Comparative Analysis of Stock Price Prediction Models

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Abstract: Stock price prediction is the process of forecasting the future movements and trends in stock prices. It plays a vital role in financial markets as it helps investors, traders, and financial institutions make informed decisions regarding buying, selling, or holding stocks. It involves analysing historical price data, market trends, economic indicators, and other relevant factors to develop predictive models. However, due to the inherent complexities and uncertainties of financial markets, correctly forecasting stock values is a difficult task. To improve prediction accuracy many machine learning techniques have been proposed. In this study, the effectiveness of three alternative stock price prediction techniques like Linear Regression, Moving Average, and Long Short-Term Memory are compared using the JPMorgan stock price prediction dataset. The study's findings demonstrate that the LSTM method forecasts stock prices more accurately than moving average and linear regression by obtaining the lowest MSE of better prediction precision and a greater R squared value of a small model-data fit. Performance of these approaches is assessed using the R-squared error and Mean Squared Error (MSE).

1 INTRODUCTION

Stock price prediction is a critical area of research in financial markets, aiming to forecast future movements and trends in stock prices. Accurate prediction of stock prices has significant implications for investors, traders, and financial institutions, enabling them to make informed decisions and devise effective investment strategies. The complex and dynamic nature of stock price data is often difficult to capture using traditional methods for stock price prediction, such as statistical models and technical indicators. The primary goal of this study is to compare the performance of different prediction methods, including LSTM, Moving Average, and Linear Regression, in forecasting stock prices. Because of its ability to recognise long-term dependencies and non-linear patterns in sequential data, LSTM networks, a type of recurrent neural networks, have become highly effective in time series forecasting. Moving Average, on the other hand, is a simple and widely used method that calculates the average of a certain number of previous stock prices to make predictions. Linear Regression, a classical statistical technique, fits a linear equation to historical price data to estimate future prices. Performance measures like Mean Squared Error (MSE) and R-squared are used to assess these approaches. The accuracy of the model is demonstrated by the MSE, which calculates the average squared difference between the anticipated and actual stock values. The percentage of variance in the stock prices and predictors represented by the R-squared number indicates how well the model fits the data. By comparing the performance of these methods, we aim to identify the most effective approach for stock price prediction. The findings of this study can contribute to the field of financial forecasting, providing valuable insights for investors and financial professionals in their decision-making processes. Furthermore, it offers insights into the effectiveness of different prediction techniques. By comparing the performance of LSTM, Moving Average, and Linear Regression, investors and financial professionals can gain a better understanding of the most suitable approach for forecasting stock prices. During the stock price prediction process using the code provided, various algorithms or models are considered and evaluated. Firstly, the data is pre-processed using a MinMaxScaler to bring them

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within a specific range. Each algorithm is trained on the pre-processed data to learn the patterns and relationships between stock prices. Subsequently, the trained models are tested on a dataset to assess their performance and accuracy in predicting stock prices. Evaluation metrics such as Mean Squared Error (MSE) and R-squared are utilized to quantify the performance of each algorithm. The remainder of the paper is divided into the following sections. There is a comprehensive literature review in Section II. The methodology is explained in Section III. A dataset that was utilised in our studies is provided in Section IV, together with a thorough analysis of the outcomes, which compares the effectiveness of the various models. The implications of our conclusions are covered in Section V. Finally, Section VI summarises our findings and provides potential directions for further investigation.

2 LITERATURE SURVEY

In recent years, stock price prediction has attracted significant attention in the field of finance and machine learning. Researchers have explored various techniques, including Long Short-Term Memory (LSTM) models, to capture the complex dynamics of stock market data and improve forecasting accuracy.

Cheung and Chong (1995) used support vector machines and moving averages to empirically analyse stock prices. They investigated how well these techniques predicted changes in stock prices. According to the study's findings, moving average and support vector machines can give investors important information about short-term stock price patterns and aid in their decision-making.

Hochreiter and Schmidhuber (1997) introduced LSTM models as a powerful tool for learning and retaining long term dependencies in sequential data. Their significant work laid the foundation for LSTM's application in various domains, including stock price prediction.

