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Predicting Market Trends: A Stock Prices Forecasting with Artificial Neural Network for Apple Inc. and Microsoft Corp.

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ABSTRACT

Machine learning plays a crucial role in predicting stock prices, as it aids investors in making well-informed decisions amidst the vast array of stocks traded on the stock exchange. The unpredictability of stock price behaviour, influenced by numerous factors, adds complexity to this process. Consequently, numerous studies have explored the use of machine learning for stock price forecasting. Hence, this study employs an Artificial Neural Network model as a machine learning algorithm for forecasting stock prices. The model is based on daily stock prices for Apple Inc. and Microsoft Corp. obtained from Yahoo Finance. Data preprocessing entailed normalizing stock prices to ensure that the input features were on a similar scale. The model was trained using a backpropagation approach, with weights optimized based on the mean square error loss function. The proposed model's performance is evaluated using the Root Mean Square Error (RMSE) and Absolute Error (AE) to assess its effectiveness in analyzing the data. The results show that the ANN model can accurately and reliably forecast stock prices. The RMSE and AE metrics demonstrated that the ANN model could effectively capture the underlying trends in stock price movements, giving investors valuable insights for decision-making.

Keywords: Machine learning, artificial neural networks, stock price, stock market, forecasting.

1 INTRODUCTION

A stock price is the cost of purchasing one share of a corporation and is subject to daily moves resulting from market factors. Share price movements are influenced by the balance between supply and demand. If the demand for a stock exceeds its supply, the price typically increases. On the other hand, if there is an excess of supply compared to demand, as more investors want to sell the stock than buy it, the price tends to decrease. Consequently, the stock market is recognized for its dynamic and non-linear nature. Predicting stock prices has historically posed a significant challenge for business analysts and researchers [1]. Investors find the prediction of stock prices intriguing, as it aids them in making profitable investment decisions by providing insights into future market conditions. Since the stock market involves time series data, researchers have extensively investigated and proposed various models for its analysis [2].

Although many papers have been published on non-linear statistical modelling of stock prices, most studies require a non-linear model before estimation [3]. Given the nature of the stock market, Artificial Neural Networks (ANNs) have emerged as a more appropriate tool for capturing the complex relationship between a stock's performance and its determining factors than conventional statistical methods [3]. Sidogi et al. [4] stated that many recent studies on stock price prediction using non-linear statistical modeling require pre-specification of a non-linear model before estimation. This method may limit the models' flexibility to the complex and dynamic nature of stock market behavior, resulting in inferior predictions. In their study, the researchers solve this gap by using ANN, which does not require prior model formulation and can learn complex patterns directly from data. Furthermore, earlier research has frequently concentrated on a small range of input variables, typically depending on historical stock prices or a limited macroeconomic data set [5]. While some researchers have attempted to incorporate heterogeneous market data, there is still a lack of comprehensive study of varied input variables that could improve forecast accuracy [6]. To increase the ANN model's robustness, the study proposed increasing the input variable set by including a larger variety of features, such as technical indicators and market sentiment.

Although there is an increasing acknowledgement of the significance of nonlinear connections in stock price movements, much research fails to effectively capture these intricacies. Traditional statistical methods frequently struggle with nonlinearities, leading to erroneous forecasts [7]. Using ANNs, this study directly addresses the requirement for models capable of capturing non-linear relationships in stock price data, improving predictive performance. Another study by Kase et al. [8] used a variety of input variables to forecast stock returns, including individual time series data, heterogeneous market data, and macroeconomic indicators. Identifying non-linear trends in stock market index returns has attracted researchers' attention to the nonlinear prediction of stock prices. Another study, Vedant [9] uses a limited set of evaluation parameters, which may not wholly represent the models' prediction ability. To address this matter, this study aims to employ the machine learning technique of Artificial Neural Networks to forecast stock prices. This study employs an ANN model that adjusts to the data without requiring prior model specification, resulting in a more flexible and accurate representation of stock price fluctuations. This study also broadens the input variable set to include more features, improving the model's capacity to capture complicated interactions that influence stock values. Furthermore, this study focuses on the non-linear correlations inherent in stock price movements using ANNs explicitly created for modeling such complexities. A comparative analysis ANN models clarifies the benefits of machine learning approaches in stock price prediction, aside from using a set of evaluation metrics to ensure a thorough assessment of the model's forecasting ability.

2 MATERIAL AND METHODS

The methodology used in this study comprises three phases:

1. Data collection and pre-processing

2. Modelling ANN

3. Performance evaluation of the model

Figure 1 illustrates the workflow of the study.

