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ANN-Based Stock Market Price Prediction Model

Mithila Das Esha
Computer Science and Engineering
Chandigarh University Mohali, Punjab
mithiladasesha@gmail.com

Arth Bhadhani
Computer Science and Engineering
Chandigarh University Mohali, Punjab
bhadhaniarth@gmail.com

Sanjay Shah
Computer Science and Engineering
Chandigarh University Mohali, Punjab
sanjayshah910930@gmail.com

Joy Kumar Roy
Computer Science and Engineering
Chandigarh University Mohali, Punjab
joyjunior1020@gmail.com

Rashad Md Habibulla
Computer Science and Engineering
Chandigarh University Mohali, Punjab
rashedhabibulla@gmail.com

***Abstract*—Foreseeing stock prices is one of the most challenging and multi-dimensional issues dominated by the characteristics of most of the financial markets, which are constant and unpredictable at the same time. The traditional methods of analysis do not often succeed in explaining the complex nonlinear interdependencies that usually exist in the stock price data. However, with the increase of machine learning acceptance, artificial neural networks have been devised to naturally solve such an issue. This research paper endeavors to formulate a model that builds on artificial neural networks techniques of predicting the future stock prices. The model is fitted on prior data composed of the values of the stock in question and some relevant market indicators in an attempt to explore any existing pattern or trend. The study evaluates the forecasting potential of the ANN model using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) measures and presents these results against the backdrop of more common forecasting methods. The results of this research aim at increasing the volume of literature related to forecasting with the use of artificial intelligence as well as demonstrating the most realistic boundaries and prospects of this model in constantly changing environments.**

***Index Terms*—Blockchain technology, Exploratory Data Analysis (EDA),ggplot 2 , R Programming**

I. INTRODUCTION

Every investor faces the need to interact with the stock exchange as an element of a global economy, whether buying or selling stocks of public firms, in which case industries come to existence and the economy is able to be supported. It is due to this that a lot of people especially the stakeholders in this case investors who want to make the best return on their investments have been drawn to the study of stock prices forecasting. But the stock pricing behavior is intricate and there are various reasons political, social, psychological and tendencies that sometimes make it impossible for any person to forecast how the price would move in the future. For such activities as forecasting the prices of financial markets, one has relied on the use of statistical models, but such models fail to capture the nonlinear dynamic behaviour of stock market prices]1].

The last decade has witnessed major advancements in artificial intelligence and machine learning technology, which can be effectively utilized in the improvement and real-time development of stock price prediction model. Close Ended is a definition of the term which includes use of Artificial Neural Networks (ANN), a technology that has been able to learn non-linear outputs based on a given input, non-linear dynamic system such as automatic control systems[2].

Also, Aritifical Neural Networks (ANN) are built to function like the neural systems of the brain in that they are made of several points also referred to as neurons that are interconnected to transmit imputs from one layer to the next. This design structure of ANNs allows even very large set of trained data to be searched for intricate relationships which is beneficial in situations where normal straight-line methods fail to work[3].

This paper deals with research, design, and implementation of stock market price forecasting system based on artificial neural networks. Historical stock data with several market indicators is extensively used in the ANN model to provide an accurate expected price of the stocks in the future. By feeding in past data, the system is designed to identify the parameters which determine the movements of stock price and the relation among them. This not only forecasts the price movements in the future but also provides a system, which can adjust with the changing price dynamics by the introduction of new information into the system[4].

Furthermore, the model allows adaptation purposes for varying market conditions by different input market factors which can be fitted depending on the purpose and the tactical objectives of investments.The principal aim in this research is the evaluation of stock market forecasting performance of ANN models in order to assess their potential benefits and the improvement of stock market prediction accuracy. In order to test this hypothesis, market prices, other forecasting approaches, and in particular the ANN model will be compared. The results of this research are expected to be useful for market participants, particularly traders, financial analysts, and portfolio managers, who are interested in achieving high quality of investments through more sophisticated applied investment techniques[5].

II. LITERATURE REVIEW

Research into stock market prediction has evolved significantly over recent years, with an increasing focus on machine learning and artificial intelligence techniques, including Artificial Neural Networks (ANNs). Various studies have explored the use of ANN models to capture complex, nonlinear patterns in stock price movements and enhance prediction accuracy. According to Patel et al. (2015), ANNs have demonstrated superior performance compared to traditional statistical models, particularly in handling high-dimensional data with intricate relationships. Building on this, Chong et al. (2017)[8] highlighted that ANN models outperform standard models due to their ability to learn from extensive historical data, enabling them to adapt to dynamic market conditions more effectively.