Fabozzi, Focardi, and Kolm (2012) presented a com prehensive book on financial econometrics, covering various modelling techniques for analysing financial data. The book provides a comprehensive overview of the basics and advanced concepts in financial econometrics, including the application of statistical methods like moving averages and regression models for forecasting stock prices.

Al-Yaseen and Sathasivam (2019) proposed a novel time series prediction algorithm utilizing LSTM models for stock market forecasting. Their study showcased the effectiveness of LSTM models in capturing the underlying dynamics of stock prices and outperforming traditional approaches.

Lim and Kim (2019) investigated the application of LSTM-based deep learning models specifically for stock price prediction. They emphasized the robustness and accuracy of LSTM models in capturing complex relationships and patterns in stock market data, highlighting the superiority of deep learning over traditional forecasting methods.

Zhang and Li (2020) focused specifically on forecasting stock prices using LSTM models. Their research provided insights into the design and hyperparameter tuning of LSTM models, leading to improved prediction accuracy.

3 EXISTING SOLUTIONS

Traditional stock price prediction methods have relied primarily on Linear Regression and Moving Average techniques. Linear Regression fits a linear relationship between past stock prices and time, but it assumes that stock prices follow a linear trend, which is rarely the case in the highly volatile and non-linear nature of stock markets. Moving Average smooths, the data by averaging prices over a period, but it suffers from lagging and fails to adapt to rapid market changes, resulting in inaccurate forecasts.

These conventional models struggle with:

- Inability to capture complex non-linear dependencies.
- Poor performance on datasets with long-term temporal dependencies.
- Susceptibility to noise and sudden market fluctuations.
- Limited capacity to model sequential patterns in financial time-series data.

Due to these limitations, there is a significant gap in developing models capable of learning and adapting to the dynamic and stochastic behaviour of stock prices.

4 PROPOSED SOLUTIONS

To overcome the shortcomings of traditional models, the proposed solution leverages a Long Short-Term Memory (LSTM) Neural Network for stock price prediction. LSTM is designed to handle sequential and time-series data, making it suitable for stock market forecasting. LSTM can capture long-term dependencies, retain useful information over

extended periods, and effectively model non-linear relationships between variables.
The proposed LSTM-based approach provides:

- Superior prediction accuracy by learning patterns that span longer timeframes.
- Better handling of non-linearity and volatility present in financial markets.
- Memory cells and gating mechanisms that prevent vanishing gradient problems, common in traditional RNNs.
- Reduction of prediction errors as demonstrated by lower Mean Squared Error (MSE) and higher R-Squared (R^2) values compared to Linear Regression and Moving Average.

By adopting LSTM, the system achieves a more reliable and efficient stock price prediction model, suitable for practical financial decision-making.

5 METHODOLOGY

5.1 Moving Average

A typical stock indicator in technical analysis is the moving average. By producing a continuously updated average price, the moving average of a stock is calculated to in smoothing out the price data and enabling rice data and enable analysts to see trends and patterns. The moving average generates a smoothed line that where represents the mean price across a defined time frame. Traders and analysts use it to identify stock market trends. For example, When the present market value exceeds the moving average, it may signal an ascending trend, whereas a price falling below the moving average could indicate a descending trend. Additionally, many traders utilize the intersection of various moving averages as a method to generate trading cues. For instance, the intersection of a brief-term moving average rising above an extended-term moving average might be interpreted as a positive market signal, potentially indicating a favourable moment for investment.

$$MA = \sum \frac{\text{closing prices over a specified period Number of periods}}{\text{Number of periods}} \quad (1)$$

The limitations of this moving average are lagging indicators because they are based on historical price data, sensitivity to timeframes as different timeframes can produce varying moving average results, rely on price data and do not take into account other critical factors that influence the stock market, such as fundamental analysis, news events, economic indicators, and investor sentiment, in volatile or choppy markets with frequent price fluctuations and no clear trend that may generate false or conflicting signals, These calculations rely on past data, which may not accurately represent present or upcoming market trends.

5.2 Linear Regression

Linear regression is a statistical technique commonly used for stock market predictions. It involves fitting a straight line to historical price data to estimate future price movements. Linear regression is a relatively simple and straightforward statistical technique. It is easy to understand and implement, making it accessible to both beginners and experienced analysts. It provides interpretable results. This model is trained and applied quickly, allowing for rapid analysis and prediction. Linear regression can help identify relevant independent variables that influence stock price movements. By examining the coefficients, analysts can determine which variables have a significant impact on the target variable, aiding in feature selection and model refinement.