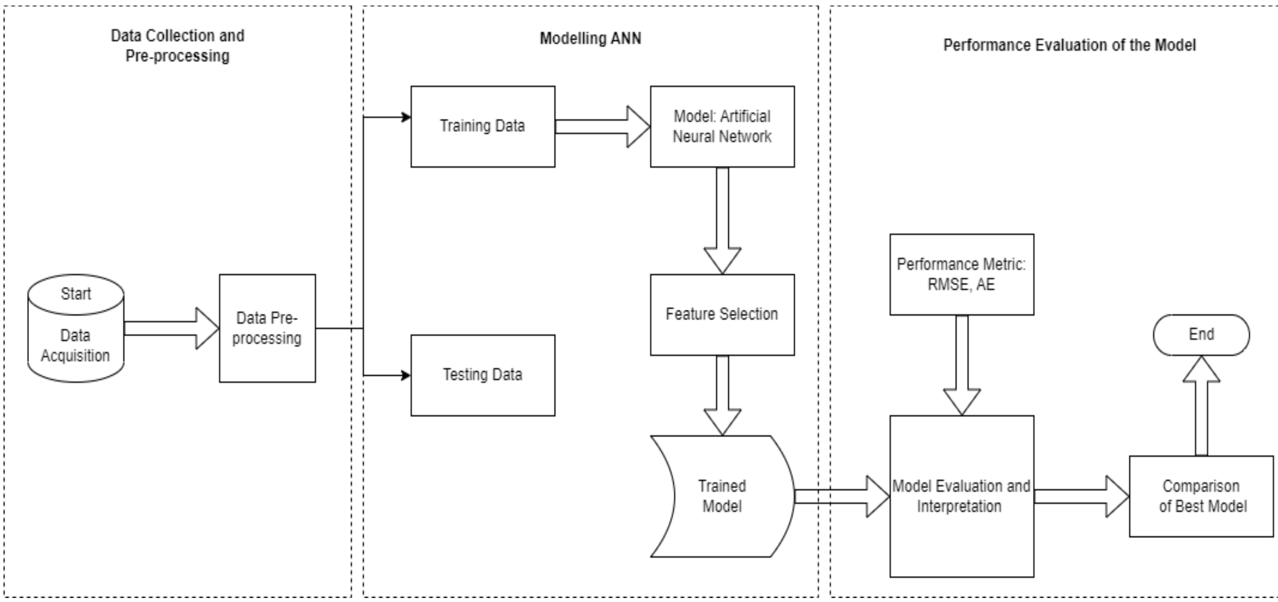

Figure 1. Workflow of the study

2.1 Phase 1: Data Collection and Pre-processing

Data collection is the process of gathering, measuring, and organizing data for a certain goal or analysis. Data collecting aims to get reliable and relevant information that can answer research questions and evaluate the study's hypotheses [10]. The obtained data is then used in several stages of data analysis, including cleaning, processing, and visualization. The first step in data collecting for this study is obtaining historical stock data. This study's data is obtained from Yahoo Finance and pertains to Apple Inc. (AAPL) and Microsoft Corporation (MSFT). The data from April 2018 to April 2023 were chosen in this study. The study uses data such as date, closing price, prior close price, open price, high price, low price, and previous close price.

Data pre-processing is the process of preparing raw data for analysis or modeling. Validation is an important phase in data analysis since it aims to improve data quality, dependability, and suitability for subsequent analysis [11]. Data pre-processing is done to:

I. Reduce noise,

II. Emphasize important relationships,

III. Recognize patterns, and

IV. Flatten the variable's distribution.

This study involves crucial procedures in data pre-processing, including data cleansing, partitioning, and feature extraction. These phases must be performed before being used for analysis or modeling. The intention is to increase data quality, reliability, and applicability for future research. Data cleaning involves identifying and correcting missing values, inconsistent data, and other data quality problems. The data's integrity is preserved by dealing with missing values, guaranteeing that a lack of critical information does not hamper the analysis. Data cleaning, when performed at the pre-processing stage, enhances the overall data quality, lowering the likelihood of biased analysis or modeling outputs [12].

After cleaning the data, it has been divided into two sets: training and testing. The division enables an impartial evaluation of the model's performance, as outlined by Taylor [13]. Assessing the model's ability to generalize to new data sets is critical. A dataset is loaded into RapidMiner Studio, and then the "Split data" operator divides it into training and testing sets. The training set can have a sample rate of 70%, whereas the testing set can have a sample rate of 30%. Feature selection is the process of identifying and selecting a subset of relevant features from a larger set of features in order to build a predictive model. Dimensionality reduction is a method for reducing the number of features in data and removing irrelevant or redundant ones. This is done to improve the performance of the model [14]. The "Select Attributes" operator makes finding and selecting the most relevant properties to use as input features in the ANN model easier. Filtering away irrelevant or redundant features reduces the dataset's dimensionality, which improves computing efficiency and model performance.

2.2 Phase 2: Modelling ANN

To develop a predictive model for predicting AAPL and MSFT prices, 70% of the data was utilized to train the dataset and 30% to test data. A separate testing set allows for discovering and resolving overfitting problems [15]. Following data preprocessing, the data is input into the ANN model for training. The ANN model can be adjusted by modifying the number and size of hidden layers, activation functions, learning rate, and other hyperparameters. Table 1 summarizes the hyperparameter used in this model.

Table 1: List of hyperparameters utilized in the model

Hyperparameter	Value
Number of hidden layers	1
Activation function	ReLU
Neurons per layer	128
Learning rate	0.01
Batch size	32
Number of Epochs	150
Dropout rate	0.3

Table 1 displays the hyperparameters for the model's ANN architecture, which includes various crucial configurations that affect the model's performance and effectiveness. These hyperparameters affect the ANN's ability to learn from historical stock price data and produce accurate forecasts. By carefully selecting and modifying these hyperparameters, the model can improve its effectiveness in forecasting stock prices for businesses such as Apple Inc. and Microsoft Corporation.

Step 1: Training Data

The training data is a subset of the dataset used to train the ANN model for predicting stock prices. The training data consists of historical stock price observations and their associated properties, which include date, open price, high price, low price, close price, and previous close price. Throughout the training phase, the ANN model is exposed to training data and optimized iteratively. It analyzes the patterns and relationships within the training data and modifies its internal parameters to reduce prediction errors [16]. The model can generate precise forecasts by discerning the fundamental patterns embedded within the previous stock price data through iterative exposure to the training data and continual adjustment of its parameters. The training approach seeks to boost the model's performance and improve its capacity to successfully generalize to novel data [17].

Step 2: Testing Data

The testing data is a subset of the dataset that is used to evaluate the trained artificial neural network (ANN) model's performance and generalization skills when forecasting stock prices. The validation data is separate from the training data, and it includes previously unknown or future stock price observations that were not included in the model's training phase. The purpose of testing data is to assess the trained ANN model's ability to make correct predictions on novel and unfamiliar data [18]. The model's ability to provide precise predictions in real-world circumstances can be evaluated by running it on test data. The testing data has the same features as the training data, including the date, open price, high price, low price, and closing price. During the testing phase, the trained artificial neural network (ANN) model analyzes the test results and forecasts stock values. The predicted and actual values are compared to evaluate the model's performance. Figure 2 depicts the ANN model.

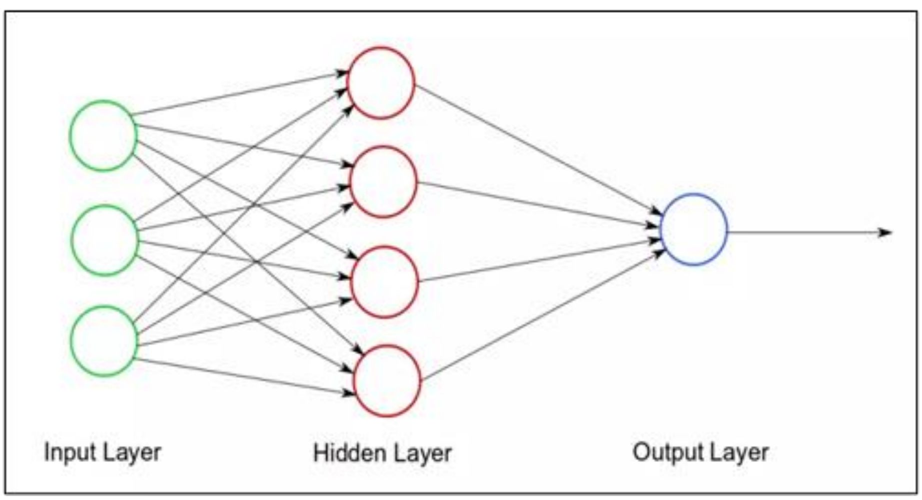

Figure 2: Artificial Neural Network (ANN) Model

a) Input Parameters

The input parameters are a collection of attributes that serve as features for predicting stock prices. Each parameter captures the stock's historical price movements and patterns, enhancing the model's predictive capabilities. Six input parameters were used in this study.

