IOSR Journal of Computer Engineering (IOSRJCE)
ISSN: 2278-0661 Volume 1, Issue 1 (May-June 2012), PP 60-64
www.iosrjournals.org

Stock Market Index value prediction using Artificial Neural Network

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Abstract:
Utilizing artificial neural networks (ANNs) for predicting stock market values, such as those of the Indian Stock Exchange (ISE) market index, stands as a highly valuable application. Your initial research exhibits thoroughness, particularly in the selection of crucial input factors like the preceding day's index value, the INR/USD exchange rate, the overnight interest rate, and dummy variables representing weekdays. This underscores a comprehensive understanding of potential factors influencing stock market fluctuations in India.
The standard practice of training ANN models with approximately 90% of the dataset and evaluating them with the remaining 10% serves to gauge model efficacy. Employing Multi-Layer Perceptron (MLP) and Generalized Feed Forward networks as network architectures offers flexibility in capturing intricate data patterns.
Exploring various configurations of hidden layers (1, 2, and 4) to achieve a mean-squared error value of 0.003 demonstrates a commitment to optimizing the network architecture for enhanced performance. This approach facilitates fine-tuning of the model to strike a balance between complexity and predictive accuracy.
Benchmarking the results against moving averages for 5 and 10-day periods serves as a valid comparison technique. It is encouraging to observe that the ANN models outperform moving averages, indicating the effectiveness of ANNs in capturing the nonlinear relationships inherent in stock market data.
Overall, your approach seems systematic and rigorous, laying a solid foundation for using ANNs to predict the ISE market index values. Future research could explore additional input variables or refine the network architecture further to enhance predictive performance.
Keywords: *Artificial Intelligence, Neural Network, Stock Market*

I. Introduction:

Artificial neural networks (ANNs) find diverse applications in finance, spanning from stock market forecasting to bankruptcy prediction and corporate bond classification. ANNs prove effective due to their capacity to emulate the learning capabilities of the human brain, rendering them adept at handling intricate financial datasets.

Nonetheless, as you've highlighted, ANNs encounter hurdles in grasping intricate data patterns, particularly when confronted with substantial data volumes. Mitigating data redundancy and streamlining data dimensions can enhance the efficacy and adaptability of ANN models.

Several studies, including those by Kimoto et al., Mizuno et al., Sexton et al., and Phua et al., have demonstrated the effectiveness of ANNs in stock market prediction, with varying degrees of success. These studies highlight the importance of factors like momentum, random starting points in the learning process, and the incorporation of genetic algorithms to enhance prediction accuracy.

In Turkey, while ANNs have been predominantly used for predicting financial failures, there's a gap in research focused on forecasting Turkish stock market values. Your aim to utilize ANNs for predicting the Istanbul Stock Exchange (ISE) market index values fills this gap and presents an opportunity to leverage this powerful technique for financial forecasting in Turkey.

By applying ANNs to the ISE market index, you have the potential to contribute valuable insights into the dynamics of the Turkish stock market and provide stakeholders with predictive tools to make informed decisions. This research could pave the way for further advancements in financial forecasting and risk management in Turkey.

a. Artificial Neural Network Approach

The machine learning approach, particularly using connectionist models like artificial neural networks (ANNs), is indeed appealing due to its ability to learn from training data and improve performance through experience. ANNs consist of interconnected nodes with weighted connections, where the weights represent the strength of influence between nodes.

In artificial neural networks (ANNs), every connection holds a numerical weight denoted as Wij, determining the impact of the preceding node Uj on the subsequent node Ui. Positive weights signify enhancement, whereas negative weights indicate suppression. Initially, these connection weights are typically chosen randomly.

Feed-forward networks, pioneered by Rosenblatt, represent a prevalent type of ANN structure. These networks typically comprise an input layer, one or more hidden layers, and an output layer. The input layer accepts input patterns, which are then processed through the hidden layers to produce output outcomes in the output layer. Crucially, in feed-forward networks, information flows exclusively in one direction from the input layer through the hidden layers to the output layer.

Such a design facilitates the discernment of intricate relationships within the data and the extraction of significant patterns, rendering feed-forward networks highly suitable for a variety of machine learning tasks, including pattern recognition, classification, and prediction.

Figure-1.Connecting weightbetweentwo nodes.