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta nxn \quad (2)$$

The target variable and the independent variables are assumed to have a linear relationship using linear regression. However, stock market data often exhibits nonlinear patterns and complexities, which may limit the accuracy of predictions using linear regression alone. To enhance predictions, additional techniques such as polynomial regression, time series analysis, or machine learning algorithms can be employed to capture nonlinear relationships and incorporate more sophisticated modelling approaches.

5.3 LSTM

The purpose of LSTMs is to capture long-term dependencies and patterns in sequential data. Unlike moving averages and linear regression, which do not inherently consider the sequential nature of the data, LSTMs can learn from the historical sequence of stock prices and capture complex temporal relationships. Stock price movements often exhibit nonlinear patterns, which can be challenging to capture with linear regression. LSTMs, with their ability to model complex nonlinear relationships, can capture the intricate dynamics of the stock market by leveraging the memory cells and gating mechanisms within the LSTM architecture. Moving averages and linear regression often rely on a limited set of features, such as historical prices or technical in dicators. LSTMs have the capability to automatically identify and extract relevant features from raw data inputs. This allows them to potentially uncover more subtle and meaningful patterns that may not be immediately obvious or captured by alternative methods. LSTMs have an advantage over simple moving averages and linear regression when dealing with long-term dependencies. They are equipped with memory cells that can store and recall information over extended time periods, allowing them to capture dependencies that occurred further back in time, which is particularly valuable for stock price prediction. LSTMs A. Data Preprocessing can adapt and learn from changing market conditions by continuously updating their weights and biases during training. This adaptability enables the model to adjust to new patterns and trends in the stock market, making it more robust to evolving market dynamics compared to fixed formulas like moving averages or linear regression. Unlike fixed length moving averages or regression models, LSTMs can handle sequential data of varying lengths. This flexibility is essential in stock price prediction, as historical price data may have different time spans, irregular intervals, or missing data points. LSTMs can incorporate additional contextual information, such as news sentiment, market indicators, or macroeconomic factors, alongside historical price data. This broader set of input features allows the model to capture more comprehensive information and potentially improve prediction accuracy. Figure 1 shows the workflow of LSTM whereas Figure 2 shows the Moving Average and Linear Regression.

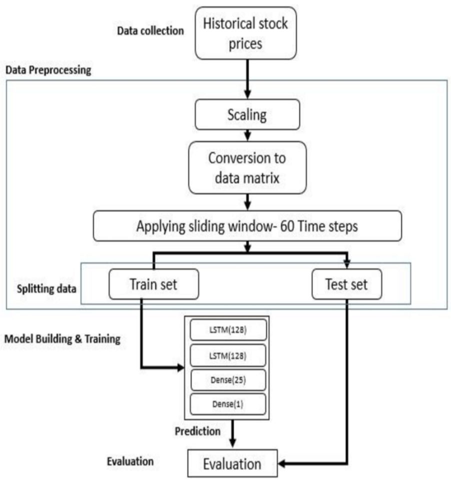

Figure 1: Workflow of LSTM.

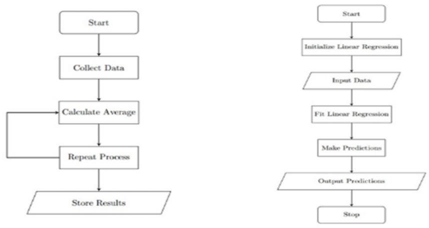

Figure 2: Workflow of moving average and linear regression.

6 EXPERIMENTAL RESULTS

6.1 Data Set Summary

The data set includes columns for date, which includes the open and close dates for stock market data. When trading begins, the stock's initial price; during the trading session, the stock's maximum value attained; throughout the trading period, the stock's minimum value reached; and at the conclusion of trading, the stock's final price, as well as volume, or the total number of shares or contracts exchanged on the day. The dataset's Open column was chosen as the target variable for processing and training the LSTM model, which was then used to the test set to provide predictions.

