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Design and Modeling of Stock Market Forecasting Using Hybrid Optimization Techniques

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Abstract

In this paper, an artificial neural network-based stock market prediction model was developed. Today, a lot of individuals are making predictions about the direction of the bond, currency, equity, and stock markets. Forecasting fluctuations in stock market values is quite difficult for businesspeople and industries. Forecasting future value changes on the stock markets is exceedingly difficult since there are so many different economic, political, and psychological factors at play. Stock market forecasting is also a difficult endeavour since it depends on so many various known and unknown variables. There are several ways used to try to anticipate the share price, including technical analysis, fundamental analysis, time series analysis, and statistical analysis; however, none of these approaches has been shown to be a consistently reliable prediction tool.

We built three alternative Adaptive Neuro-Fuzzy Inference System (ANFIS) models to compare the outcomes. The average of the tuned models is used to create an ensemble model. Although comparable applications have been attempted in the literature, the data set is extremely difficult to work with because it only contains sharp peaks and falls with no seasonality. In this study, fuzzy c-means clustering, subtractive clustering, and grid partitioning are all used. The experiments we ran were designed to assess the effectiveness of various construction techniques used to our ANFIS models. When evaluating the outcomes, the metrics of R-squared and mean standard error are mostly taken into consideration. In the experiments, R-squared values of over.90 are attained.

Keywords: Stock Market, ANN, CNN, Machine Learning, ANFIS.

I. INTRODUCTION

The growth of stock market has been identified as an economic strength of a country. So accurate prediction of stock market is incredibly vital issue in commerce, mathematics, engineering, finance and science domain because of its prospective investment returns [1]. On the other hand it provides an aid to shareholders to take relevant, timely and felicitous decision. Especially, the persons connected directly with share market may escape nasty astonishments. Appropriate and proper speculates may offer significant and helpful information for achieving financial reliability in India. As we know the stock market is difficult to predict due to its higher rate of uncertainty and volatility. It holds more risk rather than other speculation region. So it is the basis why stock market is so demanding to predict. Thus a soft computing tool i.e., artificial neural networks can be used in stock market prediction. Neural networks have many features as a data analysis tool and relatively efficient implementation scheme in accordance with computation rate and computer memory requirement. ANN model also exhibits complex and non-linear relationship without rigorous assumptions regarding the distribution of samples [2, 3] and can identify new sample even if they have not been in training set.

The stocks markets are one of the foremost investment opportunity avenues available for millions of investors around the world and advances in information technology, computing infrastructure and online trading systems have encouraged many individual investors to actively participate trading activities of stock market (Tsai, C.-F. and Wang, 2009). For individual investors who are interested to invest their hard earned money in stock markets is a major financial decision to earn superior returns compared to other financial instruments (Paisarn, 2021). Investment in stock markets needs sound understanding of the risks involved in the stock price evaluation which depends on the technical and fundamental features of the stock. Majority of the investors do not understand the complex dynamics of stock markets nor are they qualified to select stocks for investments (Qiu, Kandhai, & Sloot, 2007). For many classes of investment community around the world, it is not viable for them to take

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hire investment advisors who can manage their investments in the stock markets. The reputation of these financial advisors has also been in question many times due to the wrong decisions they have taken without any consideration for risk vs reward calculations (Egan, Matvos, & Seru, 2019). Many of the financial advisory websites related to stock price prediction have not been accurate and have been a cause for financial doom for many small time investors (J. A. Turner & Muir, 2014). Based on the above facts, the researcher infers that there is a necessity of an Automated Decision Support System which automatically establishes the relationship between stock fundamentals and its price, perform detailed analysis and automatically create a portfolio of top performing premium stocks to diversify risk and give good returns.

This research study mainly deals with financial markets in general and stock markets in particular, therefore the researcher discusses and introduces the general concept of financial markets and provide some details about the stock market environment in terms of market participants, definition of stocks and shares and the importance of stock markets for investments (Arouri, 2010).

Investment is an allocation of certain funds by individual or companies in a financial structure or model in a hope that they receive more money than they have invested in terms of returns. The amount of return they expect is called the Return on Investment (ROI). There are various financial vehicles for investments, In particular for stock investments, the money of the investors is invested on stocks via the stock markets in the hope that the stock prices go high and give handsome returns back to them.

Attempts at discovering knowledge and gaining insights from the processes have been made from generations long before the advent of computers. Gaining insights and using this knowledge to forecast future events has been the core principle of machine learning techniques. The various types of Machine learning algorithms are depicted in figure. Machine learning algorithms assist computing machines to gather knowledge (i.e. learning) from existing or historical data and come up with inferencing models to predict future (Dhall, Kaur, & Juneja, 2020). Learning is a key area in machine learning used for self-improvement and a key behavior of intelligent systems. The salient features of machine learning systems are:

- Automated Machine learning systems demonstrate a high level of learning behavior and inference logic which is un-matched by humans when massive datasets are involved (Royal Society of Great Britain, 2017).
- Automated machine learning systems are powerful as they are able to learn and understand both numeric as well as symbolic data.
- The inference logic built by the automated machine learning systems are much faster than human intuition and thus in areas where quick response is required, machine learning systems outperform humans.

