KMANPUB | AI and Tech in Behavioral and Social Sciences Vol. 2 No. 1 (2024): 46-55

Article history:
Received 09 October 2023
Revised 20 November 2023
Accepted 04 December 2023
Published online 01 January 2024

Predicting Stock Prices Using Data Mining Algorithms in the Stock Market of Iran

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A r t i c l e   I n f o

Article type:
Original Research

How to cite this article:
Reyhani Nezhad Alla, M., Ghane, S., & Salehi, A. (2024). Predicting Stock Prices Using Data Mining Algorithms in the Stock Market of Iran. *AI and Tech in Behavioral and Social Sciences, 2*(1), 46-55.
https://doi.org/10.61838/kman.aitech.2.1.6

A B S T R A C T

Given the role of the stock market in financial markets, the role of the stock market in the overall financial market is essential. How to predict the actual revenue of transactions and maximize benefits in the trading process has been an issue that researchers and financial experts have long investigated. Deep learning networks can extract features from a large amount of raw data, which has potential advantages for stock market prediction. One of the main advantages of the LSTM neural network is that it can extract features from a large amount of raw data without relying on the predictors' prior knowledge. This makes deep learning particularly suitable for stock market prediction. In stock market forecasting, many factors influence stock prices in complex and nonlinear ways. If there are factors with predictable evidence, these factors can be used as part of the deep learning input data to determine the relationship between these factors and stock prices. Stock return prediction is performed by simulation in MATLAB software with LSTM using GA and PSO algorithms. As a result, stock returns are somewhat predictable, and the initial input level consists of lagged stock returns. The data is presented, and an LSTM neural network is built to predict future stock returns.

Keywords: *Metaheuristic Algorithm, Stock Return Prediction, LSTM, Deep Learning*

1. Introduction

Prediction is one of the fundamental needs of life and planning. Investment and activity in the capital market heavily require the examination of various aspects of this activity for precise planning (Maqbool et al., 2023; Mintarya et al., 2023). Without precise planning, an investor does not enter the capital market rationally (Ashtiani & Raahemi, 2023; Avini et al., 2022; Mostafavi & Mostafavi, 2022). Therefore, prediction in the capital market has become a fundamental pillar of activity in this market. Through prediction, the investor can outline the future of their activity and incorporate risk and return within their analysis (Behera et al., 2023; Chen et al., 2023; Fard & Ghassemi, 2023).

In today's financial world, for investing in stocks, acquiring financial knowledge, reducing costs, selecting superior and more profitable stocks, and making optimal use of capital are integral parts of investors' actions and activities. The existing differences between growth and value stocks and the influencing factors have led investors to invest in stocks by acquiring modern financial knowledge and paying more attention to market conditions and time periods (Chen et al., 2023; Karimkhani et al., 2023; Maqbool et al., 2023). The transition from an underdeveloped economy to a developed economy requires capital and investment. Therefore, in this process, the provision and equipping of capital resources and the optimal allocation of these resources to the most efficient sectors are necessary conditions for economic success (Mohammadi & Mansourfar, 2022; Mostafavi & Mostafavi, 2022).

On the other hand, from an individual perspective, it can be said that in any ordinary society, all individuals seek to increase their welfare. Therefore, it is natural that investors pursue their investment opportunities to achieve the highest returns. Investing in stocks whose prices are higher than their intrinsic value leads to suboptimal resource allocation and failure to achieve the expected returns, and may even impose losses on investors (Chen et al., 2023).

From the above points, we understand that making the right decision for stock investment (selling stocks during price increases and buying stocks during price decreases) is important and necessary. Therefore, the issue of stock selection is one of the complex and challenging issues that companies, organizations, and even the general public deal with. However, the complexity of selecting the appropriate stock is due to the fact that stock profits depend on multiple factors, including political events, economic conditions, traders' expectations, and other environmental and social factors. These issues have turned stock prices into a dynamic, nonlinear, criterion-less, and disordered issue (Chen et al., 2023; Ehsani Chimeh & Karami, 2018; Fard, 2023).