i. **Open Price**. The open price is included in this study so that the ANN model can grasp the initial market dynamics and investor behavior, which indirectly influence subsequent price changes throughout the trading day.

ii. **High Price**. The inclusion of this high price in the study allows the ANN model to learn about potential resistance levels and investor enthusiasm, both of which are critical for predicting future price movements. Analyzing high prices can also reveal market trends and investor confidence.

iii. **Low Price**. The low price assists the ANN model in identifying support levels, where purchasing demand may emerge, and can predict possible price rebounds. By analyzing high and low prices, the model acquires a full understanding of the stock's trading range, which is essential for successful forecasting.

iv. **Close Price**. The close price is used as a reference point by investors and traders, indicating the market consensus on the stock's value at the end of the trading session. By including the closing price, the ANN model may effectively learn from final market sentiment and price behavior, which is critical for future forecasts.

v. **Previous Close Price**. The ANN model may identify trends, reversals, and momentum shifts by comparing the current and past close prices. This comparison is especially beneficial for discovering gaps and shifts in investor sentiment, which provide essential context for forecasting future price movements.

vi. **Date**. Stock prices are influenced by seasonal, weekly, and monthly trends, as well as specific events like earnings announcements and market news. By including the date, the ANN model can learn time-related patterns, assisting in identifying cyclical behaviors and trends that may not be immediately obvious from price data alone.

By carefully selecting key input parameters, such as Open Price, High Price, Low Price, Close Price, Previous Close Price, and Date, the ANN model gains substantial features that reflect the essential dynamics of stock price fluctuations. Each parameter improves the model's ability to learn complicated correlations and patterns in data, ultimately increasing forecast accuracy.

b) Hidden layer

The hidden layer refers to an intermediate layer of nodes utilized in the ANN for stock price prediction. In this study, a single hidden layer was employed between the input and output layers of the ANN. The ANN can comprehend and learn intricate patterns and connections within the input data by incorporating a hidden layer. The intricacy of the stock price prediction problem justifies the use of a single hidden layer. Frequently, a single, hidden layer may efficiently understand the underlying patterns and relationships within the data [19]. Adding more hidden layers may not necessarily improve the model's performance and may result in overfitting or higher computational complexity.

By employing only one concealed layer, the model achieves a trade-off between collecting important characteristics and maintaining a reasonably uncomplicated network structure [20]. This method's simplicity can help speed up the training process, improve generalizability to novel data, and reduce the chance of overfitting. The choice to employ a solitary concealed layer in this endeavor is rationalized by the characteristics of the stock price forecasting assignment. It seeks to strike a harmonious equilibrium between the model's intricacy and performance.

Step 3: Develop ANN Model

The primary goal of an Artificial Neural Network (ANN) is to acquire the ability to learn a mathematical function that can effectively associate input data with corresponding output data. Artificial neural networks (ANNs) generally comprise three layers, with interconnected neurons in these levels linked by weighted connections. These links carry numerical values, and signals are transmitted from one neuron to another or multiple neurons.

Throughout the training phase, the ANN adjustment process is facilitated by an optimization algorithm, commonly employing backpropagation. This algorithm updates the parameters based on the chosen algorithm. The objective is to minimize the difference in the output between the predicted and the actual. The fundamental architecture of the ANN, comprising an input layer, a hidden layer, and an output layer, is a straightforward yet potent configuration capable of capturing intricate associations within the dataset.

Step 4: Feature Selection

Feature selection is critical in developing a practical machine-learning model for stock price forecasting. The choice of input features can significantly impact the model's performance and interpretability. The features selected are used as model input, and then the model is trained to forecast stock prices. This study uses the commonly used features to predict stock prices, focusing on historical stock prices, such as date, open price, high price, low price, close price, and previous close price. Including the date feature is crucial for capturing temporal patterns and trends in stock price movements. Stock prices can be influenced by market cycles, seasonal effects, and specific events that occur on certain dates. The model can learn to identify and adapt to these time-dependent patterns by incorporating the date, potentially improving its predictive accuracy. The previous close price is included to capture the stock's closing price from the previous trading session. This feature helps identify price trends, momentum, and potential reversals. By comparing the current price to the previous close, the model can learn to detect patterns and make more informed predictions about the stock's future performance.

While the commonly used features mentioned above, several other potential features could have been considered for exclusion. Trading volume is often used as an additional feature in stock price forecasting models. It provides information about the level of market activity and can help identify periods of increased buying or selling pressure. However, in this study, trading volume has been excluded due to the specific focus on historical price data, and it was believed that it may not significantly improve the model's performance. Technical indicators, such as moving averages, relative strength index (RSI), and Bollinger Bands, are also commonly used in technical analysis to identify trends, support and resistance levels, and potential buy or sell signals. Including relevant technical indicators could enhance the model's ability to capture complex patterns in the data. However, the study has focused solely on raw price data to maintain simplicity, and the technical indicators may not provide additional value. This study also excludes macroeconomic factors, such as interest rates, inflation, GDP growth, and unemployment rates, that can influence stock prices. This is because this study believes that historical price data is sufficient for making accurate predictions, and it wants to limit the complexity of the model by focusing on a smaller set of features.

The feature selection process in this study focuses on commonly used historical price data, including the date, open price, high price, low price, close price, and previous close price. These features provide a solid foundation for predicting stock prices and are widely accepted in financial forecasting. While other features, such as trading volume, technical indicators, and macroeconomic factors, could potentially enhance the model's performance, this study has excluded them due to specific reasons or research objectives. The selected features balance simplicity and capture the essential patterns in stock price movements.

Step 5: Training Model

This study uses RapidMiner to train the ANN model. The technique begins by importing the historical stock price dataset, which contains attributes such as open price, high price, low price, closing price, previous close price, and date. This dataset serves as the foundation for training the Artificial Neural Network (ANN) model. Before training, the dataset is pre-processed to ensure its suitability for efficient model training. The data is then divided into training and testing sets, with approximately 70% designated for training and 30% for evaluating the model's performance. The ANN model is developed using RapidMiner's operators, which allow it to provide the required architecture, such as the number of nodes in the input layer, hidden layer(s), and output layer. This study uses a single hidden layer. The training data is fed into the ANN model using RapidMiner's "Neural Network" operator. The model modifies the weights and biases of node connections using iterative optimisation techniques, with the goal of minimising prediction errors and optimising model parameters.