The Machine learning techniques are categorized based on the specific problem area involved and has three main categories namely (Domingos, 2012):

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

II. OBJECTIVE AND SCOPE

Objective:

Applications of ANN to various prediction problems have been a popular research area for many years and are still expanding today. However, when compared to other nations, India has not produced as many works in this area. Therefore, the goals of this work are to:

• Create adaptive neuro-fuzzy hybrid models for stock market forecasting

• Observe and investigate whether neural networks can be used to predict future stock market price indices.

• To carry out an evaluation of the models created for GSPC companies' daily closing price movements.

• To evaluate the models created for changes in the daily closing prices of GSPC companies. ***Scope***

The major scope to apply ANFIS for prediction of stock market are given below:

- The data for stock market is extremely complicated which is very tough to model, so it is more beneficial if we designed it with a non-linear model.
- To explain a particular stock a rich volume of interrelated input series is necessitated.
- Often to illuminate a particular stock we required a set of enormous input sequence, only the ANFIS can provide it.

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III. LITERATURE REVIEW

Mehar Vijh, 2020 Making precise estimates of market returns is a very challenging task since the stock markets are so unpredictable and non-linear. Programmable techniques of prediction are now more accurate in predicting stock prices because to developments in artificial intelligence and computational power. In this study, artificial neural networks and random forest techniques were used to forecast the closing prices of five enterprises from distinct industry sectors. The open, high, low, and close prices of the stock are utilized to generate new variables that are inputs into the model. The models are assessed using two popular strategic metrics, RMSE and MAPE. The models' ability to predict closing stock prices is demonstrated by the low values of these two indicators.

(Milad Shahvaroughi Farahani, Seyed Hossein Razavi Hajiagha, 2021) The stock market of today fulfills an important function and may be used to assess one's financial status. People have the opportunity to make a big return by putting their money in the stock market. But it is challenging since there are so many considerations. There are therefore many methods for predicting share price change. The main goal of this paper is to anticipate stock price indices using an artificial neural network (ANN) trained with novel metaheuristic algorithms as the social spider optimization (SSO) and bat algorithm (BA). We made use of various technical indicators as input variables. Then, we employed evolutionary algorithms as a heuristic method for feature selection and choosing the best and most relevant indicators (GA). We used a variety of loss functions, such as mean absolute error, as a standard for evaluating errors (MAE). On the other hand, using time series models like ARMA and ARIMA, we predicted stock price. Finally, we compared the results obtained utilizing ANN-Metaheuristic techniques and time series models.

Mehtabhorn Obthong, G. Wills, and N. Tantisantiwong, 2020). Stock traders need fast information at their disposal in order to make informed judgments. A stock market trades a range of stocks, therefore several factors might affect the decision-making process. Additionally uncertain and difficult to predict is the behavior of stock prices. These elements make stock price forecasting both an important and challenging process. As a result, research efforts are concentrated on identifying the prediction model that has the lowest mistake rate and best forecast accuracy. This article reviews studies on machine learning techniques and algorithms that improve the accuracy of stock price predictions.

Zhongbao Zhou, Helu Xiao, and M. Gao, 2020) We employ a number of heterogeneous data sources, such as historical transaction data, technical indicators, stock postings, news, and Baidu index, to predict the movements of stock prices. With an emphasis on the unique prediction patterns of active and inactive stocks, we assess the support vector machine's (SVM) capacity to forecast in various degrees of activity for a single stock. We construct a total of 14 data source combinations in accordance with the aforementioned 5 heterogeneous data sources and choose three forecasting horizons, namely 1 day, 2 days, and 3 days, in order to investigate the forecast effects of stock price movements in the China A-share market under various data source combinations and forecasting horizons. It is shown that the best data source combinations for active and inactive stocks differ from one another. Active stocks obtain the most accuracy when integrating many non-traditional data sources, whereas inactive stocks earn the highest accuracy when fusing traditional data sources with non-traditional data sources. After further classifying each stock into inactive, active, and extremely active phases, the expected impacts of the same securities at various points in time are compared. We find that, for most data source combinations, the more active the stock is, the greater accuracy we are able to achieve, demonstrating that our technique is better at forecasting stock price movements during active and highly busy times.

(U. Singh, G. Kumar, and Sanjeev Jain, 2020) The social and economic foundation of a country depends on the stock market. Stock market forecasting is one of the most challenging challenges for investors, professional analysts, and researchers in the financial sector because to the extremely noisy, nonparametric, volatile, convoluted, non-linear, dynamic, and chaotic character of stock price time series. Given the increased risk involved in participating in the stock market, stock market forecasting is a crucial responsibility and a well-known study area in the financial sector. However, the majority of the risk may be minimized with the advancement of very powerful computational technology. This in-depth investigation focuses on the application of computationally intelligent stock market forecasting approaches, such as artificial neural networks, fuzzy logic, genetic algorithms, and other evolutionary methods. This paper reviews the current research on computationally intelligent stock market forecasting

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methods. The chosen papers are organized and discussed in this article from the standpoints of six main areas: (1) the stock market under investigation and the related dataset, (2) the type of input variables investigated, (3) the pre-processing techniques used, (4) the feature selection techniques to select effective variables, (5) the forecasting models to address the stock price forecasting problem, and (6) performance metrics used to evaluate the models. This work's major contribution is to provide academics and financial professionals with a systematic methodology to develop intelligent stock market forecasting algorithms. This study also describes upcoming work that will increase the efficiency of the techniques now in use.