Several methods used by investors to predict stock prices include technical analysis, fundamental analysis, and mathematical models of data information for predicting stock prices (Maqbool et al., 2023; Mintarya et al., 2023). This information can be gathered from the trend of stock price movements. From this trend, predictions can be made about the future direction of stock prices. This research provides a solution to minimize risk with a stock price prediction model that can minimize investment risk in stocks. Therefore, choosing an appropriate and optimal prediction method with high accuracy is essential.

Today, several methods can be used to predict a dataset. Machine learning, classified as an artificial intelligence method, is widely implemented in classification tasks, spam filtering, and prediction (He et al., 2014; Vakili et al., 2024). One machine learning method that can be used is the Artificial Neural Network (ANN), which is one of the most accurate and widely used prediction methods (Chen et al., 2023; Ehsani Chimeh & Karami, 2018). ANN is a mathematical model inspired by biological neural networks (Vakili et al., 2024; Zamani et al., 2021). The advantage of ANN is that it can provide an easy way to model nonlinear pattern data (Chen et al., 2023; Mintarya et al., 2023). One of the developments of the ANN model, the Recurrent Neural Network (RNN), is also a model that can be used to predict time series data patterns. RNN has also been used in previous time series data prediction research, where its performance could outperform Support Vector Machine (SVM) regression, which was 1.687% compared to 1.86% (Zamani et al., 2021).

In another study, RNN, which produced a MAPE value of 1.5617%, performed better than the Back Propagation Neural Network (BPNN), which only produced 2.9561% (Ashtiani & Raahemi, 2023; Behera et al., 2023).

Among artificial intelligence algorithms, the use of neural networks is prioritized in prediction discussions; this is due to the neural network's ability to work with a large number of variables, provide a very accurate fit for time series, not be influenced by distant data, have no limitation for a specific degree of non-linearity, and be flexible to model parameter changes. Many researchers noted that neural networks outperform classical models and other artificial intelligence algorithms in their research (Ashtiani & Raahemi, 2023; Behera et al., 2023; Chen et al., 2023; Ehsani Chimeh & Karami, 2018; He et al., 2014; Mintarya et al., 2023; Vakili et al., 2024; Zamani et al., 2021).

Given the reasons stated and the results obtained in other studies, a portion of which have been mentioned, we also chose neural networks to predict stock prices in this dissertation. The important point in using neural networks in this model is that these networks initially enter the learning process using 75% of the data (generally). In this stage, due to the high capability of neural networks to process complex curves, the network may identify a more complex model than the initial state. This causes the predicted values to be closer to the actual values or to provide an accurate estimate in the training phase. The point is that a degree of variation and discrepancy between the predicted and actual values is due to the randomness of these variations (Chen et al., 2023; Ehsani Chimeh & Karami, 2018). This random component exists in all prediction models, but neural networks use a higher number of values to estimate these, although these values are random and not predictable. This property, known as overfitting, is the biggest problem of neural networks (Mintarya et al., 2023).

To eliminate this overfitting, the neural network inputs should be reduced. In other words, overfitting should not be allowed for neural networks. In this article, data mining is used to reduce the number of variables. Data mining is the science of exploring data to discover knowledge. It provides various solutions, with the first principle being to eliminate unnecessary data and branches. Hence, several data mining techniques, which will be described later, are used here. Also, as mentioned, models used for short-term predictions are time series models and technical analysis. Since we aim to predict daily stock closing prices, we use a combination of these two methods with the help of technical analysis indicators and past prices (Ehsani Chimeh & Karami, 2018).