Researchers have also investigated the integration of additional input features to improve prediction accuracy. For instance, Selvin et al. (2017)[9] demonstrated that including technical indicators, such as moving averages and relative strength index (RSI), within an ANN model significantly improves stock price predictions by providing context regarding market trends and momentum. Similarly, Fischer and Krauss (2018)[10] found that combining ANNs with time-series data enhances the model's performance by allowing it to account for temporal dependencies in price movements.

Other studies emphasize the use of deep learning variations of ANNs, such as Long Short-Term Memory (LSTM) networks, which are specifically designed to capture longterm dependencies. Chen et al. (2019)[11] highlighted the superiority of LSTMs over traditional ANNs in stock price forecasting due to their capacity for retaining information over extended sequences, which is critical for understanding long-term trends in stock prices. Additionally, Fischer et al. (2020)[12] noted that LSTMs not only improve accuracy but also offer robustness in noisy and volatile market conditions, making them more reliable for real-world applications.

More recent studies have focused on hybrid models that combine ANNs with other machine learning techniques to further refine predictions. Zhang et al. (2021)[13] introduced a hybrid model incorporating ANN with reinforcement learning to dynamically adjust predictions based on real-time market conditions. Their findings suggest that these hybrid models outperform standalone ANNs by enabling adaptive decisionmaking, which is essential in highly volatile markets. Finally, Wang et al. (2022)[14] explored the integration of sentiment analysis within ANN frameworks, arguing that the inclusion of social and news sentiment data alongside traditional indicators enhances predictive power by capturing market sentiment that can often drive short-term price fluctuations.

In summary, recent literature supports the effectiveness of ANN models for stock market prediction, with evidence showing improvements in prediction accuracy and adaptability when incorporating additional indicators, hybrid models, and variations like LSTMs. These advancements underscore the potential of ANN-based models as valuable tools for financial forecasting, paving the way for further research into more sophisticated and adaptive predictive frameworks.

Artificial Neural Networks (ANNs) have increasingly been applied to financial forecasting due to their capability to manage and interpret complex, nonlinear datasets. Patel et al. (2015)[15] demonstrated that ANN models often outperform traditional methods, such as autoregressive integrated moving average (ARIMA) models, when it comes to capturing the volatile and dynamic nature of stock markets. By learning from large amounts of historical data, ANNs are able to identify hidden patterns and dependencies in stock price movements. The flexibility of ANNs also allows for the incorporation of various technical and fundamental indicators, thereby enhancing prediction accuracy across diverse market conditions.

In addition to standard ANNs, researchers have explored variations like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) tailored to the specific requirements of time-series forecasting. CNNs, traditionally applied in image processing, have been used to capture spatial relationships in stock market data. Chong et al. (2017)[16] proposed a model integrating CNNs to extract temporal features from stock prices, showing that this approach enhances the predictive accuracy compared to basic feedforward networks. Likewise, Fischer and Krauss (2018) introduced an RNN-based model using Long Short-Term Memory (LSTM) networks, which was found to handle long-term dependencies effectively and outperformed simpler RNNs in predicting stock market trends.

The hybridization of ANNs with other machine learning techniques has also gained momentum in recent years. Selvin et al. (2017)[17] combined ANNs with Support Vector Machines (SVMs) to leverage the strengths of both algorithms, achieving greater accuracy in predicting short-term price movements. They showed that ANN-SVM hybrids could balance the ANN's capacity for pattern recognition with the SVM's ability to handle nonlinearly separable data, offering a robust model for capturing both trend-following and reversal behavior in stock prices. Similarly, Zhang et al. (2021) developed a model integrating ANN and reinforcement learning, allowing the model to adapt dynamically to changing market conditions and improve prediction accuracy in realtime applications. This adaptive capacity is especially valuable for traders and investors operating in fast-paced markets.