Following the training phase, the ANN model is assessed with testing data. The testing data is fed into the trained model, which generates forecasted stock prices. The model's performance is then evaluated by comparing these predictions to the actual prices from the testing data. Evaluation metrics, including Root Mean Squared Error (RMSE) and absolute error, are used to assess the model's accuracy and efficacy in predicting stock prices. RapidMiner allows the development of a robust ANN model for accurate stock price predictions in this study by providing a comprehensive workflow that includes data preprocessing, model configuration, training, assessment, and interpretation.

2.3 Phase 3: Performance Evaluation of the Model

a) Performance Evaluation Metrics

The last phase of this study is evaluating the model's performance. During this phase, the output predicted by the model trained is compared with the actual output of the stock prices. This model's performance will be measured using Root Mean Square Error (RMSE) and Absolute Error as the performance metrics. The formulas are presented as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum(predicted\ price - actual\ price)^2} \tag{1}$$

$$Absolute\ Error = |predicted\ price - actual\ price| \tag{2}$$

Interpreting the evaluation metrics is an essential part of the performance evaluation step. Lower values of RMSE and absolute error indicate better performance, suggesting that the model's predictions are closer to the actual values [21].

b) Comparison Between Other Methods

One way to accomplish this is by conducting a comparative analysis of each study's statistical methods and data analysis techniques. For example, if the study employs a more intricate statistical methodology, it would be deemed to have utilized a greater number of computations. Furthermore, it is possible to evaluate various methodologies for data analysis across different research projects, including the utilization of distinct software or tools. Studies employing specialist or advanced software for data analysis are deemed to include more computations than studies utilizing less advanced software. In addition, it is essential to recognise that the number of computations used in a study does not always indicate its level of quality. The impact of the number of computations on the study's performance may vary based on the research question, data, and methodology used.

3 RESULTS AND DISCUSSION

The Results and Discussion section summarises the analysis of AAPL (Apple Inc.) and MSFT (Microsoft Corporation) stock prices. The models produced precise forecasts utilising historical data and relevant characteristics, providing significant insights into investment strategies, risk management, and portfolio administration. Stock price forecasting often includes the open price, high price, low price, close price, and past closing price. These features are critical for capturing essential aspects of a stock's trading behaviour. Integrating these features into predictive models enables the identification of past patterns and trends, allowing for more informed decisions about future price changes. Stock price forecasting takes into account a variety of factors, including volume of trade, market indices, business fundamentals, and external implications. All of these factors are combined to construct robust and comprehensive models that improve forecast accuracy and reliability.

AAPL Inc.

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root_mean_squared_error: 1.474 +/- 0.114 (micro average: 1.478 +/- 0.000)
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Figure 3: RMSE value for AAPL stock prices

