may actively influence its currency's value. However, most nations freely exchange their currencies, resulting in ongoing volatility.

Since the commencement of the 2018–19 fiscal years, the Indian rupee has experienced depreciation against major international currencies. This decline can be attributed to factors such as reduced foreign commerce, an increased balance of payments, and a spike in crude oil prices. In this study, the focus is on examining how the performance of the National Stock Exchange of India Ltd. (NSE) is impacted by the exchange rates of three major currencies: the dollar, the pound, and the euro.

II. LITERATURE REVIEW

The movement of the Sensex and Nifty is greatly influenced by FDI and FIIs. In addition to helping the Indian economy grow, the flood of FDI and FII allowed Indian businesses to modernise their technology, acquire access to managerial skills globally, develop efficient methods to employ their natural and human resources, and obtain a competitive edge in the global market. The data indicates that there is a strong positive correlation between FII and Nifty and a marginally positive correlation between FII and Sensex Researchers[9] assert that short-term changes in the stock market are influenced by currency value. FDI and FII combined will then be responsible for the increase in stock market investment. A growing economy that has technological restrictions will see higher FDI inflows and currency depreciation. However, currency depreciation will cause FDI inflows to decline if technological developments are helping an economy. For instance, India has relatively little prior experience with technological advancement. As a result, currency depreciation always attracts foreign direct investment, which increases the economy's exports. FDI's arrival into the stock market eventually contributes to the increase of India's SENSEX.

The researchers [10] assert that the value of the dollar has a greater impact on the Indian stock market. The Nifty market may also be impacted by other unanticipated events because only a small percentage of the NIFTY price was taken. They make an effort to draw attention to the important industries in this research, but many more could face repercussions because of their exposure to foreign exchange. "If you want to analyse the impact of currency movement on a stock market of your choice," according to them, "you need to focus on basic pointers like company status (net exporter and net importer)

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and how much hedging company does so to mitigate the effect of exchange rate fluctuation on its profitability."

The NIFTY and SENSEX indexes of the Indian stock market are no longer impacted by the USD/INR exchange rate, according to the study [11]. Nevertheless, the ANOVA reveals that there is very little exchange rate volatility in the NIFTY and Sensex, and the regression test indicates that there is no correlation between the exchange rate and the NIFTY and Sensex. They conclude that there is no relationship between the exchange rate and the Indian stock market. After doing the analysis[12], they found that one of the main factors influencing the Indian stock market is currency swings, with the Nifty seeing particularly high levels of foreign exchange rate volatility.

III. Artificial Neural Network Approach

The machine learning technique is fascinating for artificial intelligence as it is based on the concept that learning evolves from experience and training. In the context of machine learning, connectionist models such as Artificial Neural Networks (ANNs) are particularly suitable when altering connection weights to improve network performance. An ANN is depicted as a network of nodes connected by directed arcs, each carrying a numerical weight denoted as i j w in Figure 1. These weights signify the strength of the connection, illustrating how the preceding node, j u, influences the subsequent node, i u. Positive weights indicate reinforcement, while negative weights suggest inhibition. [5].

Figure-1. Connection weight between nodes.

The initial connection weights are often chosen at random.Rosenblatt was the first to study feed-forward networks [6]. The input layer is made up of a number of inputs that provide the network with input patterns. There will be one or more intermediate layers, sometimes known as hidden layers, after the input layer. The results can then be attained by moving on to the output layer, which comes after the hidden layers (Figure 2). All connections in feedforward networks are unidirectional.

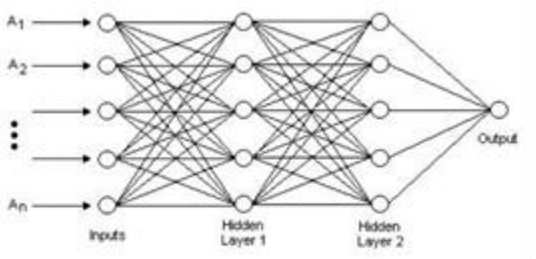

Figure-2. 2-hidden layers network with n inputs and 1 output.

Multi-Layer Perceptron (MLP) networks, which are structured as layered feed-forward networks, are commonly trained using the static backpropagation method. These networks, also known as backpropagation networks [7], are widely utilized in applications that require static pattern classification. The backpropagation algorithm involves selecting a training example, conducting forward and backward passes, and repeating this process until convergence is achieved with a predetermined mean squared error value. The notable advantages of MLP networks lie in their simplicity and capability to approximate any input/output map. However, their drawback is a slow training pace and a substantial need for training data. A more effective approach to address these issues is found in generalized feed-forward (GFF) networks, which are an extension of MLP networks allowing connections to span one or more layers.[8].