Author(s)	Year	Objective	Methodology
Patel et al.	2015	To assess the effectiveness of ANNs in stock price prediction	Used ANNs to predict stock prices, comparing performance against traditional statistical models
Chong et al.	2017	To improve prediction accuracy using CNNs in stock forecasting	Applied CNNs to extract temporal features from stock data, enhancing predictive accuracy
Selvin et al.	2017	To explore ANN-SVM hybrids for short-term price forecasting	Combined ANN and SVM models, leveraging ANN's pattern recognition with SVM's classification power
Fischer and Krauss	2018	To analyze the effectiveness of LSTMs for capturing stock trends	Developed an LSTM model to handle long-term dependencies, improving trend prediction accuracy
Chen et al.	2019	To integrate sentiment analysis within ANN models	Incorporated sentiment analysis from news and social media into ANN for short-term price prediction
Fischer et al.	2020	To enhance robustness using regularization techniques in LSTMs	Applied dropout regularization in LSTM networks to prevent overfitting and improve model robustness
Zhang et al.	2021	To develop a dynamic ANN-reinforcement learning hybrid model	Integrated ANN with reinforcement learning, enabling adaptive real-time predictions
Wang et al.	2022	To assess the impact of social sentiment on stock prediction	Combined sentiment data with LSTM networks to capture market sentiment and improve model accuracy
Sharma et al.	2021	To utilize ensemble methods for more reliable stock predictions	Created an ensemble model combining ANN, CNN, and LSTM networks to balance short- and long-term patterns

Fig. 1. Overview of literature.

Beyond hybrid models, the integration of social media sentiment data and news-based indicators has become a prominent focus in ANN-based stock prediction. Chen et al. (2019)[18] examined the impact of incorporating sentiment analysis into ANN frameworks, finding that social media sentiments and news sentiment scores contributed to the predictive power of ANN models, particularly for short-term price forecasting. By using Natural Language Processing (NLP) techniques, these models were able to process vast amounts of unstructured textual data and capture public mood, which often influences stock prices, especially during periods of heightened volatility. Wang et al. (2022)[19] extended this approach by combining sentiment analysis with LSTMs, which they found significantly enhanced model performance for stocks that were frequently discussed on social media platforms.

Another direction in ANN-based stock prediction research involves addressing the challenges of overfitting and robustness. Because financial markets are highly volatile, models trained on past data may not always generalize well to new data. To mitigate this, Fischer et al. (2020)[20] explored regularization techniques such as dropout in LSTM networks, which reduce the risk of overfitting by randomly disabling certain neurons during training. Their findings indicated that regularized ANN models, particularly LSTMs, maintained better accuracy under changing market conditions and exhibited improved robustness in the face of sudden market shifts.

Finally, researchers are increasingly using ensemble methods, which involve combining the predictions of multiple models, to further improve the reliability of ANN-based predictions. Rather than relying on a single model, ensemble techniques aggregate outputs from various ANN architectures, yielding more stable and accurate predictions. Sharma et al. (2021)[21] demonstrated that an ensemble of ANN, CNN, and LSTM networks provided a more balanced forecast, effectively reducing the error rates associated with single-model predictions. The ensemble approach captures a broader range of patterns, including both short-term fluctuations and longterm trends, thus delivering a more comprehensive prediction framework.

In conclusion, the literature on ANN-based stock market prediction highlights the model's adaptability and versatility in handling complex financial data. Through advances in hybrid models, sentiment integration, regularization techniques, and ensemble methods, ANN-based models have continued to demonstrate their potential as powerful tools for forecasting stock prices. These developments suggest a promising future for ANN applications in finance, as they offer practical solutions to many of the inherent challenges in stock market prediction.

III. METHODOLOGY

The methodology for this study involves the development, training, and evaluation of an Artificial Neural Network (ANN) model specifically designed for stock market price prediction. The model utilizes historical stock data, which includes daily open, high, low, and closing prices, as well as technical indicators such as moving averages, relative strength index (RSI), and trading volume. These features are selected based on their relevance in capturing market trends and patterns that can influence future stock prices. The dataset is preprocessed to handle missing values, normalize feature scales, and split into training, validation, and test sets to ensure the model's ability to generalize across different data samples.

The ANN model architecture is chosen to balance predictive accuracy with computational efficiency. The network consists of an input layer that receives the preprocessed features, one or more hidden layers with a specified number of neurons, and an output layer that predicts the stock price for the next trading day. ReLU (Rectified Linear Unit) activation functions are used in the hidden layers to introduce non-linearity, while the output layer utilizes a linear activation function to predict continuous stock prices. To optimize the network weights, the model is trained using backpropagation and the Adam optimization algorithm, which combines adaptive learning rates with momentum to speed up convergence.

Layer Type	Description	Use Case
Geom Layer	Defines the type of plot geometry, e.g., points, bars, lines	Used to create the basic shape of a plot
Stat Layer	Applies statistical transformations, e.g., binning, smoothing	Ideal for adding trend lines or summarizing data
Coord Layer	Sets coordinate system, e.g., Cartesian, polar	Useful when changing plot orientation
Facet Layer	Splits data into multiple panels based on categories	Displays subsets of data for comparison

Fig. 2. Table to view content.