6.2 Evaluation Metrics

Mean Squared Error (MSE) computes the average of the squared disparities between predicted and actual values. This metric assesses the overall prediction error, with lower MSE scores indicating higher prediction accuracy.

$$MSE = (1/n) \sum(y_{predict} - y_{actual})2 \quad (3)$$

where n is the total number of predictions, $y_{predict}$ is the predicted value, and y_{actual} is the actual value. R-Squared calculates the share of the model's independent variables (predictors) that can be used to explain the variance in the dependent variable (stock market values). It indicates how well the model fits the information.

$$R^2 = 1 - (RSS/TSS) \quad (4)$$

Where TSS and RSS are given by

$$TSS = \sum(y_{actual}, i - y)2 \quad (5)$$

$$RSS = \sum(y_{actual}, i - y_{predict}, i)2 \qquad (6)$$

R^2 ranges from 0 to 1, where a value of 0 means that the model explains no variation and a value of 1 means that it fits the data perfectly. Higher R^2 values show a better fit between the model and the data.

Table 1: Evaluation of Models on JP Morgan Stock Price Dataset.

Method	MSE	R Square
Linear Regression	56.8002	0.8638
Moving Average	175.4034	0.6037
LSTM	27.9309	0.9369

Table-1 shows that LSTM performs best with the lowest MSE of 27.9309 and the highest R-Square of 0.9369, indicating strong predictive accuracy. Linear Regression performs moderately, while the Moving Average method has the highest MSE and lowest R-Square, making it the least effective. These results highlight the advantage of deep learning models for stock price forecasting.

Figure 3 visualizes stock price predictions using Moving Averages, Linear Regression, and LSTM models. The actual stock price (red) shows high volatility, while the Moving Average (blue) smooths fluctuations but lags behind trends. Linear Regression (green) provides a simple upward trend but fails to capture variations. The LSTM model (orange) closely follows actual stock movements, demonstrating its ability to learn complex patterns. This aligns with Table-1, where LSTM had the lowest MSE and highest R-Square, confirming its superior predictive accuracy.

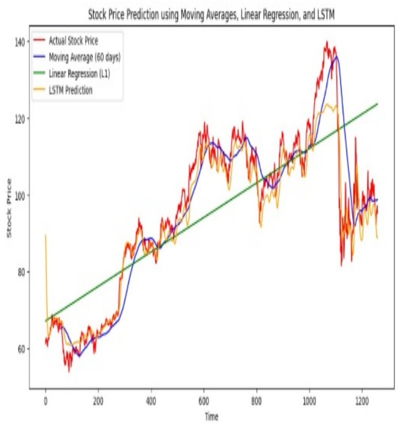

Figure 3: Stock price prediction using moving average, linear regression, and LSTM.

7 DISCUSSIONS AND CONCLUSIONS

Sentiment analysis is beneficial for stock price prediction because it helps capture the influence of investor sentiment and market psychology on stock prices. Monitoring Social Media Sentiment: Sentiment analysis can track and analyse sentiment expressed on social media platforms such as Twitter, Reddit, or Stock Twits. By monitoring relevant hashtags, company mentions, and discussions related to the upcoming earnings report, sentiment analysis algorithms can assess the overall sentiment expressed by retail investors and traders. Positive sentiment may indicate optimism about the company's performance, while negative sentiment may suggest concerns or pessimism. The performance of the LSTM model can be fine-tuned by optimizing its hyperparameters. To determine the ideal set of parameters, methods like grid search or Bayesian optimisation might be used, such as the number of LSTM units, dropout rate, and learning rate. This process can lead to further improvements in prediction accuracy. Exploring additional relevant features such as trading volume, historical trends, and news sentiment can potentially improve the predictive power of the model. Incorporating these features into the model can capture more nuanced patterns and enhance the accuracy of stock price predictions.

In this study, we explored various stock price prediction techniques using the JPMorgan stock price dataset. We implemented Moving Averages, Linear Regression, and Long Short-Term Memory (LSTM) models to forecast future stock values. While Moving Averages provided a simple trend analysis and Linear Regression established a linear relationship with time, the LSTM model outperformed both by capturing complex temporal dependencies in stock prices. Our results highlight the effectiveness of deep learning for financial forecasting, demonstrating that LSTM models offer more accurate predictions by leveraging sequence modeling and historical patterns.

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