IV. PROPOSED METHODOLOGY

Research methodology is a method used to find the answer to a specific challenge known as a research problem. Our study issue may be divided into two parts as follows:

1. Gathering and analyzing data

2. The MATLAB software's Neural Networks toolbox is utilized for training.

This chapter's opening section demonstrates data gathering, analysis, and format preparation. In the second part, ANN model training using MATLAB software will be discussed. The ANN models are tested and trained using the aforementioned dataset.

Material and Methods

The NSE (National Stock Exchange) Nifty 50 Index's daily closing price movement is the research data set that this study is based on. The entire data collection spans the timeframes of 4 January 2010 and 31 March 2016. The total trading days for the cases are 1538.

The World Wide Web was utilized to get the stock market information for this study. The information was gathered from historical data made available on the National Stock Market website. The first, original data was sent to us in soft copy (.csv format).

Finally, a file with specified data fields that included all of the daily closing prices of the index for that specific time period was created. ANN models have a direct impact on the neural network's performance. Therefore, it is important to carefully consider a number of crucial factors when modeling a neural network, such as the identification of input-output variables, parameter selection, network structural design, and performance assessment statistics.

For each scenario, four technical indicators are used as input and output variables, and we classified them as independent and dependent variables during the model-building procedure. These examples demonstrate a dependent variable and three independent variables.

depended-on variable:

Everyday closure: Nifty 50 index closing information per day a separate variable

FII inflow: Gross Purchase by Foreign Institutional Investors FII outflow: Total sales of foreign institutional investors Rate of exchange: USD to IN

Data for the dependent variable and the independent variables (FII inflow, FII outflow, and exchange rate) were processed in the proper format after being acquired from the corresponding websites. The independent variables are crucial because they have a significant impact on closing price values. Since the training process only required numeric values, all fields had values that are numbers. Therefore, we used the "roundup" tool provided by MS Excel 2007/CSV to convert the values of the dependent variable (Daily close) into whole numbers because if we expressed this field in decimal values, then algorithms would not be capable of accurately understanding the pattern as we wish. It displays chosen data with easily comprehensible dependent and independent variable identification.

Artificial Neural Network Model Development

An huge parallel distributed connection made up of neurons that store knowledge is what is meant by an ANN. The capacity of ANN to extract meaning from ambiguous or complicated data allows it to be used to uncover patterns and trends that are too complex for either human or computer methods to detect on their own. We employed a three-layered feedforward neural network model with an input layer connected to a hidden layer and a hidden layer further connected to an output layer to anticipate the price index fluctuation of the stock market. The input for the network is represented by three neurons of the input layer as FII inflow, FII outflow, and Exchange rate. One neuron produces an output that represents the direction of movement. Either 0 or 1 is the output. The number of neurons in the hidden layer was chosen using the heuristic. The structural layout of the three-layered feedforward ANN model is shown in Figure 4.1.

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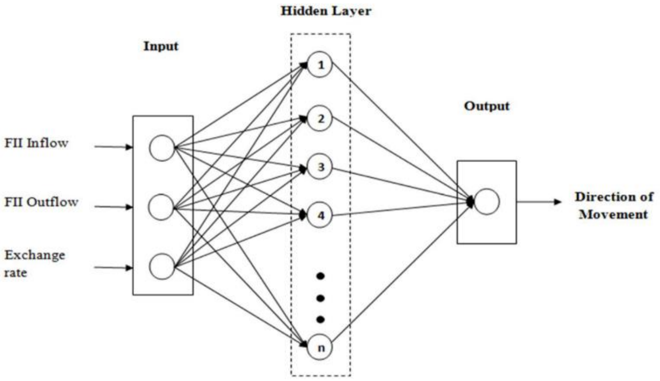

Figure 4.1 Structural Design of Three Layered Feed forward ANN

Neurons from one layer in a network are linked to neurons from the next layer with some weight. The network weights that correctly identify particular input patterns for a given input-output set are modified using a learning approach. These weights were initially given at random. The number of hidden nodes determines how many connections between inputs and outputs are necessary, and this criteria may change depending on the particular topic being studied. A neural network will get over-trained if a large number of nodes are used in the hidden layer, which will lead to poor prediction. The learning rate (lr) is used to change the network weights during incremental training with the goal of getting the predicted value as near to the observed value as possible. The greatest error (e) at which the network must converge for the length of training is referred to as training tolerance. Following convergence, an approximative function is produced and used to make future predictions. This trained neural network is currently being tested using multiple data sets without including any output data. In this work, we employed the back-propagation learning approach to train ANN models (Rumelhart, Hinton and William, 1986). The performance of ANN models is assessed using RMSE (Root Mean Square Error). Tansig() and Purelin(), two activation functions, are regarded as activation functions.

