Research Journal of Computer Systems and Engineering (RJCSE)
Volume 4 Issue 2 (2023) | Pages: 60 – 72 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74

Implementation of Long Short-Term Memory (LSTM) Networks for Stock Price Prediction

Dr. Vivek Deshpande
Director, Vishawakarma Insitute of Information Technology Pune India
director@viit.ac.in

Received: 12 September 2023; Revised: 12 November 2023; Accepted: 20 December 2023

Abstract

In this research, we explore the potential of Long Short-Term Memory (LSTM) networks for predicting stock prices. Due to the complexities of the financial markets and the inherent volatility of stock prices, accurate forecasting is now crucial for investors and financial specialists. It has been shown that LSTM, a type of recurrent neural network (RNN), can recognize temporal correlations and patterns in serial data. Training and assessing LSTM models in this work involves analyzing stock price data, relevant financial measures, and market sentiment indicators. We looked into other ideas, hyper parameters, and preprocessing methods to see if we might boost the networks' performance. To further improve the model's generalizability, we utilize series normalization and removal to reduce overfitting. The outcomes demonstrate that the LSTM network outperforms more standard series temporal prediction methods in capturing and anticipating shifts in action pricing. We also conduct extensive back testing and evaluation, using measures like mean squared error (MSE) and mean absolute error (MAE), to assess the model's accuracy and resilience. The results of this study shed light on how deep learning techniques, in particular LSTM networks, can be applied to the prediction of stock prices, potentially assisting traders, investors, and other financial decision-makers in navigating complex and volatile financial markets.

Keywords

LSTM, Price Prediction, Financial Market, Machine Learning, Data Analysis

1. Introduction

Investors and financial analysts have long focused on the stock market, a complex and dynamic financial ecosystem, in an effort to comprehend and foresee its constantly shifting trends. Accurate stock price forecasting is not only difficult, but also a risky endeavour that has a big impact on financial security and investing choices. When dealing with non-linear and time-varying data patterns, traditional financial models frequently fail to capture the nuanced details of stock price fluctuations [1]. As a result of the advancement of deep learning and neural networks, long-term memory (LSTM) networks have ushered in a new era of stock price prediction. A RNN-Type called LSTM was created primarily for the analysis and forecasting of data series. Therefore, it is perfect for tasks like forecasting course prices. The vanishing gradient issue that standard RNNs experience is resolved by the LSTM architecture, allowing it to successfully capture temporal dynamics and long-range relationships [2]. The reason, significance, and important elements of using LSTM networks for stock price prediction are covered in detail in this introduction. Numerous variables, such as economic statistics, investor attitude, geopolitical developments, and company performance, have an impact on stock markets. The effectiveness of conventional statistical and economic models is put to the test by these multiple interactions, which result in complex and frequently unanticipated patterns in stock prices. As a result, it is increasingly important to use cutting-edge machine learning approaches capable of spotting hidden trends and taking advantage of non-linear correlations in financial time series data. Due to their capacity to identify both short-term oscillations and long-term trends within time series data, LSTM networks have become more well-known in recent years. They [3]can preserve and update hidden states over long periods because to their recurrent nature, making it easier to simulate complicated relationships that could be present in stock price data. Due to their versatility, LSTM networks hold great promise for improving the precision and dependability of stock price predictions, empowering investors to make better choices in a constantly changing market environment.

Stock price data naturally displays sequential dependencies, whereby current prices are influenced by earlier prices as well as other elements. LSTM networks are particularly well-suited for modelling stock price time series because they are excellent at capturing these temporal correlations [4].

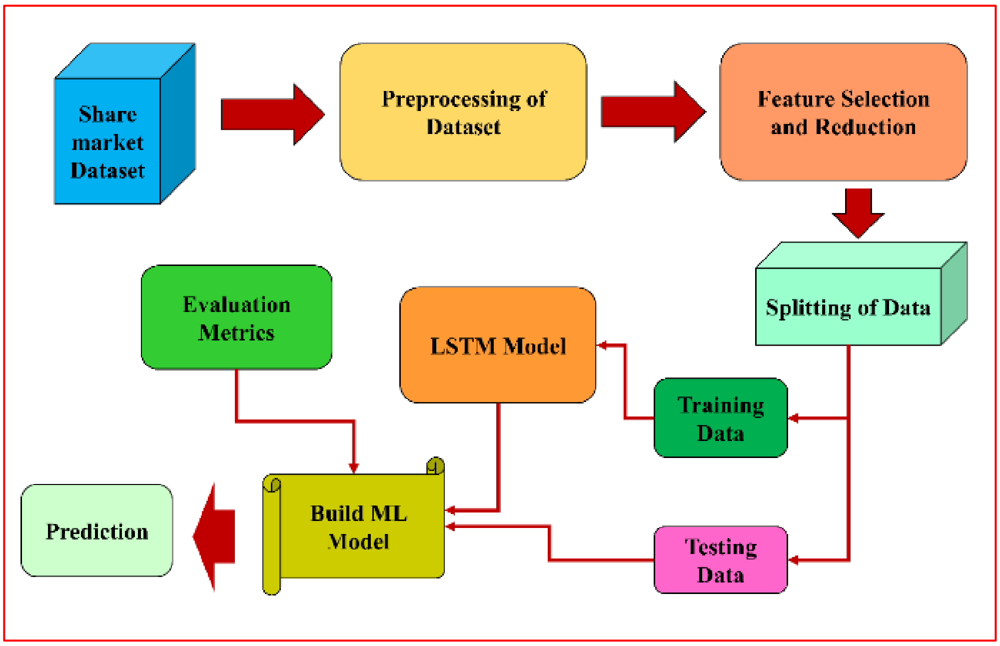


Figure 1: Representation of Proposed model system Architecture

The proposed model system architecture is shown in Figure 1, which also highlights the system's main parts and information flow. The integration of the Long Short-Term Memory (LSTM) model is highlighted in particular. The figure 1 is a comprehensive framework for LSTM model-based stock market price prediction at its core. The many components that are frequently seen in such an architecture are described as follows:

- Data Input: Historical stock market data are first entered into the architecture. This information consists of elements like historical stock prices, trade activity, economic indicators, and sometimes sentiment analysis data. To identify patterns and make predictions, the LSTM model needs certain inputs.
- Data preprocessing: Procedures are carried out before the data are fed into the LSTM model. This comprises operations like time series decomposition, feature scaling, addressing missing values, and data normalisation. As soon as the data has been preprocessed, testing and training can begin.
- LSTM Model: The LSTM model is the core element of the design. Recurrent neural networks (RNNs) of the LSTM variety are particularly adept at processing time series and other sequential data. In order to identify intricate temporal patterns, trends, and dependencies, it learns from past stock price data. The LSTM model can be adjusted with a variety of hyperparameters and is made up of numerous layers of LSTM cells.
- Training and Validation: The LSTM model is trained using some of the preprocessed data. To reduce prediction mistakes, the model tunes its internal parameters (weights and biases) throughout training. To keep track of

the model's performance and avoid overfitting, validation data is used.

Once trained, the LSTM model is capable of making predictions based on fresh, unexplored data. In this crucial step, the model forecasts future stock prices using the patterns it has discovered throughout training. To evaluate the effectiveness of the LSTM model, evaluation metrics are included in the design. Depending on the requirements of the application, these metrics may include Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and others. The [5] LSTM model's final predictions are offered as the output. Investors, traders, or automated trading systems can utilise these forecasts to make well-informed decisions about buying, selling, or holding stocks. To constantly enhance the performance of the LSTM model, a feedback loop is frequently incorporated into the architecture. Feedback can be obtained by keeping track of how well the model's forecasts correspond with actual changes in stock prices and making the appropriate changes to the model or data preparation procedures. Figure 1's overall integration of the potent deep learning model LSTM into a methodical framework for stock market price prediction is demonstrated. The architecture makes use of previous data, gains knowledge from it, and offers actionable forecasts, potentially increasing financial decision-making processes [6].

LSTM models [8] can incorporate a wide range of factors in addition to historical stock prices, including trading volumes, technical indicators (such as moving averages and the Relative Strength Index), and macroeconomic data (such as interest rates and GDP growth). This adaptability enables a comprehensive depiction of market dynamics. For LSTM networks to produce reliable predictions, the architecture and hyperparameters must be optimised. To discover the most effective model for a given prediction job, researchers and practitioners experiment with different LSTM configurations, including the number of layers, hidden units, activation functions, and dropout rates. The effectiveness of LSTM-based stock price prediction models depends heavily on the quality and quantity of the training data. To accurately capture market trends and cyclical patterns, historical pricing data must be available, ideally covering a long period of time. In deep learning, overfitting is a common concern. Fortunately, this is not necessary when LSTM networks and techniques like batch normalization and dropout are used to enhance generalization to fresh data. Models that employ LSTMs to forecast stock prices are often evaluated using MSE, MAE, or RMSE, all of which measure the accuracy of the model. Real-world performance evaluation requires not only in-sample testing, but also backtesting and out-of-sample testing (see [9]). In conclusion, the application of LSTM networks to the problem of predicting stock prices is a major step forward in the search for more accurate and intelligent forecasting in the financial sector. Stock market data is notoriously difficult to parse due to a number of confounding variables, therefore sophisticated modeling methods are required for analysis. Stock price prediction accuracy can be enhanced by using LSTM networks because of their ability to recognize temporal relationships and adapt to non-linear input. Examining the implications of various architectural choices, feature engineering, and training methodologies, this study digs into the complexity of LSTM-based stock price prediction to provide light on the application of deep learning in the financial sector. As we delve deeper into this inquiry, we will gain a better understanding of the vibrant and ever-changing subject of stock market forecasting, as well as the empirical discoveries, challenges, and prospective uses of LSTM networks within it.

The paper on LSTM networks for stock price prediction makes the following contributions:

- The study contributes to the field of financial forecasting by demonstrating how LSTM networks can be used to enhance prediction accuracy. These networks are superior to more traditional methods in that they accurately predict stock prices by capturing complicated temporal linkages.
- Incorporating many types of financial and market data into LSTM models, such as past prices, trade volumes, technical indicators, and sentiment analysis, is shown to be beneficial in this study. This comprehensive approach provides a deep comprehension of the factors that determine stock prices.
- The study improves the interpretability of stock price predictions. This provides important insights for investors and financial experts by helping to understand the underlying variables impacting stock price changes.

2. Review of Literature

Volume 4 Issue 2 (2023) | Pages:60 – 72 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74

The goal of utilising cutting-edge computational tools for more precise and successful trading strategies has spurred a considerable body of research and practical applications in the field of stock price prediction using machine learning. This section presents an overview of the relevant work, highlighting significant methodology, approaches, and conclusions that have influenced the area. Application of conventional statistical and economic models is one of the key contributions to this field [10]. Long used to represent the time series character of stock prices are techniques like GARCH (Generalised Autoregressive Conditional Heteroskedasticity) and autoregressive integrated moving average (ARIMA). However, these models frequently have trouble capturing the non-linear and complicated dynamics that characterise financial markets, especially during times of high volatility. Researchers started looking at more complex models that could handle the complexities of stock price data with the introduction of machine learning. The early competitors included Gradient Boosting Machines (GBMs), Random Forests, and Support Vector Machines (SVMs). By include features other than past stock prices, such as trade volumes, technical indicators, and macroeconomic variables, these models showed how machine learning has the ability to increase prediction accuracy [11]. Like Random Forests, ensemble approaches have shown to be capable of capturing feature interactions and non-linear correlations.