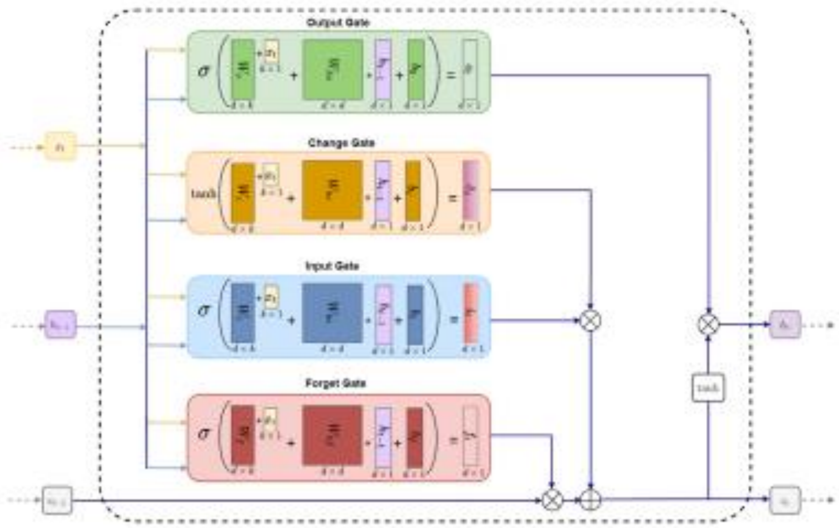
The competitive environment is heavily influenced by the complexity and uncertainty caused by changes in the business cycle stages of companies and changes in production processes. These changes make companies in the competitive environment evaluate new production processes and alter traditional production systems to deliver their products on time and with quality (Maqbool et al., 2023; Mintarya et al., 2023). To create competitive ability in companies, their internal capabilities and resources must be converted into factors for organizational success and competitive advantage over other competitors. In other words, developing and nurturing production capabilities is one of the most important tasks of production strategy (Behera et al., 2023). In fact, evaluating competitive production processes helps companies outline their goals and priorities to choose appropriate processes and harness various resources, including human resources, technology, information technology, and so on, to enhance their competitiveness (Karimkhani et al., 2023). Competitive priorities and strategic production decisions are among the most important components of production strategy. After determining competitive functions, companies use various tools, such as Total Quality Management (TQM), Data Envelopment Analysis (DEA), and other production engineering methods, to offer the highest effectiveness (Maqbool et al., 2023). Competitive advantage arises when a company has a coherent understanding of its business cycle based on production capacities. In other words, the complexity, interconnection, and growing speed of production developments create significant challenges for competitive organizations. Attention to a company's intellectual capital maturity and creating alignment between it and production processes enable companies to compete more effectively (Mohammadi & Mansourfar, 2022; Mostafavi & Mostafavi, 2022). Intellectual capital can help enhance production technology, learning, better product adaptation to customer needs, and other factors, creating more added value for the company. This organizational knowledge is extensive and broad, allowing a company to continuously adapt to changing conditions and significantly improve its competitive status by increasing the added value for key stakeholders (Mohammadi & Mansourfar, 2022). On the other hand, focusing on production can accelerate industrial growth and development in a correct and principled path. Therefore, the knowledge and mechanisms existing within an organization can effectively increase competitive advantage. Understanding and utilizing critical unclear resources help companies maintain and gain a competitive edge, with those companies achieving higher knowledge levels due to the maturity of their intellectual capital being more successful in this regard (Chen et al., 2023). It is noteworthy that the existence of intangible assets is considered knowledge-enhancing, creating effective competitive advantages to strengthen production functions with greater efficiency. Intangible assets create intellectual capital maturity when individuals' participation aligns with the overall strategies and sub-strategies, such as production strategies (Bonabi Ghadim et al., 2022; Sirghani et al., 2023). In other words, changes in cultural and managerial practices regarding intangible assets strengthen the drivers for increasing intellectual capital maturity, which facilitates effective competitive production processes for capital market companies. Therefore, referring to the notification 491/10077 approved on 2021-05-10 by the Islamic Consultative Assembly to the Ministry of Economic Affairs and Finance and the Ministry of Industry, Mine, and Trade to remove barriers to competitive production and enhance the country's financial system in the capital market sector, this research aims to evaluate the production capacity functions in the competitive market environment based on the effectiveness of intellectual capital disclosure to reduce competitive barriers at the production level. Consequently, the resolution of companies active in the capital market, given the country's economic conditions and macro strategies aligned with the 2025 Vision, should utilize all their capacities to develop effective production, reduce costs, and increase competitive effectiveness in global markets. This research, focusing on the development of intellectual capital maturity capacities, aims to assess the effective level of competitive production mechanisms based on analytical techniques such as Data Envelopment Analysis.