IV. Analytical Impetus

Initially, we gathered the necessary information from websites A, B, and C. The information was gathered between April 1, 2018, and March 31, 2023. As shown in Figure 1, we have transformed the initial original data into the necessary format (an MS Excel file), giving us a total of 1183 days of data. Following the gathering of particular data fields, we have determined the independent and dependent variables. As seen in Figure 3.3, there are three independent variables and one dependent variable.

S.No.	**Date**	**Gross Purcha se**	**Gross Sales**	**Dollar to Rupee Exchange Rate**	**Close**	**DC Roundup**
		FII In Flow	**FII Out Flow**		**Daily Closing**	**Daily Closing Round OFF**
1	2-Apr-18	15,806.65	16,064.77	65.13	10211.8	10212
2	3-Apr-18	5,478.65	5,953.63	64.92	10245	10245

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3	4-Apr-18	4,495.71	4,204.03	65.04	10128.4	10128
4	5-Apr-18	5,189.27	4,653.37	64.89	10325.15	10325
5	6-Apr-18	3,992.98	4,083.73	64.92	10331.6	10332
6	9-Apr-18	4,492.70	5,777.21	64.88	10379.35	10379
7	10-Apr-18	4,205.12	4,922.40	64.95	10402.25	10402

Such As-
Dependent Variable-
DC Daily closing data of Nifty 50
Independent Variable –

- ✓ FII Inflow (Foreign Institutions Investors Gross Purchase)
- ✓ FII Outflow (Foreign Institutions Investors Gross Sale)
- ✓ ER (Exchange Rate of Dollar)

We select the requisite data stored in an MS Excel file for the purpose of machine learning and training. To ensure compatibility with training algorithms that exclusively work with numeric values, all fields within the dataset are assigned numeric values. In Figure 3.3, a segment of the data is displayed, clearly delineating the independent and dependent variables. The initial columns in Figure 3.3, starting from the left, serve the purpose of identifying the Date (DT) and Serial number (SN) but hold no further significance during the training phase or subsequent studies; their role is solely to index records. However, due to the presence of decimal values in the output variable (DC), the algorithms struggle to accurately discern the desired pattern. To address this, we employed the 'roundup' function available in MS Excel, converting the output field (DC) values into whole numbers. It's worth noting that the data is accessible online.[1]

For the supervised training of Neural Network models, the training dataset includes both independent variables (also referred to as feature variables or predictor variables) and dependent variables (target variables). The independent variables, serving as inputs to the neural network, are utilized to predict the dependent variables, which represent the outputs from the network.

Upon identifying the independent and dependent variables, two partition strategies were implemented for training the Neural Network Model using Matlab. The first strategy involves a split of 65% for training and 35% for testing, where out of 1183 records, 65% are allocated for training purposes, and the remaining 35% are reserved for testing. The second strategy follows a split of 70% for training and 30% for testing, with 70% of the 1183 records designated for training and the remaining 30% for testing.

In both strategies, there are three input/independent variables (such as FII Inflow, FII Outflow, and ER) and one output/dependent variable (such as DC). The output variable is also referred to as the dependent variable, while the input variables are designated as independent variables. The distribution of records for each strategy is as follows: [Provide specific details based on the data]
1. Strategy 65% 35% (Training Data -65% [Training Record- 769], Testing Data – 35% [Testing Record-414])-
2. Strategy 70% 30% (Training Data -70% [Training Record- 828], Testing Data – 30% [Testing Record-355])-

The initial set of data illustrates the training dataset, encompassing a total of 769 records, which constitutes 65% of the overall 1183 records. Each record is assigned a serial number for counting purposes (S. No.), although this serial number is not utilized further in the process.

The subsequent set of data represents the training dataset, specifically from S. No. 770 to the 1183rd record, making up the remaining 35% of the total 1183 records. Similar to the first block, serial numbers are assigned to each record solely for counting purposes and are not utilized beyond this.

In both cases, the last column (DC) contains data that will be forecasted.

This same approach is maintained in Figure 3.5 (Strategy 70%, 30%), where the number of training and testing records varies based on the selected strategy.