Adaptive Neuro Fuzzy Inference System Based Stock Index Forecasting

Two strategies are often used to examine or monitor financial securities. Fundamental analysis is one type. The second is referred to as technical analysis. In order to assess a company's physical position in the market and, consequently, its investment profitability, fundamental analysis examines the company's product sales, manpower quality, infrastructure, etc. Contrarily, technical analysis doesn't examine the company's physical makeup. Instead, it assesses the securities based on market patterns and movement. It makes the supposition that changes in stock prices or other financial instruments represent the company's core values. Therefore, a few factors need to be assessed in order to comprehend the firm and its profitability through its stock prices on the market. This may help an investor make an informed choice. Both Indicators and Oscillators are the names of these parameters. RSI, Moving Averages, MFI, MACD, etc., as examples. Few assumptions are made while utilizing technical analysis to forecast stock values: The market is said to follow trends. History repeats itself, meaning that stock values respond similarly when exposed to stimuli of a similar nature. Prices often follow the trend rather than bucking it.

We must comprehend the ideas of stock momentum and subsequent trends in order to characterize the movement of stock prices. As its name implies, momentum measures the degree of movement in the stock price over the prior time frame.

Selection of Parameters

There are 52 distinct metrics, indicators, and oscillators that have been defined for technical analysis of stock market data. Using every indication will make the system complex and sluggish, even though each one adds a little bit of extra information about the stock. The ANFIS structure would need to include at least 252 rules to accomplish this. In order to accurately forecast the kind of movement without increasing system complexity, it is necessary to determine the parameters (feature vectors of the financial data). We choose to focus on Divergence, Weighted Moving Average, and RSI (Relative Strength indicator) based on practical observations and a knowledge of the amount of information an indicator conveys. These variables aid in determining the direction and magnitude of stock price movement, which aids in forecasting the appropriate course of action. A moving average provides insight into how prices are changing generally over a long period of time. Therefore, the moving average offers us a sense of the current trends. contrasting the moving averages across two time frames, let's say 15 and 50 days.

A closer examination of the situation reveals that the stock really becomes favorable at the point when the 15-day moving average crosses the 50-day moving average in an upward manner (Cross over), as it is exhibiting a tendency to increase in price in the future. Similar to this, when the stock begins to exhibit signals of collapse at the point where the 15

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day Moving Average crosses the 50 day Moving Average in a negative manner (Support), it loses appeal.

One more of the most popular and well-known momentum indicators in technical analysis is the relative strength index (RSI). Overbought and oversold circumstances in a security are signaled by RSI. The indicator is displayed on a graph with a range from 0 to 100. A rating of greater than 70 indicates that a security is overbought, and a reading of less than 30 indicates that it is oversold.

RSI =100 - (100/ (1+RS))

RS is defined as the average of 14-day increments divided by 14-day decrements.

This indicator aids traders in determining if the price of an asset has been unfairly driven to the current levels and whether a reversal may be imminent.

The foundation for the RSI calculation is 14 trading days, however this number may be changed to suit the circumstances. The RSI will be more volatile and utilized for shorter term trades if the trading period is changed to use fewer days.

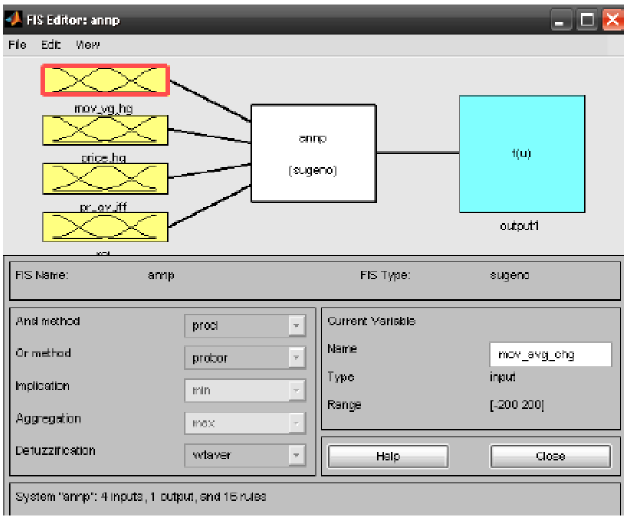

Figure 4.2 Structure of ANFIS

Any fuzzy system that operates employs the rules established by a professional who is familiar with the underlying theories and workings of the system. The system requires a set of rules that match to the different input combinations that form a real-world scenario, and it must be aware of how to act in each context. See how the market responded after seeing a certain input (market condition) first. Then attempt to locate the same circumstance once more in the data collection to observe how the behavior has changed. There is a relationship between the inputs that may be utilized to generalize the scenario if the behavior is the same. However, if the behavior varies for the same sort of inputs at various times, it either suggests that the feature vector is not yet capable of making predictions or that the system is acting erratically and not consistently.

For instance, empirical research into stock prices and the derived parameters showed that the market nearly always moves downward when the price changes are negative and the moving average changes are positive and below the price. As a result, it assisted in establishing the appropriate rule to "SELL" the share when this circumstance occurs. The following statements provide information on the rules that were put into effect:

- If (mov_avg_chg is Neg) and (price_chg is Pos)and (pr_mav_diff is Down)and (rsi is Low)then(output1 is Buy)
- If (mov_avg_chg is Neg) and (price_chg is Pos)and (pr_mav_diff is Down)and (rsi is high)then(output1 is Buy)
- If (mov_avg_chg is Pos) and (price_chg is Neg)and (pr_mav_diff is Up)and (rsi is High)then(output1 is Sell)

Understanding the significance of the neuro-fuzzy architecture's membership functions is also crucial. Membership features were created to lessen the impact of minute modifications or variations that might influence the system's success rate. For instance, the "positive" membership function of the % change in price and the percentage change in moving average doesn't reach value 1 right away after 0 for either. We can't be certain that there is an upward tendency in the pricing until the price change is roughly 5%. Therefore, "Positive" and "Negative" membership functions overlap. Membership functions in triangles and trapezoids were employed.