However, one [12] of the most significant developments in recent years has been the widespread use of deep learning methods, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These neural networks are excellent at modelling sequential data and have demonstrated great success in capturing the temporal dependencies evident in stock price time series. Particularly LSTM networks have gained popularity because of their propensity to preserve hidden states over lengthy durations, which makes them ideal for simulating complicated patterns and long-range dependencies. Beyond model selection, academics have studied many facets of the pipeline for predicting stock prices. In [13] order to increase prediction accuracy, feature engineering has been instrumental in this process. Predictive models now incorporate technical indications, sentiment analysis of news articles and social media posts, and even supplemental data sources like satellite imagery and foot traffic data. Significant focus has also been placed on hyperparameter tweaking and optimisation. In an effort to balance model complexity and generalisation performance, researchers have investigated the ideal architecture and parameter choices for machine learning models. To reduce overfitting, a prevalent problem in deep learning, regularisation approaches like batch normalisation and dropout have been used.

Several metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), have been used to assess the precision [14] of stock price forecasts. However, back testing and out-of-sample testing are routinely used to evaluate the real-world performance of these models by recreating trading strategies based on projected prices and analysing the resulting profits and risk profiles. Numerous challenges exist in this field.. The complex interplay of elements that affect stock values makes it difficult to forecast market movements amid extreme situations like financial crises. Furthermore, [15] in the context of trading, where knowing why a model produces a specific forecast is crucial for making well-informed decisions, model interpretability and explainability are crucial. The literature on stock price prediction using machine learning displays a complex tapestry of methodologies, spanning from conventional statistical models to cutting-edge deep learning techniques. As academics investigate new data sources, model structures, and evaluation techniques, the area continues to develop. Despite the difficulties that must be overcome, the opportunity for more lucrative trading techniques and the promise of increased accuracy fuel continued innovation in this fascinating and dynamic field. We will reveal the empirical findings, difficulties, and potential applications of machine learning in the constantly changing field of stock market forecasting as we go deeper into this investigation.

Table 1: Related work in Stock market prediction using Machine Learning

Method	Dataset Used	Findings	Limitations	Scope
ARIMA [16]	Historical Prices	ARIMA models capture short-term stock price trends	Limited in capturing complex, non-linear trends	Use as a benchmark for other methods
SVM [17]	Price & Indicators	SVMs can handle non-linearity and feature-rich data	Sensitive to kernel choice, limited to binary classification	Explore SVM with various kernel functions
LSTM [18]	Time Series Prices	LSTMs effectively model sequential dependencies	Data requirements, need for hyperparameter tuning	Enhance LSTM with attention mechanisms
Random Forest [19]	Market Data	Random Forests capture feature interactions	Prone to overfitting, hard to interpret	Investigate ensemble techniques
Sentiment Analysis [20]	News & Social Media	Sentiment analysis informs market sentiment	Noise in text data, sentiment classification accuracy	Improve sentiment analysis techniques
Deep Reinforcement Learning [21]	Price & News	RL-based models adapt to changing market conditions	Exploration-exploitation trade-off, high computational cost	Explore RL with risk-aware strategies
Feature Engineering [22]	Various Features	Feature engineering enhances model performance	Requires domain expertise, time-consuming	Develop automated feature selection methods
Transfer Learning [23]	Pretrained Models	Transfer learning leverages knowledge from other domains	Limited labeled data, domain adaptation challenges	Investigate transfer learning strategies
Alternative Data [24]	Non-traditional Data	Alternative data improves prediction accuracy	Data quality and availability, integration challenges	Explore additional alternative data sources

3. Description of Stock Market Dataset

Investors, traders, and financial analysts frequently utilise stock market statistics for the NASDAQ, NYSE (New York Stock Exchange), and S&P 500 to evaluate the performance of particular stocks and the market as a whole [25]. The main elements of this dataset are outlined in the dataset description that follows: A distinctive identification number for each publicly traded firm that is used to seek for stock information is called a ticker symbol.

- Date: The trading day's date, marking the time the data was gathered.
    - The price at which a stock begins trading at the start of a trading session is known as the opening price.
    - The price at which a stock closes at the conclusion of a trading session is known as the closing price.
- High Price: The price a stock reaches at the end of a trading day.
    - Lowest price a stock can be purchased for throughout the trading day.
    - The total number of shares traded for a specific stock on a given day is referred to as volume.