As an illustrative example, a sample training dataset is presented for explanation, assuming a total of 10 records. This sample is depicted in tabular form. As see in Table 3.2
Nevertheless, for our research objectives, we will utilize a total of 1183 records.

Table 1 encompasses a comprehensive dataset of 1183 records, featuring three input or training variables (FII Inflow, FII Outflow, and ER) and one output or testing variable (DC Roundup). Each variable or field comprises 1183 records.

To train a sample Neural Network (NN) model, we have adopted a strategy of 65%, 35%, where the total dataset of 1183 records is partitioned. The initial 65% of records are

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employed for NN model training, while the remaining 35% are designated for NN model testing purposes
Variable 'p' contains the training data set.As-

p= [15806.65 5478.65 4495.71 5189.27……7169.19 12221.30 6526.39;16064.77 5953.63 4204.03 4653.37…..6491.31 8329.98 7488.07; 65.13 64.92 65.04 64.89…..72.71 72.69 72.50;];

Variable't' contains the target data set for training purposes. It contains first 65% of total records of DC Roundup field. Remained 35% of total records of the same field will be forecasted by the trained neural network model. As-
t= [10212 10245 10128 10325……..15175 15031 14930];

Variable 'pnew' contains the testing data set of remained 35% of corresponding training or input data set. As-

pnew= [13501.58 10587.82 8154.54 23425.89….7146.92 9915.58 12995.37;6244.21 7356.42 6840.35 22639.67..5200.07 9080.33 10629.13; 72.53 72.29 72.66 72.44……82.16 82.25 82.18];

The input (input data set consisting of training and target data set) and output (output data set, also called testing data set) have been chosen for sample study[5] in the above section partition strategy[4]. The code block with the required training parameters to train the neural network model is shown in Figure 3. All of the parameters that are needed to train the NN model are listed in Table 2 in the necessary quantity (varying).

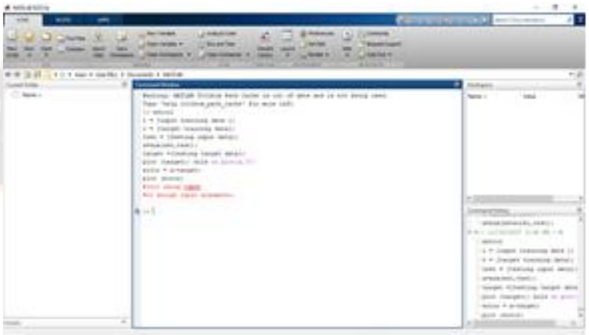

Table 2

Neural Network Model Training Parameter With Their Values	
Learning Rate	0.1
Goal	0.1
Neurons	10
Epoch	10000
Hidden Layer	1
Training Function	traungd, traingdm, traingdx, traingda, trainrp, traincf, traincgp, traincgb, trainscg, trainbfg, trainoss, trainlm
Partition Strategy	65%35%, 70%30%
Total Number of Models Per Strategy	12
Total Models	12x2=24
Model Testing	Each model is trained at least one time, optimal result has been taken.

[4]*Partition Strategy*- It is a way divide total no of training records in to training and testing data set for the purpose of achieving better forecast results.
[5]*Sample Study* – Sample study is used to better explain NN model training terms and terminology. Here, for sample study we selected total 10 records among them we made only (footnote continuous from previous page) one partition strategy (Strategy 65% 35%). Based on that partition strategy we made efforts to explain NN model training process.

Parameters for Training the Neural Network Model -

Table 2 provides a comprehensive overview of essential training parameters, including Learning Rate, Goal, Neurons, Hidden Layer, Training Function, Partition Strategy, and the total number of Models per strategy, among others. A detailed description of each parameter is available in Table 3.4.

V. TRAINING WITH THE NEURAL NETWORK TOOLBOX IN MATLAB

The second stage of the methodology involves the utilization of various training functions in MATLAB for training purposes. In the preceding phase, we examined the analysis of input data, the selection of pertinent data, the choice of the input (training) dataset, and the adoption of suitable strategies for training using Artificial Neural Networks (ANN) through MATLAB.