These factors make it challenging to model such systems. Modeling and prediction of complex systems have increasingly been done using data-driven methodologies. These techniques are able to learn complicated correlations between inputs and outputs and do nonlinear modeling without any prior knowledge. Recent research on hybrid systems tries to address artificial neural networks' lack of knowledge explanation.

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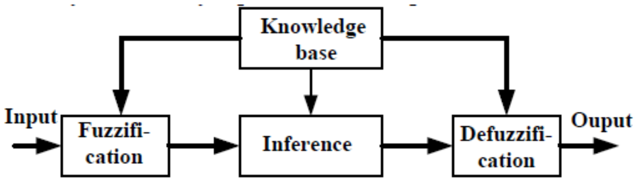

Figure 4.3 Structure of Fuzzy Logic based Decision Making System

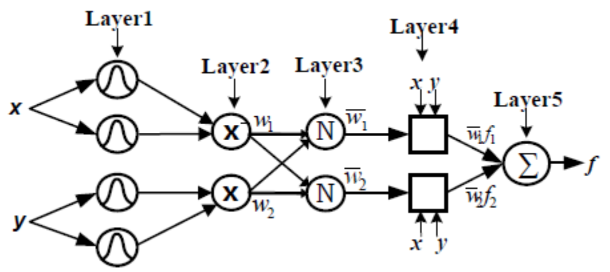

Figure 4.4 Structural Design of Multi-layer-ANFIS

Due to their capacity for mapping nonlinear and many input-output data pairings, artificial neural networks and fuzzy logic are predicted to be used to get around this constraint. The Adaptive Neuro Fuzzy Inference System (ANFIS), developed by J-S. R. Jang [8], is a specific architecture of neuro-fuzzy systems. The fuzzy inference system employed by ANFIS is seen in Fig. 5 and is made up of four functional blocks.

Consider the following two fuzzy if-then rules based on a first order Sugeno model to succinctly define the ANFIS architecture:

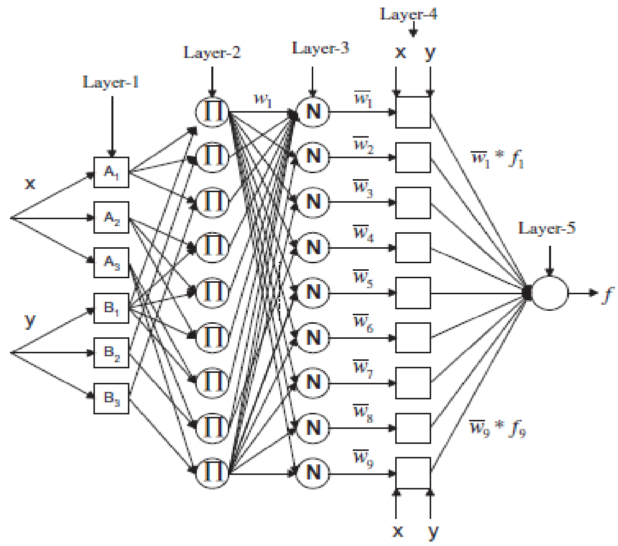

Figure 4.5 Structural Design of Multi-Layer- ANFIS

Rule 1: if (*x* is *A1*) and (*y* is *B1*) then (*f1 = p1 x +q1 y + r1*)

Rule 2: if (*x* is *A2*) and (*y* is *B2*) then (*f2 = p2 x +q2 y + r2*)

Where x and y are inputs; *Ai* and *Bi* are appropriate fuzzy sets; p1, q1, and r1 are output parameters. *f1* and *f2* contribute to the output of the system.

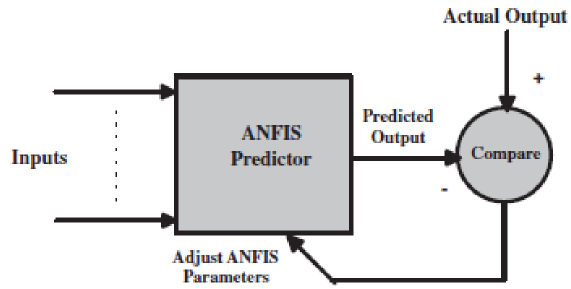

Figure 4.6 General Block Diagram of ANFIS

To simplify the explanations, the fuzzy inference system under consideration is assumed to have two inputs (and y) and one output (z). For a first order of Sugeno fuzzy model, a typical rule set with base fuzzy if-then rules can be expressed as:

If x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

where p, r, and q are linear output parameters.

This architecture is formed by using five layers and nine if-then rules:

Layer-1: Every node i in this layer is a square node with a node function.