2. Methods and Materials

LSTM is a popular deep learning technique in RNN for time series prediction. Although RNNs have superiority in retaining information compared to traditional networks, they are not effective in learning long-term dependencies due to the vanishing gradient problem. LSTM uses memory cells to overcome the vanishing gradient problem. It consists of an input layer, a hidden layer, a cell state, and an output layer. The LSTM layer component is the cell state that passes through the chain, maintaining the flow of information linearly and unchanged. The LSTM gate mechanism removes or changes cell state information. This is a method for selectively transferring information, consisting of a sigmoid layer, a hyperbolic tangent layer, and pointwise multiplication operations. Figure 1 shows the LSTM architecture at time t, designed for modeling sequential input.

Figure 1

Long Short-Term Memory (LSTM) Architecture



For certain multivariate time series data collected from various sources, the goal of the proposed model is to predict the next day's closing price using a multivariate sequence of input features. The following LSTM implementation procedures are considered to achieve this.

From the primary dataset $X=(x1,x2,\ldots,xn)$ of size $k\times n$, the sequences $\{x1,x2,\ldots,xn-1\}$ and $\{y1,y2,\ldots,yn-1\}$ are created, where $xt\in Rk\times 1$ is the input sequence and $yt\in Ryt$ ∈R is the next day's closing price at time tt. Here, kk and nn are the number of input features and the total number of observations, respectively. Additionally, to match the dimensions required by the LSTM architecture, the input sequence Xt is formed by taking mm continuous sequences $xt{:}xt+m-1$ into a matrix of shape $k\times m$ for $t\in\{1,2,\ldots,n-m-1\}$. The LSTM output ht is a feature representation for the input sequence Xt at time t. Mathematically, ht can be expressed as: ht=LSTM(Xt,$ht-1$,$ct-1$,w)(3−10)

where ww represents all learnable parameters. Since the final hidden state hf encodes the most information from the input sequence, it is converted into a vector using a dense layer.

Code:

Algorithm 1 (Pseudo Code for Hyperparameter Tuning Procedure). Input Preparation: Split train and validation data sets and create input of the form [#observations, time step, #features]

Input: [#observations, time step, #features]; choices of optimizers, learning rates, and batch sizes.

Initialize: Set number of epochs sufficiently large and patience = 5

For ‘‘choice of optimizers’’, Do

For ‘‘choice of learning rates’’, Do

For ‘‘choice of batch sizes’’, Do

For ‘‘range of number of replicates’’, Do

Train the model, monitor validation loss;

Continue Until training loss at epoch $n \leq$ training loss at epoch $n + 1 \leq \cdots \leq$ training loss at epoch $n + 4$, Or maximum epochs are reached.

Evaluate model on the validation data.

Calculate RMSE scores. End Do.

Calculate average RMSE scores. End Do.

End Do.

End Do.

Output Set of best hyperparameters, average RMSEs, best average RMSE.

Algorithm 2 (Pseudo Code for LSTM Model after Hyperparameter Tuning). Input Preparation: Split train and test data sets and create input of the form (#observations, time step, #features) Input: [#observations, time step, #features];

chosen hyperparameters (optimizer, learning rate, batch size) obtained from Algorithm 1 for each model. Initialize: Set number of epochs sufficiently large and patience = 5

For choice of layers and neurons’’, Do

For ‘‘range of number of replicates’’, Do

Train the model, monitor training loss;

Continue Until training loss at epoch $n \leq$ training loss at epoch $n + 1 \leq \cdots \leq$ training loss at epoch $n + 4$, Or maximum epochs are reached.

Evaluate model on the test data.