Figure 3 depicts the root mean square error (RMSE) value for the AAPL dataset. A prediction of Apple Inc.'s (AAPL) stock price has an RMSE value of 1.474 +/- 0.114. A RMSE value of 1.474 is the average error between the forecast and actual values of AAPL stock. Regarding RMSE, the micro average of 1.478 +/- 0.00 indicates a consistent performance across all indicators, indicating a high degree of predictability for the AAPL stock price. By analyzing the RMSE values and their standard deviations, the prediction results show that Apple's stock price is accurate and fixed.

```
absolute_error: 1.178 +/- 0.114 (micro average: 1.178 +/- 0.893)
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Figure 4: Absolute Error value for AAPL stock prices

According to Figure 4, the absolute error for predicting the stock price of Apple Inc. (AAPL) is 1.178, with a range of +/- 0.114 (micro average: 1.178 +/- 0.893). With an average absolute error of 1.178, the predictions deviate from actual prices on average by 1.178 units. An average value of 0.114 indicates a relatively consistent performance regarding the standard deviation or dispersion of absolute errors around the average value. The micro average absolute error of 1.178 +/- 0.893 comprehensively assesses the prediction performance for all occurrences. Based on the findings, the predictive model yielded a precise estimation of the AAPL stock price, demonstrating a minimal average absolute error and a reliable outcome.

Table 2 shows the AAPL dataset's actual close price and predicted close price for the year 2018.

Table 2: Example of AAPL Inc dataset (year 2018)

Date	Close	prediction(Close)
Apr 27, 2018	40.580	42.776
Apr 30, 2018	41.315	43.825
May 3, 2018	44.222	45.311
May 4, 2018	45.958	46.661
May 10, 2018	47.510	48.249
May 11, 2018	47.147	48.193
May 16, 2018	47.045	47.924
May 18, 2018	46.577	46.684
Jun 4, 2018	47.958	49.091
Jun 6, 2018	48.495	47.800
Jun 8, 2018	47.925	48.370
Jun 11, 2018	47.807	47.383
Jun 14, 2018	47.700	47.543
Jun 20, 2018	46.625	47.815
Jul 5, 2018	46.350	47.594
Jul 26, 2018	48.553	49.744
Aug 2, 2018	51.847	50.261

Table 3: Example of close prices for dates in training and testing data for AAPL (year 2018).

Date	Close	Predicted(close)
27/4/2018	40.580	42.776
30/4/2018	41.315	43.825
1/5/2018	42.275	
2/5/2018	44.142	
3/5/2018	44.222	45.311
4/5/2018	45.958	46.661
7/5/2018	46.290	
8/5/2018	46.513	
9/5/2018	46.840	
10/5/2018	47.510	48.249
11/5/2018	47.147	48.193
14/5/2018	47.037	
15/5/2018	46.610	
16/5/2018	47.045	47.924
17/5/2018	46.748	
18/5/2018	46.577	46.684
21/5/2018	46.908	
22/5/2018	46.790	

23/5/2018	47.090	
24/5/2018	47.037	
25/5/2018	47.145	
29/5/2018	46.975	
30/5/2018	46.875	
31/5/2018	46.717	
1/6/2018	47.560	
4/6/2018	47.958	49.091
5/6/2018	48.327	
6/6/2018	48.495	47.800
7/6/2018	48.365	
8/6/2018	47.925	48.370
11/6/2018	47.807	47.383
12/6/2018	48.07	
13/6/2018	47.675	
14/6/2018	47.700	47.543
15/6/2018	47.210	
18/6/2018	47.185	
19/6/2018	46.423	
20/6/2018	46.625	47.815
21/6/2018	46.365	
22/6/2018	46.230	
25/6/2018	45.543	
26/6/2018	46.107	
27/6/2018	46.040	
28/6/2018	46.375	
29/6/2018	46.276	
2/7/2018	46.795	
3/7/2018	45.980	
5/7/2018	46.350	47.594
6/7/2018	46.992	
9/7/2018	47.645	
10/7/2018	47.588	
11/7/2018	46.970	
12/7/2018	47.758	
13/7/2018	47.833	
16/7/2018	47.728	
17/7/2018	47.862	
18/7/2018	47.519	
19/7/2018	47.970	
20/7/2018	47.860	
23/7/2018	47.903	
24/7/2018	48.250	
25/7/2018	48.705	
26/7/2018	48.553	49.744
27/7/2018	47.745	
30/7/2018	47.478	
31/7/2018	47.572	
1/8/2018	50.375	
2/8/2018	51.847	50.261

In this study, the forecasting horizon is set to 1 day, which means that the ANN model is designed to predict the close price of a stock for the very next trading day. The model is trained using historical data, including information about the stock's previous trading days. By analysing patterns, trends, and relationships in the historical data, the ANN model learns to capture the short-term dynamics of the stock market. It is important to note that this study focuses on short-term forecasting, providing insights into immediate price movements rather than longer-term trends. Concentrating on a 1-day forecasting horizon aims to capture the volatility and fluctuations that can occur within a single trading day. Based on the result, some dates are missing from the table. This is because, during the training phase of a neural network, specific dates are used exclusively for training the model by adjusting its internal parameters. These dates are not included in the testing phase, which aims to evaluate the model's performance on unseen data. As the data is divided into 70% for training and 30% for testing, some dates may be present only in the training or testing set. As a result, certain dates may be missing from the final result obtained from the testing phase of the neural network model. Table 3 shows examples of close prices for dates in training and testing data for AAPL (year 2018), in which the green rows are the data utilised in the testing phase. By analysing these results, it is clear that the predicted close prices closely align with the actual prices, showcasing high accuracy. This is supported by the relatively low RMSE value of $1.474 +/- $0.114 (micro average: $1.478 +/- $0.00) and the absolute error value of $1.178 +/- $0.114 (micro average: $1.178 +/- $0.893). The predicted close prices consistently align closely with the actual prices, exhibiting minimal deviation. For example, on Mei 3, 2018, the predicted close price of $45.311 was close to the actual closing price of $44.222. Similarly, on Mei 4, 2018, the forecasted closing price of $46.661 is close to the actual close price of $45.958. The small differences between the predicted and actual close prices demonstrate the predictive model's efficacy in forecasting AAPL stock values. The low RMSE and absolute error values indicate the accuracy and reliability of the predictions, confirming the model's excellent performance.

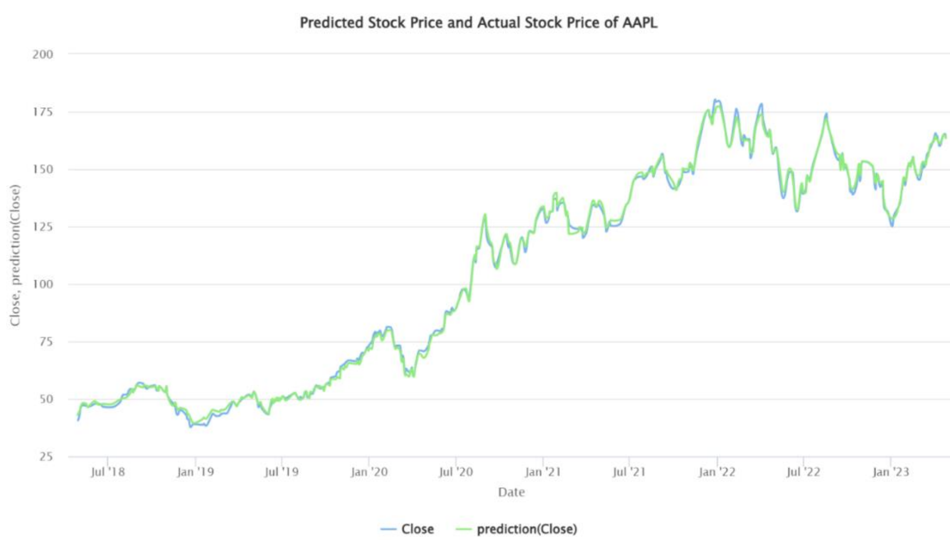

Figure 5: Graph of Predicted Stock Price and Actual Stock Price of AAPL Inc.