To train the ANN model using MATLAB, two methods are available: Graphical Interface and Command Interface. In this instance, we are utilizing the Command Interface. The provided diagram illustrates a code block for training the neural network, wherein several parameters can be modified as needed during training. These parameters include:

- Partition Strategy-wise data (p, t, and pnew)
- Learning Rate (net trainParam.lr=0.1). In our case, we employed 0.1.
- Goal (net trainParam.goal=0.1). Our selection was 0.1.
- Neurons (net new[minmax(pn)].[10 1), ('tansig,'purelin'), 'trained')). In our study, we utilized 10 neurons.
- Training Function. 'traingd' is the chosen training function, although we considered 12 options (traingd, trained, traingdx, traingda, trainrp, traincgf, traincgp, trainegb, trainscg, trainbfg, trainoss, and trainlm).
- Epoch (net.trainParam.epochs 10000). The fixed number of epochs is 10000; however, it can be adjusted if necessary.

• Activation Function (tansig','purelin'). If required we can change. Here activation functions are fixed.

In the provided code block, we configured essential settings such as Learning Rate, Performance Goal, Training Function, Number of Neurons, Activation Function, etc. The steps for training the proposed neural network model are outlined as follows:

i. To initiate the training process, the code block is inserted into the MATLAB Neural Network Toolbox Command Window, followed by pressing the ENTER key. Potential training outcomes are illustrated in the accompanying diagram.

ii. Upon achieving the 'Performance goal,' a subsequent code is required for testing the trained network. The testing code is provided.

After pressing the ENTER KEY, the command prompt of the NN Toolbox Command Window is reactivated. Figure 3.15 depicts the final results. To view the output, 'anew' (the network's name) is typed, followed by pressing enter. The output is displayed in the command window.

The output extracted from MATLAB's NN Toolbox Command window is stored for error calculation (using Mean Squared Error and Regression) or to assess the variance between actual and forecasted output. This process, known as the supervised training/learning method, involves comparing the forecasted output with the actual output. If the difference is not minimal, adjustments to training parameters (e.g., LR, Goal, Neurons, training function, etc.) can be made to achieve more accurate results. This difference is commonly referred to as error.

MODEL 1 (65,35)

Training Function	**No. of Neurons**	**Epoch (E) 10000**	**Training Time**	**MSE**	**Regression**			
					Training	**Validation**	**Test**	**Overall**
Traingd	10	25	00:00	5026756	0.26353	0.19696	0.40163	0.27321
Traingdm	10	29	00:00	4926400	0.13325	0.020973	0.19435	0.06874
Traingda	10	4089	00:10	1454934	0.66686	0.67883	0.74657	0.67969
Traincgb	10	769	00:06	1179574	0.76113	0.67737	0.7104	0.74225
Traincgf	10	511	00:04	941047	0.72249	0.76768	0.72925	0.73043
Traincgp	10	569	00:04	1288706	0.71255	0.71741	0.64995	0.70569
Trainbfg	10	2620	00:39	1727876	0.67081	0.68181	0.68679	0.67355
Trainlm	10	1125	00:35	981806	0.77816	0.81536	0.54964	0.75625
Traingdx	10	1739	00:04	1091176	0.68406	0.73129	0.66473	0.68925
Trainrp	10	1277	00:03	1307102	0.69528	0.70128	0.69138	0.69687
Trainoss	10	2395	00:30	1272036	0.76365	0.73863	0.64694	0.74428
Trainscg	10	2404	00:08	1188206	0.76459	0.76717	0.6263	0.74137

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AVERAGE VALUE	**1865468**	**0.634697**	**0.624564**	**0.608161**	**0.625132**

MODEL 2 (70,30)

Training Function	No. of Neurons	Epoch (E) 10000	Training Time	MSE	Regression			
					Training	Validation	Test	Overall
Traingd	10	24	0:00	10081743	0.072992	0.35245	0.1628	0.12752
Traingdm	10	28	0:00	134145943	0.17124	0.25696	0.35981	0.20825
Traingda	10	10000	0:25	1565767	0.67615	0.64551	0.56786	0.65768
Traincgb	10	80	0:00	1686312	0.63024	0.75521	0.74467	0.66468
Traincgf	10	1328	0:09	1774274	0.72996	0.7062	0.64378	0.71116
Traincgp	10	868	0:06	1581134	0.71715	0.68069	0.72941	0.71482
Trainbfg	10	9568	2:13	2199997	0.66706	0.54561	0.68082	0.65539
Trainlm	10	1286	0:41	1295274	0.7636	0.79714	0.57163	0.71871
Traingdx	10	1956	0:05	1615460	0.67402	0.68355	0.55314	0.66097
Trainrp	10	1836	0:04	1716562	0.68302	0.73064	0.67327	0.68888
Trainoss	10	1744	0:23	1676162	0.69836	0.73691	0.54618	0.68326
Trainscg	10	1288	0:04	2078258	0.69981	0.68017	0.56162	0.66873
AVERAGE VALUE				**13451407**	**0.598634**	**0.63092**	**0.566249**	**0.596671**

Here we described the way in which we conducted our research. We analyzed the training data before starting to train ANN models. We conducted 2 partitioning strategies of different combination of training and testing data set.