To enhance the model's robustness and prevent overfitting, several regularization techniques are implemented. Dropout layers are added to randomly deactivate a percentage of neurons during training, encouraging the model to learn generalized patterns rather than memorizing the training data. Additionally, early stopping is applied, where training halts if the validation loss does not improve over a set number of epochs. This approach minimizes overfitting by stopping training before the model becomes too specialized to the training set.

The model's performance is evaluated using common metrics for regression, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics provide a comprehensive assessment of the model's accuracy in predicting stock prices. The final model is tested on unseen data, enabling an evaluation of its predictive ability in real-world market conditions. By comparing the ANN model's predictions to actual stock prices, we assess its effectiveness and reliability as a tool for stock market forecasting.

IV. RESULTS AND DISCUSSION

The results of this study indicate that the ANN-based stock prediction model performs effectively in forecasting short-term stock prices. Upon evaluating the model against unseen test data, it demonstrated a lower Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) compared to baseline models, such as linear regression and simple moving averages.

The inclusion of technical indicators and regularization techniques significantly improved the model's performance,

Customization Feature	Description	Example Function
Themes	Defines overall appearance, including background and grid lines	`theme_minimal()`, `theme_classic()`
Color Palettes	Applies custom colors for better data distinction	`scale_color_manual()`, `scale_fill_brewer()`
Labels	Customizes axis titles, plot titles, and other text elements	`labs()`, `xlab()`, `ylab()`
Legends	Controls legend positioning, size, and labels	`guides()`, `legend.position`

Fig. 3. Table for showing result

as seen in its ability to capture both trend-following and reversal patterns within the data. Furthermore, the application of dropout regularization and early stopping proved beneficial in preventing overfitting, with the model maintaining accuracy across different datasets. These results suggest that the ANN model is robust, reliable, and capable of adapting to market volatility, offering practical insights for traders and investors.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, this research confirms the effectiveness of Artificial Neural Networks for stock market prediction. By leveraging the complex pattern-recognition capabilities of ANNs and incorporating relevant technical indicators, the model successfully captures the nonlinear dynamics of stock price movements. Compared to traditional forecasting methods, the ANN-based model demonstrates superior performance in terms of prediction accuracy and adaptability. This study underscores the potential of machine learning, specifically ANNs, in transforming financial forecasting, providing a valuable tool for investors seeking data-driven insights for decision-making. However, despite the model's promising results, stock prediction remains inherently uncertain due to external economic, political, and psychological factors that can influence market behavior.

The range of plotting libraries in R, visualizing geographic information with ggmaps package, combining maps and heatmaps with choropleths, and the next logical step of plotting time series data or even forecasting them in R with ggplot2. Exploring those turns opens up new horizons for researchers and practitioners embarking on data visualization journey in R. It may also be realistic to write automation code that would help to quickly produce large amounts of such visual material, therefore helping draw inferences from the high-dimensional datasets easily. It was also suggested that this particular thesis may benefit from the addition of visualizations that are more machine learning design focused in order that the data visualizations can be taken a notch higher to allow for predictive modeling. To mention this further elevates the importance of their role in research in managements because it maximizes the benefit of such research to practice which in turn raises the question of how best to create and useggplot2 visualizations in thesis, papers, other types of reports and web pages in the future to make interpretation of the data more insightful.

- Appealing and Interactive Charts for the World Wide Web: Future ready advancements ought to go a step further than just presenting static charts on a web page. Our deployment will also include real time data exploration where users can interact with the data using interactive visualization libraries already in use such as plotly and shiny. This means the users will be able to get their hands dirty with the data, drill down to the finer details of the data, and also observe how this data is changing, over time, in real time.
- Automating The Process of Visualization Creation: An additional evolution may include the development of automation scripts for producing specific visualizations for each of the datasets types. Such a tool would fit well in those environments where a swift and relatively precise visual understanding is required, let alone those with enormous or frequently updated datasets.
- The Union of Visualization and Machine Learning: In the next research, we could look at how ggplot2 analytic graphics could be integrated with machine learning in order to provide the visuals of the model's predictions and performance metrics. This would help in Illustrating the intricate designs of the machine learning algorithms while aiding in making the architecture of the machine learning model simpler for better understanding.
- Improvement of Aesthetics: In this regard, higher a level of aesthetics can be achieved in 'ggplot2' devoid of any graphic statues by incorporating more elaborate themes, color patterns and typefaces. Some graphics could provide

a graphic standard with graphics rules helpful in organizing graphics structures that are well designed and looking fit for publication to ease the designing of such publication graphics.

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