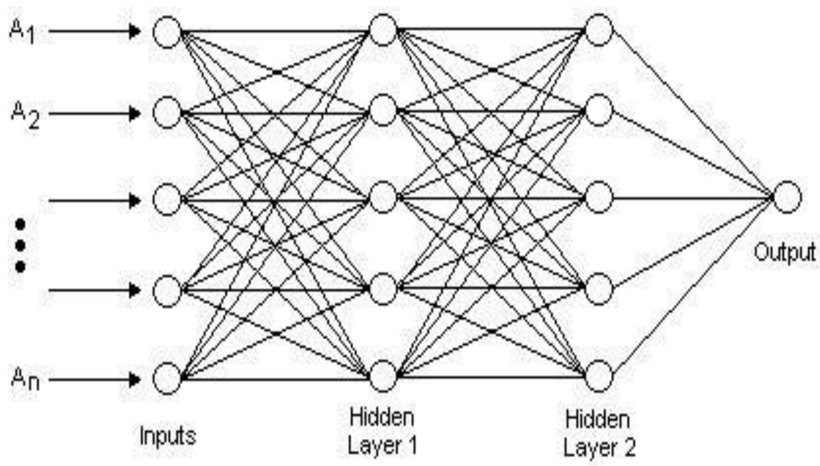

Figure: 2 hidden networks with n inputs and 1 output.

Multi-Layer Perceptron(MLP) networks, a type of layered feed-forward network, commonly employ the backpropagation algorithm for training. Referred to as backpropagation networks, they excel in tasks involving static pattern categorization. The backpropagation algorithm entails selecting a training sample, executing forward and backward passes through the network to compute errors, and iteratively adjusting connection weights until convergence to a predefined mean squared error value is achieved.

MLP networks possess the advantage of being user-friendly and capable of approximating any input/output mapping. However, they typically exhibit slow training rates and demand a substantial volume of training data to attain optimal performance.

In contrast, Generalized Feed-Forward(GFF) networks expand upon the capabilities of MLP networks by permitting connections to bypass one or more layers. This adaptability often empowers GFF networks to address problems more efficiently than conventional MLP networks.

By enabling connections to skip layers, GFF networks can capture intricate relationships within the data, potentially leading to expedited training and enhanced performance. In summary, while MLP networks are valued for their simplicity and adaptability, GFF networks present a more efficient solution for certain problem types by facilitating connections across multiple layers.

II. TrainingAlgorithm

The training phase is pivotal in the evolution of neural networks, aiming to refine the network's parameters (weights) to generate desired outputs for specified inputs. In supervised learning paradigms like Multi-Layer Perceptron(MLP) and Generalized Feed-Forward(GFF) networks, specific output nodes are honed to recognize distinct input patterns, and adjustments to the connection weights throughout training foster more versatile responses from these nodes.

Throughout the training process, input signals are disseminated across the input layer units, with the connection weights modifying these signals as they traverse the network. Hidden layers and the output layer comprise arrays of processing elements, each governed by an activation function.

The activation function plays a pivotal role in determining the output of each processing element within the network. Among these, the sigmoid function stands out as a widely utilized activation function in neural networks, especially in MLP and GFF setups. Characterized by its smooth, S-shaped curve, the sigmoid function maps input values to output values between 0 and 1, facilitating the modeling of nonlinear relationships and ensuring that each processing element's output remains within a defined range. This, in turn, enhances the network's ability to discern and represent intricate patterns within the data.

By fine-tuning the connection weights and leveraging the sigmoid activation function, neural networks can adeptly translate input patterns into corresponding output responses, rendering them invaluable assets across diverse machine learning applications, spanning classification, regression, and pattern recognition tasks.

III. Model design forIndexValue in StockMarket

The methodology and variables used in your paper on forecasting Indian Stock Exchange (ISE) index values using artificial neural networks(ANNs). It's great to see the inclusion of relevant factors such as the previous day's index value, INR/USD exchange rate, overnight interest rate, and dummy variables for weekdays, as these can all potentially influence stock market movements.

Using supervised learning models for this purpose makes sense, as you're likely aiming to train the network to learn patterns from historical data and then generalize that learning to make predictions on unseen data. The mention of learning-induced changes in connection weights and input patterns suggests that your ANNs are adapting to the data they're trained on, which is essential for accurate predictions.