TRAINCGF( ): This is the function in MATLAB . This is used for creating training the data. When we send our data set of Model 1(65,35) through this function the graphs Figure 4 a),b),c) generated are there for training performance, plot performance and the error pr noise of data for the first model 1(65, 35)

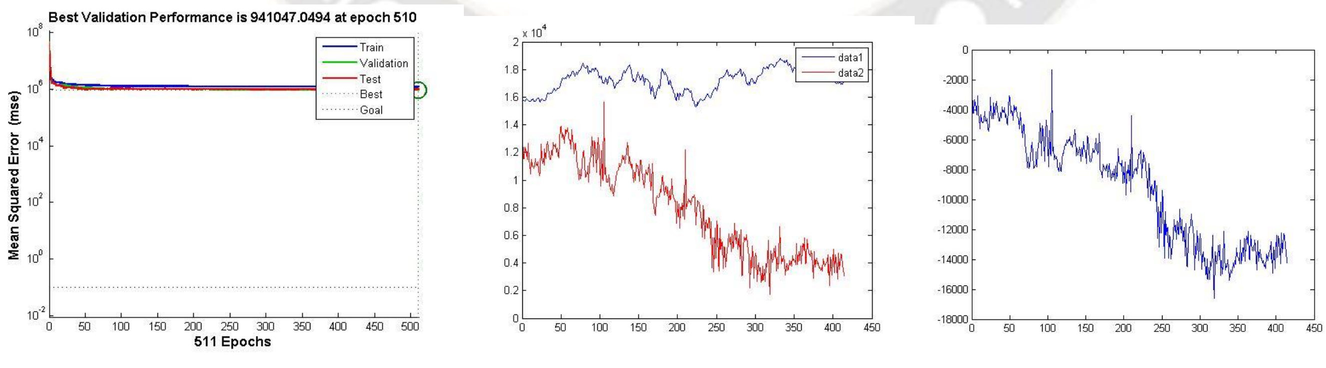

Fig 4 a) Graph for training performance b)Plot performance c) Error.

Figure 5. depicts the regression model of the TRAINCGF function. The figure value for R changes concerning the amount of data trained. The regression model can be seen here with the target in dense cluster.

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TRAINCGB: This is the function in MATLAB . This is used for creating and training the data. When we send our data of Model 2 (70,30) set through this function the graphs.