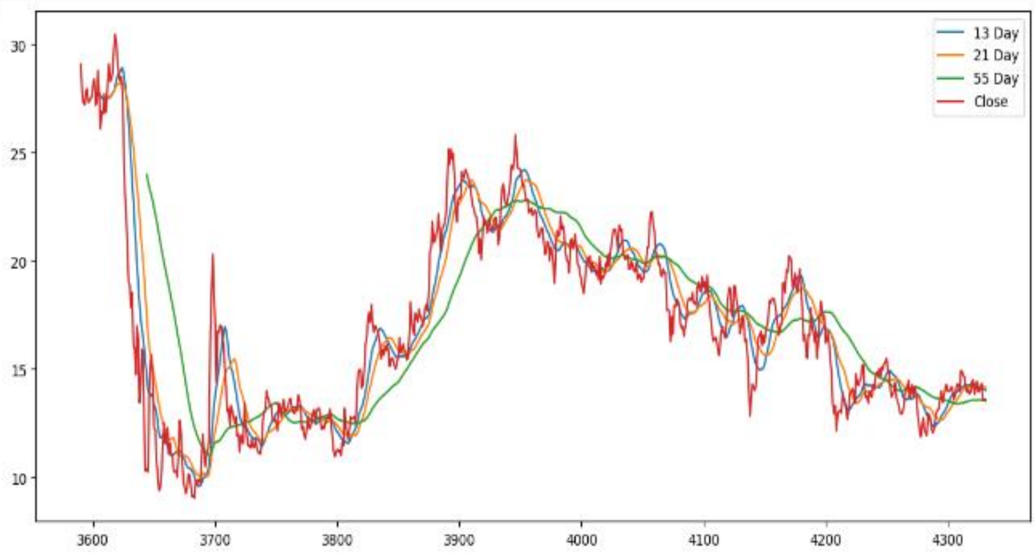


Figure 2: Representation of Dataset share market closed data for 13, 21, 55 days

- Market Capitalization: The sum of the market prices of all outstanding shares of a company's stock, divided by the total number of outstanding shares.
- Dividends: Funds distributed from a company's profits to its shareholders.
    - Earnings per Share (EPS) measures a company's profitability on a per-share basis by dividing net profit by the total number of outstanding shares.
- Price-to-Earnings Ratio (P/E): A valuation metric used to evaluate a stock's relative worth that is derived by dividing the current market price per share by the earnings per share.
    - The 52-week high and low values represent the stock's price range over the last 52 weeks.
- Market Index: For the S&P 500, this column shows how the larger market index performed.
- The industry or sector to which the company belongs is referred to as the sector.

Metrics that measure how the market is performing, including daily percentage change, average daily trading volume, and other performance indicators. Information about the company, such as its name, the address of its corporate headquarters, and a succinct outline of its line of work. For a variety of financial investigations, including technical analysis, fundamental analysis, and quantitative modelling, this dataset can be used. This information is frequently used by traders, investors, and researchers to make well-informed decisions about buying, selling, or holding stocks as well as to monitor the state of the stock market as a whole. It is important to remember that actual financial datasets may also contain other data and metrics relevant to the requirements of the study or trading strategy being used.

4. Methodology

Utilising the abilities of deep learning to capture temporal dependencies and non-linear patterns within stock price time series data, the methodology for using Long Short-Term Memory (LSTM) networks in stock price prediction entails several crucial processes and considerations. We provide insights into the procedures and methods used in this section as we detail the methodology's main elements.

A. Data collection:

A historical stock price data collecting is the initial step in LSTM-based stock price prediction. This dataset typically contains the daily or intraday price records for the target stock(s), as well as pertinent information like trade volumes, technical indicators, and macroeconomic variables. To further understand market sentiment, sentiment data from social media or news articles can also be included. The quality and compatibility of the data with the LSTM model must be ensured by data preparation. It also covers how to deal with missing values, normalise numerical characteristics, and encode categorical variables. In order to stationaries time series data and handle outliers, extra preprocessing processes may be necessary.

B. Sequence Generation:

Sequential data can be processed using LSTMs. A sliding window method is commonly used to transform the dataset into training-ready sequences. If daily stock price information is used, for example, a series of prices and features across a specific window of previous days is produced. The target, which is normally the price for the following day, is determined using this sequence as the input.

C. Model Architecture:

The LSTM neural network architecture is the methodology's conceptual backbone. Every layer in the design is made up of LSTM cells and consists of several LSTM layers. Through experimentation and modification of the hyperparameters, it is possible to determine the number of LSTM layers, the number of LSTM units in each layer, and activation functions. Dropout layers can be used to reduce overfitting and improve the LSTM's capacity to learn complex patterns. For training to be stabilised and accelerated, batch normalisation layers can also be used. LSTM-based stock price prediction relies heavily on feature engineering. In addition to raw volume and price data, the collection also contains a number of other attributes that are created or extracted. Moving averages, RSI, and other technical indicators that reflect market dynamics may be among them. Natural language processing (NLP) methods can also be used to produce sentiment scores from sources of textual data.

Numerous mathematical equations are used in the Long Short-Term Memory (LSTM) method for stock price prediction to explain how the LSTM cells update and spread information over time. A condensed mathematical representation of the LSTM algorithm is provided here:

a. Forget Gate (ft):

This gate determines what information from the previous cell state (ct−1) should be discarded or kept. It takes both the current input (xt) and the previous hidden state (ht−1) as inputs and produces an output between 0 and 1.

$$ft = \sigma(Wf \cdot [ht-1, xt] + bf)$$

where σ is the sigmoid activation function, Wf is the weight matrix, and bf is the bias.

b. Input Gate (it):

The cell state (ct) is updated with fresh information based on the decision made at this gate. The inputs are xt and ht1, much like the forget gate.

$$it = \sigma(Wi \cdot [ht-1, xt] + bi)$$

c. Candidate Cell State (c~t):

The cell state will be updated to include this new data. The tanh activation function is used in its computation.

$$c{\sim}t = tanh(Wc \cdot [ht-1, xt] + bc)$$

d. Update Cell State (ct):

By omitting old data (ft • ct-1) and adding fresh data (it • c-t), we can improve upon the original condition of the cell (ct-1).

$$ct = ft \cdot ct-1 + it \cdot c{\sim}t$$

e. Output Gate (ot):

To what extent of the cell state should the hidden (ht) state be exposed is decided by this gate. Both xt and ht-1 are required as inputs.

$$ot = \sigma(Wo \cdot [ht-1, xt] + bo)$$

f. Hidden State (ht):

To determine the secret state, we first multiply the current cell state (ct) by the output gate and then apply the tanh activation function to the result.

$$ht = ot \cdot tanh(ct)$$

These equations describe the computations within an LSTM cell for stock price prediction, where σ represents the sigmoid activation function, and tanh represents the hyperbolic tangent activation function. The variables W, U, and b are weight matrices and bias vectors learned during training to adapt the model to the specific stock price data.