IV. Model of System

Following input variables were assessed to have an impact on the stock exchange market index value.
he predictive model for the stock exchange market index value incorporates various input variables from the previous day's data, including the ISE National 100 index value (ISE_PREV), the TL/USD exchange rate (TL_USD_PREV), and the Simple Interest Rate Weighted Average Overnight (ON_PREV). Additionally, dummy variables representing each day of the week (Monday to Friday) are included in the model: M for Monday, T for Tuesday, W for Wednesday, TH for Thursday, and F for Friday.

The system model for predicting the stock exchange market index value is formulated as follows:
$fISE=f(ISE\_PREV,TL\_USD\_PREV,ON\_PREV,M,T,W,TH,F)$

This model takes into account the previous day's index value, exchange rate, and interest rate, as well as the day of the week, to forecast the future stock exchange market index value.

a. Data items

Data for this study were directly sourced from the National Stock Exchange spanning 417 days, starting from July 2, 2001, and concluding on February 28, 2003. Out of the total dataset, the initial 376 instances, constituting approximately 90% of the data, were designated for training purposes, while the remaining 41 cases were set aside for testing.

b. NetworkParameters

To attain a minimum mean squared error of 0.003 for the dataset, researchers employed two different artificial neural network (ANN) architectures, namely Multilayer Perceptron (MLP) and Gaussian Function Fitting (GFF). These models were tested with different configurations of hidden layers (HL), including 1, 2, and 4. Consequently, a total of six experimental ANN models were evaluated during the study.

c. **Training Results.**

In this investigation, six Artificial Neural Network (ANN) models were employed within a system model utilizing specialized ANN software. The efficacy of ANN models was evaluated through metrics such as the coefficient of determination (R2) and the mean relative percentage error, which gauge predictive accuracy. A higher R2 signifies superior predictions. Additionally, the mean relative percentage error, reflecting the dispersion degree, serves as another measure of prediction accuracy. Equation 6 was employed for each prediction model to compute the relative error across the testing dataset, with resultant statistics averaged and scaled by 100 to yield percentages.

Comparative assessment of ANN performance was conducted against the Moving Averages (MA) technique. This technique involves calculating the average of historical index values over specified time spans (5 and 10 days in this instance). The mean relative percentage errors were 0.022 for five days and 0.03 for ten days. Detailed information on the mean relative percentage errors for all models is presented in Table 1.

Model	**Mean Relative Percentage Error (%)**
MLP - 1 Hidden Layer	1.62
MLP - 2 Hidden Layers	1.65
MLP - 4 Hidden Layers	1.70
GFF - 1 Hidden Layer	1.59
GFF - 2 Hidden Layers	1.65
GFF - 4 Hidden Layers	1.71
MA - 5 days	2.17
MA - 10 days	3.03

Table-1 Mean relative percentage errors for all models

V. Evaluation:

The coefficient of determination served as a metric to assess the predictive precision of each Artificial Neural Network (ANN) model. It's observed that the efficacy of ANN models fluctuates based on the quantity of hidden layers employed. Interestingly, optimal accuracies were attained when utilizing a solitary hidden layer across both Multi-Layer Perceptron (MLP) and Gaussian Feedforward (GFF) network structures. Additionally, upon calculating the mean relative percentage errors across all models, it was evident that the performance of ANN models surpassed that of the MA model.

VI. Conclusion:

This paper focus onto identifying the most effective model to predicting Indian Stock market(ISE) index values by comparing the performance of various artificial neural network (ANN) models and moving averages (MA). Through this comparative analysis, you reached two main conclusions:

- ANN-based prediction models outperformed those based on moving averages. This finding underscores the effectiveness of ANNs in capturing the complex patterns and dynamics of stock market data compared to simpler methods like moving averages.
- Among the ANN models tested, the Generalized Feed-Forward (GFF) network model was identified as the most suitable for prediction. This suggests that the flexibility and efficiency of GFF networks, potentially due to their ability to skip over one or more layers, make them particularly effective for capturing the nuances of the Indian Stock Exchange market index.

These conclusions provide valuable insights into the comparative performance of different prediction models and offer guidance for practitioners and researchers seeking to forecast stock market index values. By demonstrating the superiority of ANN models over moving averages and identifying the GFF network as the most appropriate ANN architecture for this specific task, your study contributes to the advancement of predictive modeling in finance.

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