$O_{1,i} = \mu_{\mathrm{Ai}}(x)$,

for $i = 1,2,3$ $O_{1,i} = \mu_{\mathrm{Bi-3}}(y)$, for $i = 4,5,6$

where x and y are inputs to node i, and A_i and B_i are linguistic labels for inputs. In other words, $O_{1,i}$ is the membership function of A_i and B_i. Usually $\mu_{\mathrm{Ai}}(x)$ and $\mu_{\mathrm{B}}(y)$ are chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0 , such as

$$\mu_{\mathrm{Ai}}(x), \mu_{\mathrm{Bi-3}}(y) = \exp\left(\left(-(x_i - c_i)/(a_i)\right)^2\right)$$

where a_i, c_i is the parameter set. These parameters in this layer are referred to as premise parameters.

Layer-2: Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$O_{2,1} = w_i = \mu_{\mathrm{Ai}}(x) \cdot \mu_{\mathrm{Bi-3}}(y),\ i = 1,2,3, \dots, 9$$

Each node output represents the firing strength of a rule.

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Layer-3: Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \bar{w}_i = w_i/(w_1 + w_2 + \cdots + w_9),\ i = 1,2,3,\cdots,9$$

Layer-4: Every node i in this layer is a square node with a node function

$$O_{4,i} = \bar{w}_i \cdot f_i = w_i \cdot (p_i x + q_i y + r_i),\ i = 1,2,3,\ldots,9$$

where w_i is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer-5: The single node in this layer is a circle node labeled $\sum$ that computes the overall output as the summation of all incoming signals:

V. RESULT ANALYSIS

The csv-formatted dataset, which includes data on stock performance over the previous five years, was downloaded. The purpose of this statistical investigation was to determine whether there was any correlation between various price indicators and the closing price of the stock. A neural network model was applied for this. Numerous studies have shown that the opening price, high price, and low price are all reliable indicators of the closing price. It is surprising that volume has no statistical bearing on how much a stock's closing price changes. Getting a set of data for daily stock preparation, model fitting, and cross-validation Visualization The model's assessment The outcome is Price Prediction Visualization

Step 1: Data Loading

Step 2: Acquiring Daily Price Information

Step 3: Model Fitting and Valuation

Step 4: Results Visualization

Step 5: Evaluation of Parameters

Step 6: Visualization of the predicted priceThe opportunity to directly boost the likelihood of financial interpreters making money has made stock price prediction an appealing academic topic that many people have long been interested in. In this study, we attempted to forecast the SNP 500 index's closing price for the next day.Economic forecasting has made use of several conventional time series models. Recent developments in soft computing approaches offer appropriate tools to forecast chaotic situations, such as the one in which our issue: stock market closing prices, exists. In order to compare the outcomes, we built three alternative Adaptive Neuro-Fuzzy Inference System (ANFIS) models utilizing two different datasets.

Data Preparation

The historical closing prices are used to produce two distinct databases. The first one has the previous five days' worth of daily closing prices. The closing prices of the t-5 (last week, same day), t-10, t-15, t-20, and t-25 datasets are included.

Be aware that the suggested model makes no attempt to account for external factors like political or economic ones. Only historical closing prices are taken into account; the model is based on past prices and their variations over time.

Creation of Train and Test Datasets

The training and test sets are constructed by partitioning the data into two sections without shuffling, depending on the occurrence of the observations, as the dataset comprises of time series data. Not shuffled is the dataset. No sampling strategy is applied. Otherwise, information would leak due to the data's timeliness.

A test data point is the closing price of the next day, whereas training data comprises of 1000 data points. To produce results, the dataset is looped for 42 days—roughly two months. The forecasts are produced using the closing prices of the SNP500 index.

Building the FIS Models

In this work, three different FIS model types—Grid Partitioning, Subtractive Clustering, and FCM Clustering modes—are tested. On both training datasets, which include daily and weekly closing prices, the three modes are used.

The whole input space is divided up into many fuzzy subspaces using the grid partitioning technique, and each value that is represented by a given subspace is specified using a matching membership function. By analyzing the distance metrics of related data points, subtractive clustering aims to determine the likelihood that a data point might be a cluster centroid. When it is unclear how many centroids are present in the data set, this strategy is employed. It produces better results and is less challenging to use than the grid partitioning approach. The number of clusters in the fuzzy C-Means clustering technique is initially established, and then each data point is given a random weight according to the k-Means algorithm. The procedure is iteratively performed to identify the centroids of the clusters. One data point can be included in two or more clusters using this type of clustering.

By using alternative membership functions and parameters, more Genfis models may be produced. The tunefis technique

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is used to optimize the membership function parameters of generated models.

Generating the ANFIS Models

The ANFIS, or adaptive neuro-fuzzy inference system, builds a fuzzy inference system from the inputs and outputs of a dataset. The parameters of the membership functions are modified using the least squares or backpropagation algorithms, similar to a neural network. Fuzzy logic and artificial neural networks are combined to form ANFIS. There are five levels in the traditional ANFIS paradigm.

The input layer comes first. The mid-layers contain square nodes with various output criteria. The output is computed by a single node in the fifth and final layer by adding all the inputs from the layers before it.

Forecasts for the closing prices of the following days are produced using the trained ANFIS models.