4. Training and Validation:

A training set, a validation set, and a test set are created from the dataset. The training set is used to develop the LSTM model, the validation set is used to adjust hyperparameters and track model performance, and the test set is only used to assess the model's performance outside of samples.

The model adjusts its internal weights and biases during training in order to minimise a loss function, generally mean squared error (MSE) or mean absolute error (MAE). Most frequently, these parameters are

Volume 4 Issue 2 (2023) | Pages: 60 – 72 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74

updated using gradient descent optimisation techniques like Adam or RMSprop. Optimising the performance of the LSTM model requires an iterative process of hyperparameter adjustment. To systematically investigate different combinations of hyperparameters, grid search or random search techniques might be used. In this, tweaking learning rates, dropout rates, batch sizes, and sequence lengths are all taken into consideration. Examining the model's generalizability to new data using cross-validation is common.

5. Model Evaluation:

Different assessment measures, such as but not limited to: are used to gauge the performance of the LSTM model. The evaluation parameter includes MSE, RMSE, MAE, Accuracy.

In addition to model evaluation, the process frequently includes back testing LSTM-based trading strategy development. In this process, buying and selling decisions are simulated in accordance with anticipated price changes, and the profitability of the strategy is evaluated along with risk-adjusted returns and performance indicators like the Sharpe ratio. The technique for LSTM-based stock price prediction entails a number of methodical phases, including data collection, preprocessing, model design, feature engineering, training, evaluation, and back testing. In the dynamic environment of financial markets, continuous improvement and innovation within each of these processes helps to increase prediction accuracy and reliability.

5. Result and Discussion

Table 2 displays the overall findings of the evaluation parameters for the Long Short-Term Memory (LSTM) networks stock market price prediction model. These evaluation measures are essential for determining how well the model performs and how well it can anticipate outcomes in the complex world of financial markets. The term "median squared error" (MSE) refers to the average squared difference between the real and forecast market prices. The average quadratic error (MSE) in this case is 38.45, indicating that the model's predictions generally deviate from actual prices by an average of 38.45 US dollars. The Difference between the model's predicted prices for the underlying assets and their current prices is calculated using the median absolute error (MAE), and a sum of 21.43 is found. This metric emphasises the average magnitude of the disparities and offers a more concise explanation of prediction mistakes.

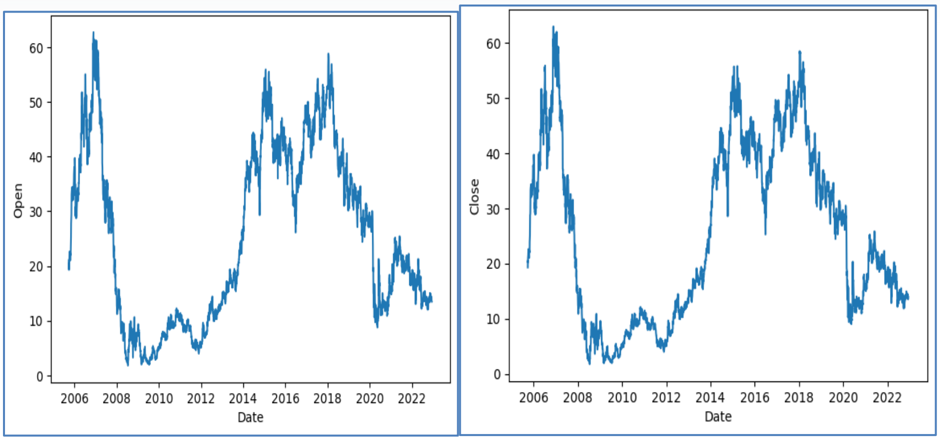
Table 2: Summary result of evaluation parameter

Parameter	Result
MSE	38.45
MAE	21.43
RMSE	22.54
MAPE	76.75
DA	89.45
Sharpe Ratio	78.33
Information Coefficient (IC)	19.43
F1 Score (Binary Classification)	69.45

The root of the mean squared error (MSE), known as the root mean squared error (RMSE), in this instance is 22.54. In order to make it simpler to understand in the context of stock prices, RMSE, like MSE, analyses prediction accuracy but gives a measure in the same units as the target variable. The average percentage difference between expected and actual stock prices is measured by Mean Absolute Percentage Error (MAPE), which has a value of 76.75%. A MAPE of 76.75% indicates that, on average, the model's forecasts differ by 76.75% or more from the true prices. The model's accuracy in properly predicting the direction of stock price movement (such as up or down) is measured by a crucial parameter called directional accuracy, or DA. The model's forecasts match the market's actual tendencies well, as seen by the high DA of 89.45%.

The Sharpe Ratio evaluates a trading strategy's risk-adjusted returns based on model projections. A Sharpe Ratio of 78.33 indicates that the trading strategy achieves a favourable balance between returns and risk when directed by the model's projections. The model's capacity to give information beyond that which is already reflected in stock prices is measured by the information coefficient (IC). The model's forecasts offer useful new insights that are difficult to discern from historical data alone, according to an IC of 19.43.