Calculate RMSE, MAPE and R scores. End Do. Calculate minimum, maximum, average and standard deviation of RMSE, MAPE and R scores.

Save key results in respective files.

2.1. Data Collection Method

In this study, we aim to predict the index and stock prices using intelligent learning based on the data from the past ten years of the Iranian stock market. For this purpose, multivariate data influencing stock prices, such as trading volume, overall index growth percentage, historical price data, total cash inflow into the stock market, and currency prices, will be included as relevant factors in the stock market prediction.

2.2. Statistical Population, Sampling Method, and Sample Size

We intend to predict the index and stock prices using intelligent learning based on the data from the past several years of the Iranian stock market. Multivariate data influencing stock prices, such as trading volume, overall index growth percentage, historical price data, total cash inflow into the stock market, and currency prices, will be included as relevant factors in the stock market prediction.

For theoretical foundation formulation, library and internet studies were used, and to complete the information, part of the necessary data was collected by referring to Persian and Latin books, articles, and internet sources. Stock prices for various industries were reviewed and collected from the tsetmc website for a ten-year period.

2.3. Data Analysis Methods and Tools

In this research, we intend to predict prices using two methods: metaheuristic algorithms and deep learning. First, data is obtained in Excel format from the TSETMC website, then pre-processed. After this stage, the data is ready for entry into the neural network. Two neural network models are proposed for this purpose. In the multilayer neural network, various network architectures were examined to ultimately achieve the best architecture of a conventional neural network. In the deep neural network, the number of layers and filters were considered as variables.

Stock prices for the metal industry were reviewed and collected from the tsetmc website for a ten-year period. Using the proposed method based on the accuracy obtained from each method in the training phase, the weight of the obtained value for combination as a weighted average is determined and then normalized according to the weights. Stock prices for the metal industry were reviewed and collected from the tsetmc website for a ten-year period.

The proposed solution uses LSTM to predict prices and extract features, and a metaheuristic algorithm. Based on the accuracy obtained from each method in the training phase, the weight of the obtained value for combination as a weighted average is determined and then normalized according to the weights.

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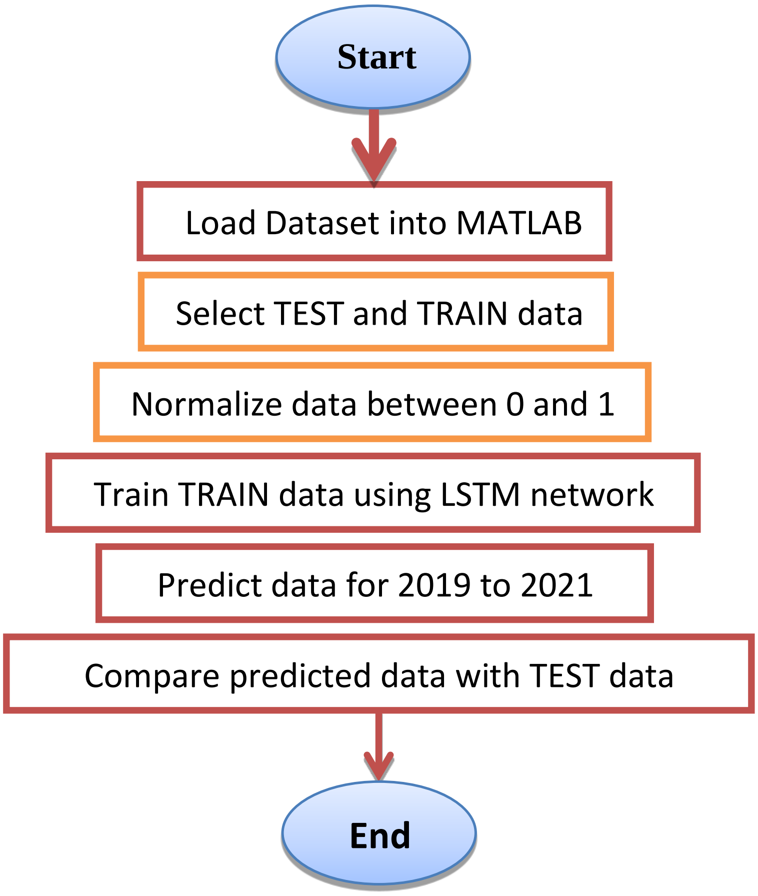
Figure 2