According to Figure 5, the blue line represents the actual closing price, while the green line reflects the predicted closing price using the ANN model. With thorough study, it is clear that the blue and green lines have a significant convergence, demonstrating the ANN model's great competency in making accurate forecasts for the Apple Inc. dataset. Several factors contribute to the ANN model's effectiveness, including parameter configurations such as the number of hidden layers, learning rate, and momentum. In RapidMiner, these parameters can be adjusted to improve the ANN model's performance. By carefully modifying the number of hidden layers and learning rate, the model's ability to recognise complex patterns in data can be improved. It is vital to note that different parameter settings yield different RMSE values and forecasted close stock prices. Certain parameter combinations may cause underfitting or overfitting, leading in higher performance assessment metrics and fewer accurate predictions. When selecting the best parameters, it is vital to take into account additional elements such as the machine learning approach, the unique dataset used, and other external variables. As a result, precise parameter adjustment via iterative testing is required to attain the needed forecast accuracy. The ANN model may make accurate predictions by continuously experimenting with different parameter choices and choosing the most appropriate ones. When selecting the best parameters, it is vital to take into account additional elements such as the machine learning approach, the unique dataset used, and other external variables. As a result, precise parameter adjustment via iterative testing is required to attain the needed forecast accuracy. The ANN model may make accurate predictions by continuously experimenting with different parameter choices and choosing the most appropriate ones.

MSFT Corp.

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root_mean_squared_error: 2.566 +/- 0.497 (micro average: 2.611 +/- 0.000)
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Figure 6: RMSE value for MSFT stock prices

Figure 6 shows the root mean square error (RMSE) value of 2.566 +/- 0.497 (micro average: 2.611 +/- 0.00) for MSFT's predicted stock price, which is the average difference between predicted and actual stock prices. The RMSE value is a measure of the predictive model's overall accuracy, indicating that the predictions differ from the actual stock prices by around 2.566 units. The small confidence interval (micro average: 2.611 +/- 0.00) boosts the model's prediction reliability by displaying consistent performance across a variety of situations. The results show that the model accurately captures changes in MSFT stock prices, providing valuable information for making investment decisions and controlling risk.

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absolute_error: 1.967 +/- 0.340 (micro average: 1.968 +/- 1.716)
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Figure 7: Absolute Error value for MSFT stock prices

According to Figure 7, the absolute error value for forecasting the stock price of Microsoft Corporation (MSFT) is 1.967 +/- 0.340 (micro average: 1.968 +/- 1.716). The average absolute error of 1.967 indicates that the forecasting deviate from the actual prices by approximately 1.967 units. The small standard deviation of 0.340 implies a restricted variance or dispersion in absolute errors from the mean, implying that the prediction model performs consistently well. The micro average absolute error, with a mean of 1.968 and a standard deviation of 1.716, gives a thorough evaluation of prediction accuracy for all occurrences in the MSFT dataset. The findings indicate that the predictive model demonstrates a reasonably low average absolute error in anticipating MSFT stock values, suggesting its capacity to create precise estimations. The dependability of the forecasts is further reinforced by their constant performance, as evidenced by the minimal standard deviation.

Table 4 shows the actual close price and the predicted close price of the MSFT Corp. dataset for the year 2018.

Table 4: Example of MSFT Corp. dataset (year 2018)

Date ↑	Close	prediction(Close)
May 3, 2018	94.070	96.106
May 4, 2018	95.160	96.461
May 8, 2018	95.810	97.653
May 11, 2018	97.700	100.588
May 21, 2018	97.600	101.947
May 22, 2018	97.500	102.927
May 23, 2018	98.660	101.809
Jun 1, 2018	100.790	104.127
Jun 19, 2018	100.860	104.007
Jun 25, 2018	98.390	101.328
Jun 28, 2018	98.630	100.300
Jun 29, 2018	98.610	103.150
Jul 2, 2018	100.010	102.920
Jul 6, 2018	101.160	105.286
Jul 13, 2018	105.430	107.956
Jul 16, 2018	104.910	108.098
Jul 25, 2018	110.830	111.972

Table 5: Table of close prices for dates in training and testing data for MSFT (year 2018).

Date	Close	Predicted(close)
3/5/2018	94.07	96.106
4/5/2018	95.160004	96.461
7/5/2018	96.220001	
8/5/2018	95.809998	97.653
9/5/2018	96.940002	
10/5/2018	97.910004	
11/5/2018	97.699997	100.588
14/5/2018	98.029999	
15/5/2018	97.32	
16/5/2018	97.150002	
17/5/2018	96.18	
18/5/2018	96.360001	
21/5/2018	97.599998	101.947
22/5/2018	97.5	102.927
23/5/2018	98.660004	101.809
24/5/2018	98.309998	
25/5/2018	98.360001	
29/5/2018	98.010002	
30/5/2018	98.949997	
31/5/2018	98.839996	
1/6/2018	100.790001	104.127
4/6/2018	101.669998	
5/6/2018	102.190002	
6/6/2018	102.489998	
7/6/2018	100.879997	
8/6/2018	101.629997	
11/6/2018	101.050003	
12/6/2018	101.309998	
13/6/2018	100.849998	
14/6/2018	101.419998	
15/6/2018	100.129997	
18/6/2018	100.860001	
19/6/2018	100.860001	104.007
20/6/2018	101.870003	
21/6/2018	101.139999	
22/6/2018	100.410004	
25/6/2018	98.389999	101.328
26/6/2018	99.080002	
27/6/2018	97.540001	
28/6/2018	98.629997	100.300
29/6/2018	98.610001	103.150
2/7/2018	100.010002	102.920
3/7/2018	99.050003	
5/7/2018	99.760002	
6/7/2018	101.160004	105.286
9/7/2018	101.849998	
10/7/2018	102.120003	

11/7/2018	101.980003	
12/7/2018	104.190002	
13/7/2018	105.43	107.956
16/7/2018	104.910004	108.098
17/7/2018	105.949997	
18/7/2018	105.120003	
19/7/2018	104.400002	
20/7/2018	106.269997	
23/7/2018	107.970001	
24/7/2018	107.660004	
25/7/2018	110.830002	111.972

Table 4 shows the actual close price, and the predicted close price of the MSFT dataset, and Table 5 shows the close prices for dates in training and testing data for MSFT, in which the green rows are the data utilised in the testing phase. The results of the actual and predicted close prices for the MSFT dataset on different dates offer insights into the performance and justification of the obtained RMSE and absolute error values. For instance, on 3/5/2018, the actual close price was $94.070, while the predicted close price was $96.106. This indicates a difference of approximately $2.036 between the actual and predicted values. Similarly, on 4/5/2018, the actual close price of $95.160 closely aligns with the predicted close price of $96.461, showing a smaller difference of around $1.301. On 25/9/2018, the actual close price was $114.450, while the predicted close price was $113.574, resulting in a difference of approximately $0.876. Similarly, on 27/11/2018, the actual close price of $107.140 was relatively close to the predicted close price of $106.295, with a difference of approximately $0.845. The RMSE value of $2.566 +/- $0.497 (micro average: $2.611 +/- $0.000) indicates the average magnitude of the differences between