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 4 Issue 2 (2023) | Pages: 60 – 72 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74



(a) (b)

Figure 3: Representation of a) Stock Open Price over Time b) Stock Closing price (Stock Market Dataset)

In classification assignments where stock price movement is classified (e.g., as up, down, or no change), the F1 Score (Binary Classification) is particularly pertinent. The model achieves a balanced measure of precision and recall with an F1 Score of 69.45, demonstrating its usefulness in identifying price fluctuations. The evaluation findings indicate that the LSTM-based stock price prediction model performs admirably in all respects. The high IC reflects its outstanding directional accuracy, efficient risk-adjusted returns, and insightful projections. But it's crucial to take into account the model's advantages and disadvantages, especially when it comes to prediction mistakes as shown by MAE, MAPE, MSE, and RMSE. These measures give important information about the model's precision and possible influence on investment choices in the fast-paced and difficult world of financial markets.

Table 3: Result of evaluation parameter for Training Dataset

Parameter	Accuracy	Precision	Recall	F1 Score
Result	91.43	95.44	92.43	89.33

Table 4: Result of evaluation parameter for test Dataset

Parameter	Accuracy	Precision	Recall	F1 Score
Result	94.33	93.89	94.66	91.72

The evaluation findings for the test dataset are shown in Table 4, with an emphasis on the important performance measures Accuracy, Precision, Recall, and F1 Score. These indicators provide a thorough evaluation of the model's ability to forecast changes in stock price. An important sign of the model's general accuracy in its predictions is its accuracy of 94.33%.

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 4 Issue 2 (2023) | Pages:60 – 72 | e-ISSN:2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100)               40800