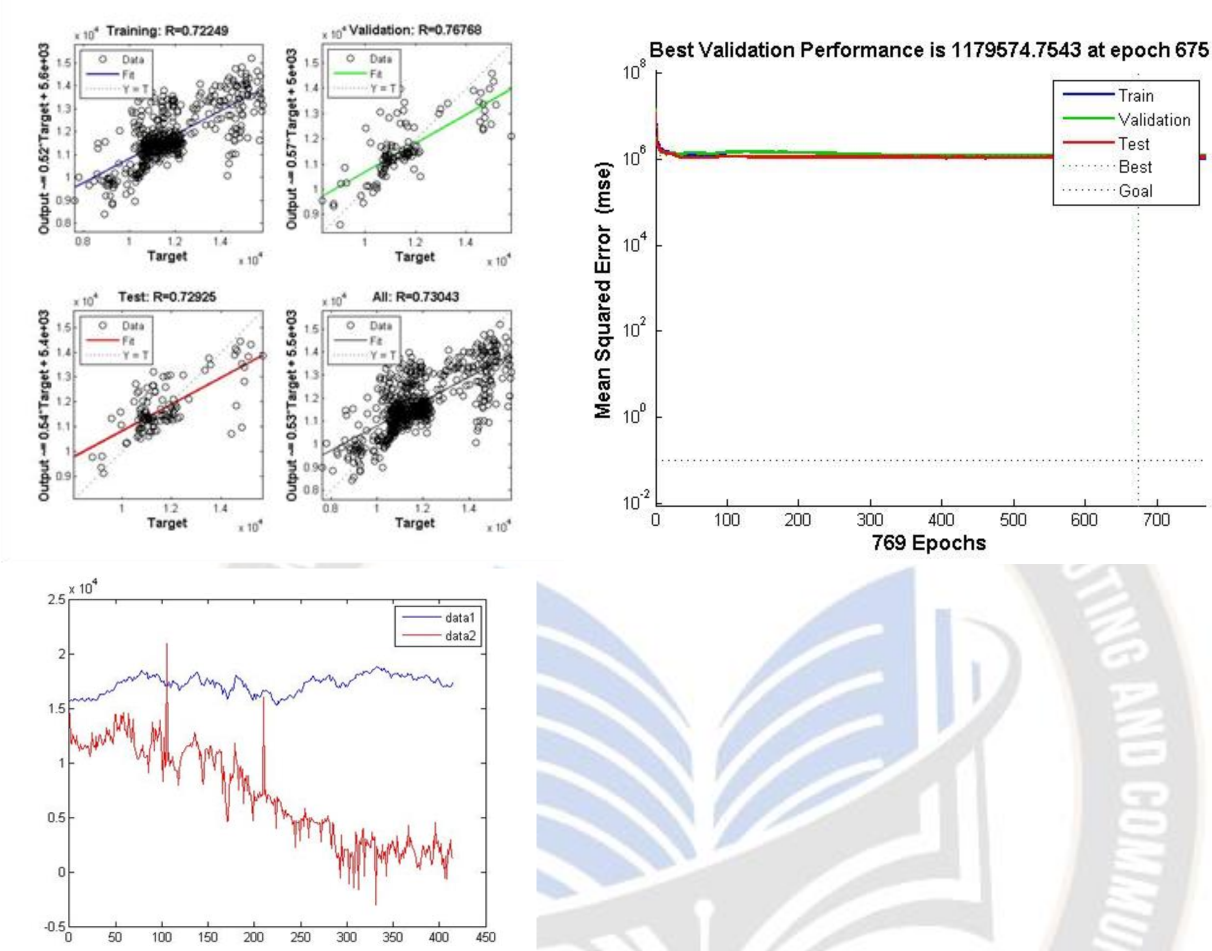

Fig 6 a) Graph for training performance b)Plot performance c) Error. Al for Model 2.

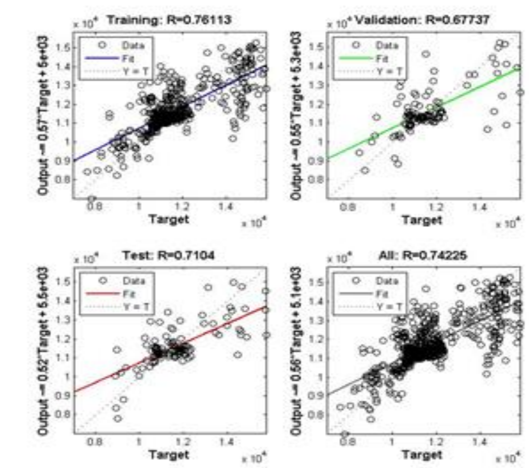

Figure 7. Depicts the regression model of the TRAINCGF function.

	Multiple Linear Regression		
	Model1	**Model2**	**Model3**
	Y=12188 .713129 + 0.013121 X1 + 0.182479 X2	**Y= - 17931.33 379 + 0.077274 X1 + 419.1903 22 X3**	**Y= - 17670.15 5032 + 0.093491 X2 + 414.1674 47 X3**
RSME	**8059840**	**4509851**	**4480571**

Table 3: Result Analysis OF MODELS

Result and conclusion

The stock market is always a volatile entity. The application of neural networks to forecast future stock price trends based on past prices is covered in this paper. We emphasized the significance of selecting the appropriate input characteristics and preparing them for particular learning models, as well as forecasting trends based on historical data. The above tables and graphs show that model 1(65,35) is performing better and the training function training and training are giving better results

Secondly, multiple linear regressions show that the dollar price plays an important role in predicting the daily closing price. Since our research has demonstrated that deep learning is capable of reliably predicting changes in stock price, we believe there is still more room to improve the investment's dynamic and delicate market responsiveness. Multiple models can be combined to improve efficiency and prediction. In addition, the models in this experiment can be optimized through hyper-parameter optimization and updated with alternative stock indices. Our deep learning techniques and the multi-agent system may be combined in the future to improve the accuracy of pricing value prediction.

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