Proposed Solution Flowchart



3. Findings and Results

3.1. Features of the Proposed Solution

First LSTM Layer with 60 Neurons: Initially, stock data is entered into the first layer (the number of neurons represents the number of hidden layers in neural networks). Weights are initially randomly determined by the Keras library in Python.

Second LSTM Layer with 60 Neurons: The output of the first layer enters this layer to increase accuracy and further training. In this layer, the network finds suitable weights for the neurons based on the weights in the first layer and completes the training.

First Fully Connected Layer: This layer consists of 25 neurons (the task of the fully connected layer is classification; there are usually two fully connected layers in artificial neural networks).

Second Fully Connected Layer: This layer has one neuron because we ultimately have one class (predicted data), and the output provides a daily stock price for each day at a specific time, as shown in Figure 3.

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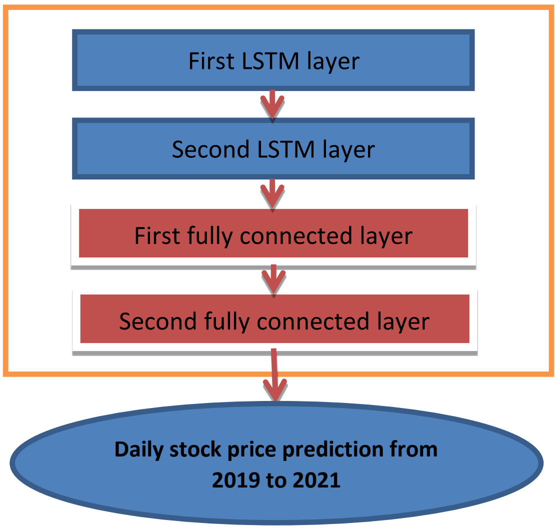
Figure 3

Proposed LSTM Network Structure



In this section, the selected features for the proposed solution are presented in Table 1.

Table 1

Features of the Proposed Solution

Feature	Definition
Close	End of the trading session
Open	Start of the trading session
High	Highest stock price during the day
Low	Lowest stock price during the day
Volume	Daily stock value
Date	Day

Figure 4

The Results of Executing Proposed Solution

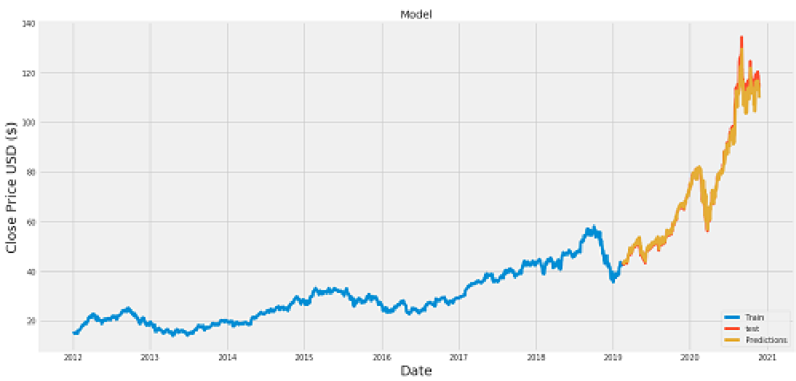


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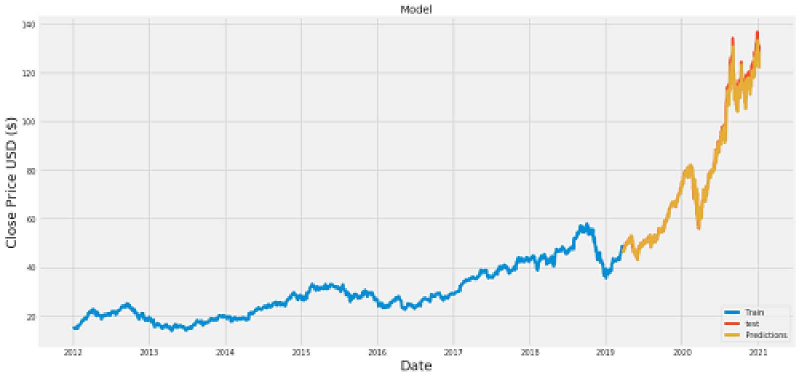
Figure 5