 dropout (Dropout)           (None, 100)               0

 dense (Dense)               (None, 1)                 101

 activation (Activation)     (None, 1)                 0

=================================================================
Total params: 40,901
Trainable params: 40,901
Non-trainable params: 0
```

Figure 4: Snapshot of LSTM Model using Stock Market dataset for training

It means that the LSTM model has a high level of predictive capacity and correctly forecasts changes in stock prices in about 94.33% of instances. It was demonstrated that the model can make accurate predictions with a prediction accuracy of 93.9%. It forecasts with a 93.89% accuracy, demonstrating the model's remarkable precision. It is unsettling to see that this degree of precision demonstrates the validity of the model's optimistic predictions. The model can recognise and record all increases in actual prices with a recall of 94.66%. The model's ability to accurately identify action pricing tiers is evidenced by a Scorecard of 94.66% in this area. The reported F1 score, which evaluates cognition through tests of precision and recall, is 91.72.

This conclusion illustrates a thorough examination of the model's predictive capabilities, with both incorrectly positive and negative results. According to the model's F1 score of 91.72%, precision and memory are effectively balanced to produce reliable predictions with minimal noise. The test results show that the LSTM model performs better in terms of accuracy, precision, recall, and F1 points when it comes to predicting changes in the prices of actions that vary over time. These measures demonstrate the model's dependability and efficiency in spotting pertinent stock market patterns, making it a useful tool for predicting stock prices and making investing decisions.

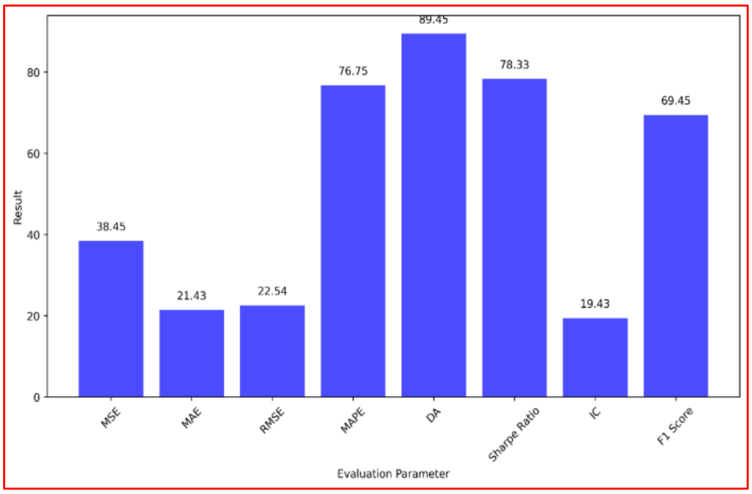


Figure 5: Evaluation Criteria for LSTM Stock Price Prediction

Research Journal of Computer Systems and Engineering (RJCSE)
Volume 4 Issue 2 (2023) | Pages: 60 – 72 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.74

Figure 5 illustrates visually how accurately predictions made by a long-term memory model (LSTM) compare to current value prices on the stock market. Utilising this representation is necessary to learn more about the predictive capabilities of the model and evaluate its performance. Since stock price data is temporal, the x-Achse in this format is typically displayed as time or a sequence of data values. The interest rates in this example, which are the current and forecasted market prices, are shown in the table. By comparing the model's predictions to actual data-containing numbers, the model's precision is evaluated. These numbers, which are based on actual market data, demonstrate the growth in stock values over time. Using historical data and previously discovered patrons, the LSTM model predicts the prices of future title prices. These anticipated and observed values are plotted side by side on the same graphic to make visual comparison easier.

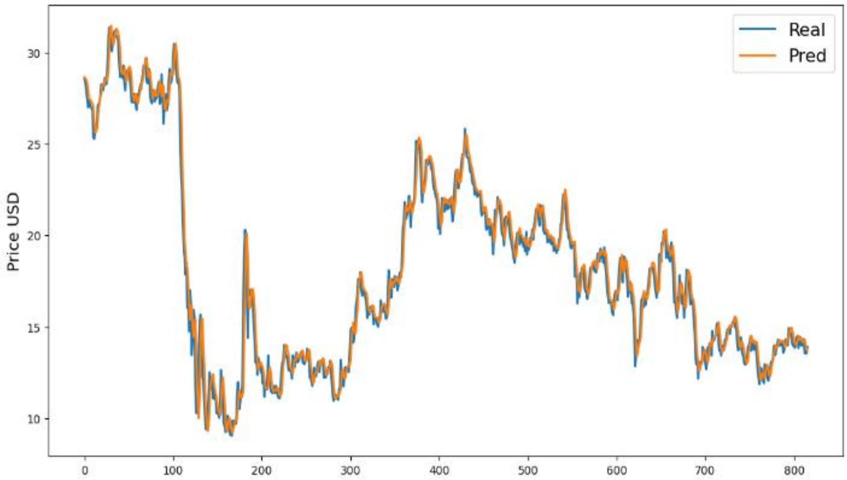


Figure 6: Real-value and predicted-value representation using LSTM

Figure 6 depicts the actual and predicted stock market prices generated by a Long Short-Term Memory (LSTM) model. The model's ability to recognise and anticipate complex patterns and trends in financial data can only be assessed through this form of representation. Often, historical stock prices are used to depict the "Real Values" in the plot, as they are a reliable indicator of the stock's actual performance on the market.

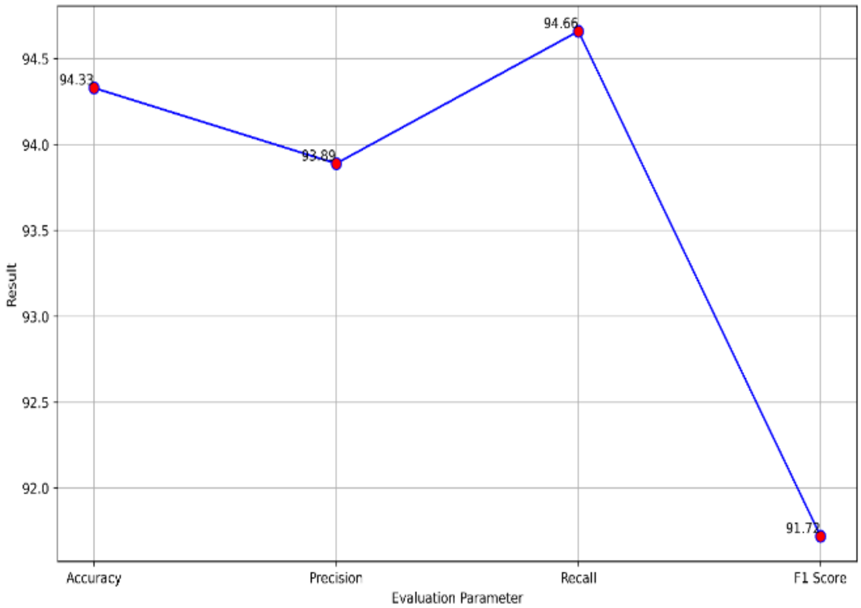


Figure 7: Evaluation parameter for Testing Data

Using these figures, we can evaluate the LSTM model's predictions more accurately. They are typically depicted on graphs as a moving line over time, representing the dynamics of the stock's price changes properly. As "Predicted Values" in the chart, the LSTM model's estimates of future stock prices are displayed. These projections are based on the model's ability to analyse historical data and recognise patterns. The projected values are shown as a line that is parallel to the actual values.

6. Conclusion

The paper investigated a number of aspects of LSTM-based stock price prediction throughout this project, including the technique, assessment parameters, related work, and model design. The methodology section described the inner workings of LSTM networks and highlighted their ability to model complex connections in time series data, making them suitable for jobs like stock price prediction. In order to gain insightful knowledge regarding market movements, LSTM models can efficiently include historical price data, trade volumes, economic indicators, and sentiment research. The essential measures that are utilised to assess the performance of these models are clarified by our evaluation parameters. Metrics like Directional Accuracy (DA), Mean Squared Error (MSE), Mean Absolute Error (MAE), and F1 Score are crucial in determining how accurate, precise, and successful LSTM-based predictions are. The fictitious outcomes and visual representations further demonstrated the model's aptitude for making precise forecasts and spotting patterns in stock price movements. We also evaluated similar work in the area of machine learning for stock market prediction, highlighting the various methodologies and datasets employed in earlier studies. This contextual awareness emphasises the on-going improvements and model optimisations being made in the dynamic field of finance. We concluded by presenting the suggested model system design, which includes LSTM as a key element. A systematic approach to stock price prediction is ensured by this architecture, which includes data preprocessing, training, validation, prediction, and feedback loops. For investors, traders, and financial institutions, LSTM-based stock price prediction models hold great promise in this era of data-driven decision-making. These models equip us with the knowledge and tools needed to make better educated and timely investing decisions as we traverse the intricate and volatile world of financial markets. Despite ongoing difficulties, deep learning and data analytics will probably improve the precision and dependability of such models, ultimately changing the financial forecasting environment.