the actual and predicted close prices across the entire dataset. A lower RMSE value indicates a smaller average difference between predicted and actual values, implying improved overall predictive model performance. Similarly, the absolute error number of $1.967 +/- $0.340 (micro average: $1.968 +/- $1.716) shows the mean absolute difference between predicted and actual close prices. A lower absolute error value indicates a smaller average deviation between the predicted and actual values. The examples show a variety of differences between actual and predicted closure prices, including both overestimations and underestimations. The RMSE and absolute error values describe the prediction model's overall performance across the dataset, taking into account the cumulative influence of these changes. It is crucial to highlight that the accuracy of the predictions and the explanation for the stated results should be examined in relation to the stock market's specific context, the time period under consideration, and stock price volatility. Further analysis, including comparisons with industry standards and similar studies, would provide a more detailed assessment of the model's performance and the disparities between actual and predicted close prices.

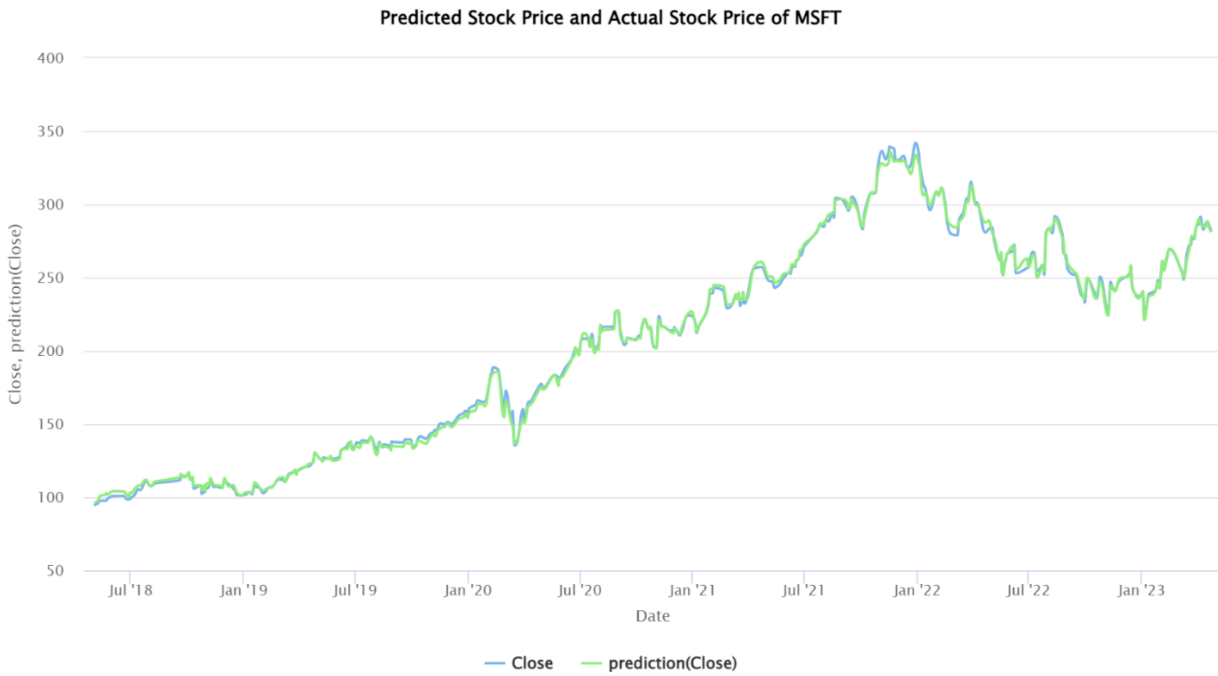

Figure 8: Graph of Predicted Stock Price and Actual Stock Price of MSFT Corp.

According to Figure 8, the graph's x-axis represents the period of the stock price evaluated, while the y-axis shows the closing and predicted closing prices for the Microsoft Corporation (MSFT) dataset. The blue line is the observed closure price, while the green line is the ANN model's predicted close price. A thorough review of the graph reveals that there is a clear convergence between the blue and green lines, indicating that the ANN model is capable of delivering reasonably accurate predictions for the MSFT dataset.

The variation in these values between the two datasets can be attributed to many sources. The RMSE values for AAPL and MSFT are 1.474 +/- 0.114 and 2.566 +/- 0.497, respectively. The micro average RMSE values are 1.478 +/- 0.00 for AAPL and 2.611 +/- 0.000 for MSFT. Here, AAPL exhibits a lower RMSE value than MSFT, indicating that the model's forecasts for AAPL stock prices have fewer overall inaccuracies than those of MSFT. In terms of absolute error values, AAPL has a value of 1.178 +/- 0.114 (micro average: 1.178 +/- 0.893), whereas MSFT has a value of 1.967 +/- 0.340 (micro average: 1.968 +/- 1.716). Lower absolute error levels suggest greater precision in forecasts. In this case, AAPL has a lower average absolute error compared to MSFT, indicating that the predictions for AAPL stock prices are closer to the actual values on average than the predictions for MSFT.

The discrepancy in performance metrics values between the AAPL and MSFT predictions obtained from the same ANN model can be attributed to several factors. Firstly, each stock has its distinct characteristics and behaviour in terms of price movements. The underlying dynamics, market factors, and investor sentiment surrounding AAPL and MSFT may differ, leading to variations in their predictability. Consequently, even with the same ANN model, the performance can diverge based on the unique attributes of the stock being predicted. Secondly, the quality and quantity of data available for each stock may vary. Issues such as missing values, outliers, or inconsistencies can impact the model's accuracy. If one dataset exhibits a higher prevalence of such data issues, it can adversely affect the predictions and result in a higher RMSE value. Thirdly, the relevance of the selected input features is crucial to the model's performance. Different stocks may possess distinct influential features that drive their price movements. Suppose the chosen features for AAPL are more informative or possess stronger relationships with the target variable (stock price). In that case, it can lead to more accurate predictions and a lower RMSE than MSFT, where the selected features may be less indicative of price movements. Lastly, market dynamics play a significant role. Many factors, including market conditions, economic events, industry-specific news, and company performance influence stock prices. These factors can differ across stocks and periods, contributing to variations in prediction accuracy. If the market conditions for AAPL during the prediction period were more stable or exhibited more predictable trends compared to MSFT, it could result in lower RMSE values for AAPL. Considering these factors is crucial when evaluating and comparing the model's performance across different stocks.

Comparison between Other Methods

The result of this study is compared with another method using Long Short-term Memory (LSTM) machine learning. Notable differences can be observed when comparing the RMSE values obtained from the ANN and LSTM models for the AAPL and MSFT datasets. Table 6 illustrates an example of forecasting using ANN and LSTM for both companies (Jan to Apr 2023). The results in Table 7 compare the Root Mean Square Error (RMSE) values obtained from two machine learning models, ANN and LSTM, to predict AAPL and MSFT stock prices.

Table 6: Example of forecasting using ANN and LSTM for both companies (Jan – Apr 2023)

AAPL			MSFT		
Close	ANN	LSTM	Close	ANN	LSTM
125.07	125.4237	125.7514	239.58	240.5516	240.6612
126.36	127.2367	128.0911	229.1	230.0709	230.962
125.02	125.6437	126.3039	222.31	223.284	223.3798
129.62	130.3562	131.1612	224.93	225.492	226.2306
130.15	130.8573	131.7593	227.12	227.3425	227.5662
130.73	130.494	130.8279	228.85	229.0471	229.6788
133.49	132.9973	133.2477	235.77	236.4477	237.0985
133.41	133.2493	134.0948	238.51	239.3193	239.4467
134.76	134.5596	134.1986	239.23	239.8432	240.2496
135.94	135.9046	135.237	240.35	240.3494	240.7056
135.21	135.9899	135.6993	235.81	235.6811	235.9049
135.27	135.9584	135.7541	231.93	231.9207	232.4929
137.87	138.0392	138.5796	240.22	239.2783	240.1719
141.11	141.4658	141.96	242.58	242.0846	242.6507
142.53	141.9784	142.9032	242.04	241.9238	241.9675

141.86	141.7771	141.8167	240.61	239.6518	239.576
143.96	143.6832	144.3802	248	247.3	247.068
145.93	145.8944	146.7481	248.16	248.1611	248.0827
143	143.0173	143.8809	242.71	243.3179	242.6333
144.29	145.0345	144.8928	247.81	248.6499	248.4835
145.43	146.0658	145.384	252.75	253.3379	252.7426
150.82	151.0349	150.3692	264.6	264.887	264.8827
154.5	154.8811	154.7746	258.35	258.4616	258.186
151.73	152.7139	151.7405	256.77	257.0671	257.9958
154.65	155.4022	154.8991	267.56	267.6916	267.737
151.92	152.0761	152.6938	266.73	267.0209	267.838
150.87	150.4649	150.9159	263.62	264.2892	264.8871
151.01	150.979	151.3241	263.1	263.5192	263.7406