The Results of MPL Neural Network Solution



3.2. Evaluation of the Proposed Solution

To evaluate, we use error functions such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The MAE function measures the errors between paired observations expressing the same phenomenon. Examples of Y versus X include trained data versus actual data, next time versus initial time, and one measurement technique versus another [15]. MAE is calculated as follows:

$$MAE = \frac{\sum_{i=1}^{n}|x_i - x_i^{\wedge}|}{N} = \frac{\sum_{i=1}^{n}|e_i|}{N}$$

The MSE function estimates the error rate, which is the difference between actual values and predicted values. MSE is almost always positive (not zero) because it is random and because the estimator does not account for information that could produce a more accurate estimate. This measure, which is always non-negative, indicates lower error rates as it approaches zero. MSE is calculated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - x_i^{\wedge})^2$$

The RMSE function evaluates how well a model can predict continuous values. RMSE units calculate the ratio of the variable to the target in the data. RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_i - x_i^{\wedge})^2}$$

The parameters of the three functions MAE, RMSE, and MSE are as follows:

- N = total observations.
- xi = actual data.
- $x_i^{\wedge}$ = trained data.

To evaluate the proposed solution, we used the parameters: number of actual data, number of trained data, and total number of data.

Parameters:

1. N=2239 records
2. xi=448 records
3. $x_i^{\wedge}$=1792 records

We obtained MAE = 1.8500815, MSE = 7.6832591, and RMSE = 2.5355968.

The results of the error functions, including MSE, MAE, and RMSE, are presented in Table 2 for the proposed solution and Rajkumar's solution. Both solutions were simulated on the APPLE dataset comprising 2239 data points, with 448 allocated to actual data (Test) and 1792 to trained data (Train).

Table 2

Comparison of Error Functions between Proposed Solution and Rajkumar's Solution

Parameter	Evaluation Metric	MSE	MAE	RMSE
Neural Network (MLP)	Proposed Solution (This Study)	17.3518619	2.83060112	4.1655566
LSTM Neural Network	7.6832591	1.8500815	2.5355968	

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4. Discussion and Conclusion

The aim of this study is to predict stock prices on the stock exchange with the least error compared to other methods. After simulation and implementation of both solutions in Python, we concluded that the proposed method is one of the best for predicting stock exchange prices using a two-layer LSTM neural network with 60 neurons in each layer and 10 iterations, due to the power of these networks in prediction. The presence of the second layer eliminates the challenge of random weights in the first layer without the challenge of too many layers failing to reach an answer. This study's results show that the LSTM neural network is one of the most effective networks for predicting stock prices. The proposed solution, based on MSE, MAE, and RMSE functions, produced MAE = 1.8500815, MSE = 7.6832591, and RMSE = 2.5355968. Therefore, this solution can be enhanced as an application and can be a suitable tool for improving confidence and assisting both small and large investors in stock and stock exchange investments.

Authors' Contributions

M.R.N.A. conceptualized the study, designed the research methodology, and supervised the implementation of the deep learning models. He was also responsible for the integration of GA and PSO algorithms with the LSTM neural network. S.G., the corresponding author, conducted the data analysis using MATLAB software, interpreted the results, and led the drafting and revising of the manuscript. A.K.S. assisted with the literature review, data preprocessing, and validation of the research tools. All authors participated in discussing the findings, critically reviewed the manuscript for important intellectual content, and approved the final version for publication.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

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E-ISSN: 3041-9433