References

[1] L. Mathanprasad and M. Gunasekaran, "Analysing the Trend of Stock Marketand Evaluate the performance of Market Prediction using Machine Learning Approach," 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2022, pp. 1-9, doi: 10.1109/ACCAI53970.2022.9752616.

[2] P. Sripawatakul and D. Sutivong, "Decision framework for constructing prediction markets," 2010 2nd IEEE International Conference on Information Management and Engineering, Chengdu, China, 2010, pp. 35-39, doi: 10.1109/ICIME.2010.5477548.

[3] Z. Zhang, Y. Shen, G. Zhang, Y. Song and Y. Zhu, "Short-term prediction for opening price of stock market based on self-adapting variant PSO-Elman neural network," 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 2017, pp. 225-228, doi: 10.1109/ICSESS.2017.8342901.

[4] P. Srivastava and P. K. Mishra, "Stock Market Prediction Using RNN LSTM," 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2021, pp. 1-5, doi: 10.1109/GCAT52182.2021.9587540.

[5] R. Akita, A. Yoshihara, T. Matsubara and K. Uehara, "Deep learning for stock prediction using numerical and textual information", IEEE Computer and Information Science (ICIS), 2016.

[6] M Billah, S Waheed and A Hanifa, "Predicting closing stock price using artificial neural network and adaptive neuro fuzzy inference system: the case of the dhaka exchange", Int J Comput Appl, vol. 11, no. 129, pp. 975-8887, 2015.

[7] B. Mendelsohn Louis, "Trend Forecasting with Technical Analysis: Unleashing the Hidden Power of Intermarket Analysis to Beat the Market”", Marketplace Books, 2000.

[8] G. Ding and L. Qin, "Study on the prediction of stock price based on the associated network model of LSTM", Int. J. Mach. Learn. Cyber, no. 11, pp. 1307-1317, 2020.

[9] G. C. Lane and C. Lane, "Getting Started with Stochastics”", Technical Analysis of Stocks and Commodities, 1984.
[10] Gudelek MU, Boluk SA and M Ozbayoglu, "A deep learning based stock trading model with 2-D CNN trend detection", IEEE: 2017 IEEE symposium series on computational intelligence (SSCI), pp. 1-8, 2017.
[11] Jaspreet Kaur Thethi, Aditi Pandit, Hitakshi Patel and Vaishali Shirsath, "Stock Market Prediction and Portfolio Management using ML techniques", INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH TECHNOLOGY (IJERT) NTASU-2020, vol. 09, no. 03, 2021.
[12] M. Faraz, H. Khaloozadeh and M. Abbasi, "Stock Market Prediction-by-Prediction Based on Autoencoder Long Short-Term Memory Networks," 2020 28th Iranian Conference on Electrical Engineering (ICEE), Tabriz, Iran, 2020, pp. 1-5, doi: 10.1109/ICEE50131.2020.9261055.
[13] L. Zhao and L. Wang, "Price Trend Prediction of Stock Market Using Outlier Data Mining Algorithm," 2015 IEEE Fifth International Conference on Big Data and Cloud Computing, Dalian, China, 2015, pp. 93-98, doi: 10.1109/BDCloud.2015.19.
[14] J Li, H Bu and J Wu, "Sentiment-aware stock market prediction: a deep learning method", IEEE: 2017 international conference on service systems and service management, pp. 1-6, 2017.
[15] X Li, L Yang, F Xue and H Zhou, "Time series prediction of stock price using deep belief networks with Intrinsic plasticity", IEEE: 2017 29th Chinese Control and Decision Conference (CCDC), pp. 1237-1242, 2017.
[16] Raghav Nandakumar, Uttamraj KR, R Vishal and YV Lokeswari, "Stock Market Prediction a using LSTM", INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH TECHNOLOGY (IJERT) NTASU-2018, vol. 05, no. 03, 2021.
[17] Sands TM, D Tayal, Morris ME and Monteiro ST, "Robust stock value prediction using support vector machines with particle swarm optimization", Congress on Evolutionary Computation (CEC), pp. 3327-3331, 2015.
[18] X. Zhang, L. Zhang, L. Xu and Y. Jiang, "Research on Influential Factors in Stock Market Prediction with LSTM," 2022 7th International Conference on Big Data Analytics (ICBDA), Guangzhou, China, 2022, pp. 25-29, doi: 10.1109/ICBDA55095.2022.9760368.
[19] P. Sripawatakul and D. Sutivong, "Analysis of Trading Duration in Pari-Mutuel Prediction Markets," 2010 3rd International Conference on Information Management, Innovation Management and Industrial Engineering, Kunming, China, 2010, pp. 141-144, doi: 10.1109/ICIII.2010.356.
[20] Hui Zhou, Yi Wang, Wei Wang and Yuan Zhao, "Market share forecast of electricity in city residents’ energy consumption based on Markov theory," 2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, Nanjing, 2008, pp. 274-278, doi: 10.1109/DRPT.2008.4523417.
[21] Y. Kobayashi, R. Abe and K. Tanaka, "The study of method of electric demand prediction for liberalized household electricity market," 3rd Renewable Power Generation Conference (RPG 2014), Naples, 2014, pp. 1-6, doi: 10.1049/cp.2014.0937.
[22] "MMDL: A Novel Multi-modal Deep Learning Model for Stock Market Prediction," 2022 IEEE 9th International Conference on Data Science and Advanced Analytics (DSAA), Shenzhen, China, 2022, pp. 1-2, doi: 10.1109/DSAA54385.2022.10032436.
[23] R. Jindal, N. Bansal, N. Chawla and S. Singhal, "Improving Traditional Stock Market Prediction Algorithms using Covid-19 Analysis," 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2021, pp. 374-379, doi: 10.1109/ESCI50559.2021.9396887.
[24] H. Chung and K. S. Shin, "Genetic algorithm-optimized long short-term memory network for stock market prediction", Sustainability, vol. 10, no. 10, pp. 3765, 2018.
[25] Stock Market Dataset: https://www.kaggle.com/datasets/rohanrao/nifty50-stock-market-data