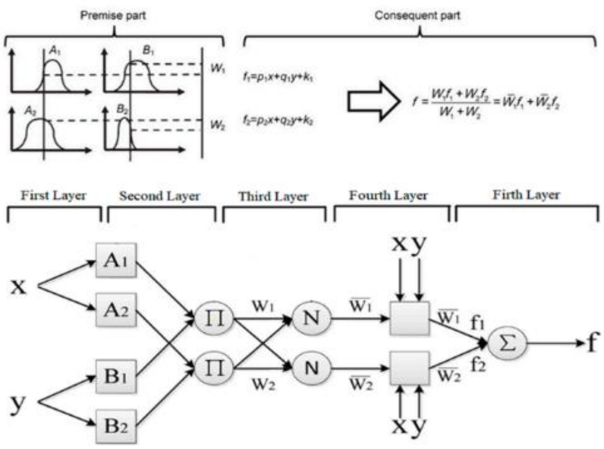

Figure 5.1: ANFIS Structure (Sugeno Model)

Constructing the Ensemble ANFIS Model

The ensemble approach is predicated on the notion that combining many prediction techniques would improve the model's performance. In order to get better outcomes, we are combining many ANFIS methodologies in this study. Although the weights of the employed predictors might be varied, we accept them as equally weighted because they are essentially the same type of predictors and for simplicity to lessen the complexity of calculations.

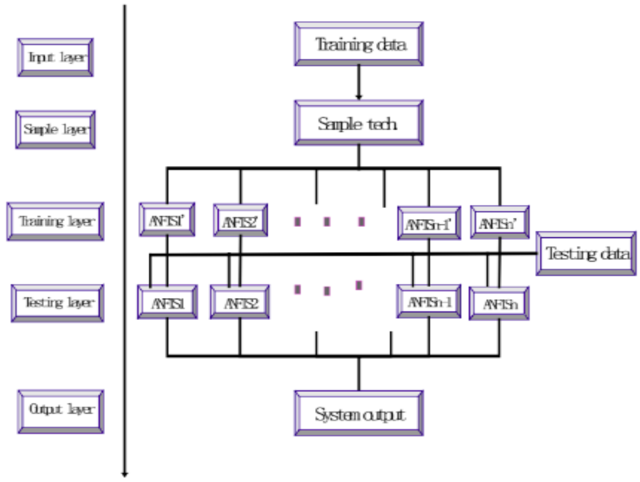

Figure 5.2: Ensemble ANFIS Structure

The output of the overall system is calculated to be the average of all Anfis models:

$$\text{EnAnfis} = \left(\sum_{i=1}^{n} \text{Anfis}_{\,i}\right)/n$$

By employing reporting and comparing Mean Square Error and Root Mean Square Error, the system's effectiveness will be evaluated. The proposed system performs better the lower the error rate.

Experiments and Results

The closing prices of the SNP500 index are used to forecast the closing price for the next day. Two sets of inputs are used: one contains information on daily closing prices, while the other does so for weekly closing prices. On these two datasets, a total of six ANFIS models are created utilizing the Grid Partitioning, Subtractive Clustering, and FCM Clustering modes of ANFIS. Each model is then tweaked to determine the best hyperparameters. The average of the tuned models is used to create an ensemble model.

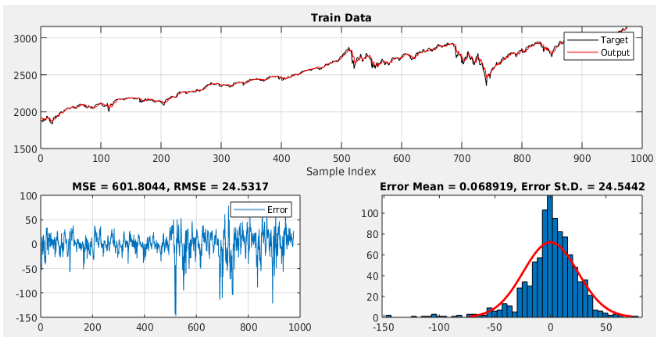

Figure 5.3: Training Dataset and Associated Errors

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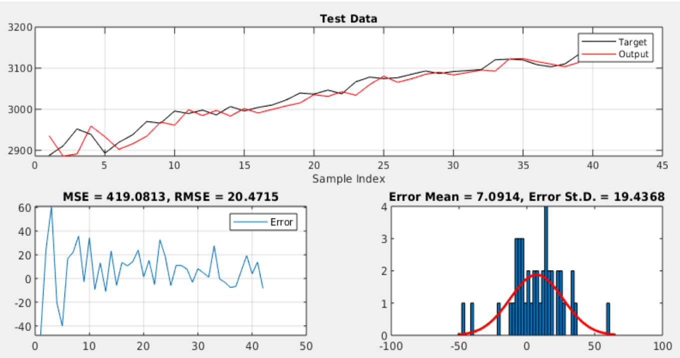

Figure 5.4: Test Output of Best Ensemble Model: Average of 3 Daily Models (Not Tuned)