153.85	152.859	153.1653	271.32	271.4962	272.4896
153.2	152.5183	153.4191	272.17	273.0016	273.7285
155.33	155.1277	155.2497	269.32	269.374	269.6043
153.71	153.2907	153.409	262.15	262.8271	263.1435
152.55	153.432	153.446	258.06	258.5557	259.2309
148.48	148.6716	149.4428	252.67	252.8763	253.7707
148.91	149.4387	150.4174	251.51	251.9903	252.658
149.4	149.8164	150.1781	254.77	254.973	255.8867
146.71	147.1082	147.3897	249.22	249.4831	249.8895
147.92	148.4527	149.1504	250.16	250.2635	251.2213
147.41	147.8733	148.3774	249.42	250.1589	250.8485
145.31	144.7642	145.6362	246.27	246.7103	247.4265
145.91	145.7688	146.2386	251.11	251.7071	250.7809
151.03	150.2081	151.1731	255.29	255.7365	255.0011
153.83	153.0837	153.1333	256.87	256.9155	256.2126
151.6	150.726	151.6743	254.15	254.3766	253.4192
152.87	152.8344	153.7512	253.7	254.5971	254.3464
150.59	150.8466	151.4737	252.32	251.6783	251.2868
148.5	149.006	149.6682	248.59	248.1903	247.4866
150.47	150.644	150.9619	253.92	253.4426	253.2005
152.59	152.7977	152.8501	260.79	260.2184	259.5665
152.99	153.667	154.6651	265.44	265.404	265.1979
155.85	155.9614	156.7398	276.2	276.1743	276.2188
155	155.0833	155.7833	279.43	279.1889	279.2506
157.4	158.3559	158.7457	272.23	271.804	271.8902
159.28	159.8623	160.7951	273.78	273.5424	273.8027
157.83	158.323	158.8537	272.29	272.8132	273.1388
158.93	159.8549	160.6328	277.66	278.2837	278.6176

160.25	159.9882	160.9133	280.57	281.064	281.6011
158.28	157.4598	158.3786	276.38	276.4876	277.0223
157.65	156.8224	157.6393	275.23	275.96	275.9802
160.77	160.649	161.0565	280.51	281.3054	281.7483
162.36	162.3563	162.8002	284.05	284.6659	285.1004
164.9	164.4479	164.8361	288.3	288.3042	288.4591
166.17	166.0661	166.762	287.23	287.5005	287.9581
165.63	164.9917	165.8576	287.18	288.0102	288.64
163.76	163.5269	164.2697	284.34	284.3886	284.2057
164.66	164.7524	165.21	291.6	292.4909	291.8242
162.03	162.7574	162.8797	289.39	289.4289	288.8569
160.8	161.7637	162.0168	282.83	283.8075	283.2404
160.1	160.4464	159.611	283.49	282.9426	282.3908
165.56	165.7319	165.3162	289.84	289.7612	288.9249
165.21	165.9601	165.5949	286.14	286.005	285.1541
165.23	165.3192	164.5339	288.8	287.8181	286.9287
166.47	167.183	166.641	288.37	287.7223	286.8821
167.63	168.5953	167.9215	288.45	287.565	287.6148
166.65	167.5725	166.8179	286.11	285.3638	286.3116
165.02	165.0773	164.5543	285.76	286.1376	286.9331
165.33	164.78	165.5947	281.77	282.3353	282.5349
163.77	163.3502	163.6007	275.42	276.1494	276.3063
163.76	162.9189	163.6643	295.37	296.0737	296.7554
168.41	169.0726	169.7014	304.83	305.6772	305.9145
169.68	169.8565	170.4186	307.26	307.312	307.906

Table 7: Performance Evaluation

Forecasting Method	ANN		LSTM	
Company	AAPL	MSFT	AAPL	MSFT
RMSE	0.550792	0.558524	0.771039	0.903302

Based on Table 7, for the AAPL stock price predictions, the ANN model yields an RMSE of 0.550792, while the LSTM model achieves a lower RMSE of 0.771039. Similarly, the ANN model produces an RMSE of 0.558524 for the MSFT stock price predictions, whereas the LSTM model yields a lower RMSE of 0.903302. This performance discrepancy underscores the strengths of LSTM in capturing temporal dependencies in stock price movements, which is a critical aspect of time series forecasting.

The difference in the RMSE values between the ANN and LSTM models can be attributed to each model's intrinsic traits and capacities. ANN, or Artificial Neural Network, is a flexible machine learning model capable of capturing intricate non-linear interactions within the data. Nevertheless, it may encounter difficulties in capturing enduring relationships and time-sensitive patterns, essential in forecasting financial time series. However, LSTM is a specific variant of a recurrent neural network that is particularly skilled at capturing temporal relationships and effectively processing sequential input. The system's architecture includes memory cells and gates, allowing it to store previous data and generate accurate forecasts for future values.

The disparities in RMSE values between the ANN and LSTM models can be attributed to their unique capabilities and architectural traits. The LSTM model's capacity to capture extended temporal relationships and time-varying patterns likely affected its exceptional performance and reduced RMSE values in the AAPL dataset. Nevertheless, the ANN model exhibited satisfactory performance in both datasets, suggesting its efficacy in capturing certain patterns and correlations in stock price data.

4 CONCLUSIONS

This study effectively demonstrates the use of an Artificial Neural Network (ANN) model to predict stock values for the US market. The model uses its predictive ability to generate future price predictions for publicly traded businesses by training the ANN on previous stock data. The study involves thorough data collection and preparation, with an emphasis on crucial parameters such as date, open, high, low, close, and prior closing prices, all of which are essential for effective forecasting. The model's performance was evaluated using metrics such as Absolute Error (AE) and Root Mean Squared Error (RMSE), which provided useful information about its accuracy and predictability. The findings show that the ANN model can identify underlying patterns in stock price fluctuations, providing accurate forecasts that can considerably improve decision-making processes for investors and financial institutions. The outcomes of these findings are significant. Accurate stock price predictions help investors make informed trading decisions, optimise their portfolios, and perhaps boost their financial returns. Financial institutions can also use the ANN model to create automated trading systems that react to real-time market fluctuations, increasing trading efficiency and profitability. However, it is crucial to recognise the limitations of this study, which include the impact of data availability and quality, as well as the precise time period examined. These factors can have an impact on model performance and should be taken into account when applying the findings to real-world circumstances. Finally, this effort makes a substantial contribution to the field of stock market prediction by demonstrating the potential of artificial neural networks in creating reliable forecasts. Future study should concentrate on enhancing these models by investigating innovative techniques and methodologies to improve their accuracy, resilience, and flexibility in volatile market situations. By strengthening the effectiveness of stock price prediction models, investors can obtain better financial results and navigate the stock market with greater confidence.

CONFLICTS OF INTEREST

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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