Table 5.1
Prediction output metrics of different models

SNP500	R_squared	MSE	RMSE	Mean(err)	Std(err)
anfis_1_d	0.8899	590.8698	24.3078	5.5338	23.9564
anfis_2_d	0.9218	419.3442	20.4779	8.7605	18.7338
anfis_3_d	0.9301	374.7983	19.3597	6.98	18.2765
anfis_1_d (tuned)	0.8898	591.0605	24.3117	5.5305	23.9613
anfis_2_d (tuned)	0.9218	419.3459	20.4779	8.7604	18.7339
anfis_3_d (tuned)	0.9301	374.8017	19.3598	6.9803	18.2765
anfis_1_w	0.4157	3135.1401	55.9923	35.5454	43.7872
anfis_2_w	0.595	2173.0302	46.6158	33.6175	32.6853
anfis_3_w	0.5042	2660.0021	51.5752	41.927	30.3996
anfis_1_w (tuned)	0.4156	3135.588	55.9963	35.5464	43.7915
anfis_2_w (tuned)	0.595	2173.1932	46.6175	33.6172	32.6882
anfis_3_w (tuned)	0.5041	2660.6111	51.5811	41.9338	30.4001
ens_anfis_tuned	0.8108	1015.2369	31.8628	22.0611	23.2688
ens_anfis_daily (not tuned)	0.9219	419.0813	20.4715	7.0914	19.4368

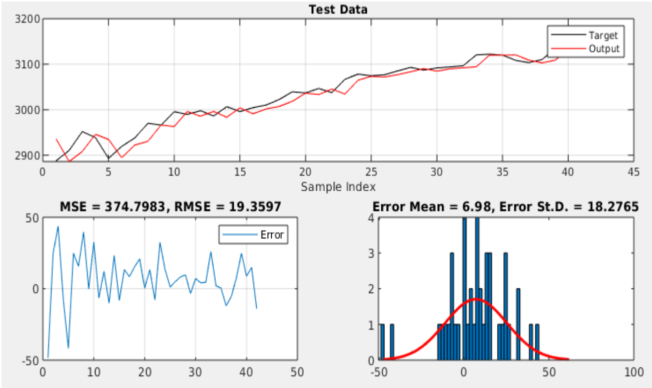

Figure 5.5: Test Output of Best Model: FCM Clustering of Daily Data (Not Tuned)

For the trained models, Table 1 displays the R squares, mean squared error, root mean squared error, mean error, and standard deviation of error values. The overall R squared and mean squared error values are significantly higher than in the final setup when training with 85% of the dataset and then predicting the remaining 15% of the values. The prediction accuracy is significantly improved by parameter tuning, though. Contrary to popular belief, in the case of day-by-day prediction, the use of parameter tuning does not reduce the prediction errors. This finding may indicate that hyperparameter tuning is more crucial for long-term results that have greater uncertainty. ANFIS is an effective tool for time series prediction, to sum up. The model can generate R squared values greater than 90% without the use of intricate combinations or ensemble models. The model can be applied to various stocks or indices as future research.

VI. CONCLUSION AND FUTURE SCOPE

Conclusion

The success of the stock market is a major factor in organizational growth, and this development has a significant direct impact on the nation's financial system. The task of forecasting the stock market index is extremely difficult, yet ANN is capable of doing it. It has been demonstrated that ANN is an effective, all-encompassing method for pattern recognition, classification, clustering, and notably for time series prediction with a high degree of accuracy. In this thesis, we made an attempt to obtain the best structural design in order to accurately anticipate the daily closing price movement in the Index of India. This study highlights the enormous potential of neuro-fuzzy architecture, such as ANFIS, for tackling challenging time series prediction and judgment problems. It demonstrates its significance in nonlinear system modeling, when other traditional approaches have not been very effective. The above-mentioned technique has certain drawbacks, including limited ability for short-term prediction and non-real-time data processing and prediction. The investor's earnings are not entirely optimized either. This is because the algorithm does not indicate "Sell" until it has determined that a downward trend has begun. Thus, the investor experiences some financial loss prior to selling that specific share.

Because accurate stock price forecasting may provide enticing rewards, predicting the stock market index return is crucial and very interesting. A financial trader often considers it while deciding whether to purchase or sell an instrument. Because there are so many variables that might affect stock values, these activities are incredibly challenging and complicated. The issues with stock markets have been effectively solved using soft computing approaches. In this study, the stock market return on the ISE National 100 Index is predicted using the adaptive neural fuzzy inference system (ANFIS). The study demonstrates that the use of ANFIS may significantly improve the performance of stock price prediction. These values are very satisfying when compared to others. The effectiveness of this method's predictions demonstrates the benefits of ANFIS. It is quick, simple to use, and reasonably priced. The results show how the ANFIS model can be used in financial applications to learn and predict. Additionally, these findings suggest that ANFIS can be a useful tool for predicting stock prices in developing markets.

Future Scope

The system's real-time data processing and acquisition capabilities will be developed in the following stage of development by connecting it to an online data source. The Membership functions can be changed through additional testing and research to enhance the test outcomes. Moving averages that have been genetically trained may also be used in the future to more precisely track price trends. (Genetic algorithms can be used to train the weights.)

Future research may choose to include additional international financial factors like the CPI (Consumer Price Index), WPI (Wholesale Price Index), IIP (Index of Industrial Production), interest rates, etc. as inputs for the model to improve accuracy. In our study, we chose three independent variables to predict the stock market. The results of the current study can be improved by using fuzzy logic or genetic algorithms. Deep learning algorithm processes are another option. By implementing n hidden layers in the architecture, it may be possible to redefine training patterns and improve performance. The intended model can be used to forecast financial markets for mutual funds, interest rates, exchange rates, gasoline prices, and other commodities. A microcontroller can be used to further program and fabricate the leading model, which can then be used as a small Android application.

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