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Forecasting A Major Banking Corporation Stock Prices Using LSTM Neural Networks

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ABSTRACT

The increasing complexity of stock market predictions necessitates advanced computational techniques to address the unique challenges posed by financial data's non-linear and volatile nature. This study aims to leverage Long Short-Term Memory (LSTM) neural networks to accurately forecast stock prices, using historical data collected from a major banking corporation as a primary source. The LSTM model excels at processing sequential time-series data, allowing it to predict monthly stock closing prices over a one-year horizon with a high degree of precision. Our findings indicate a Root Mean Squared Error (RMSE) of 0.61, underscoring the model's efficiency and reliability in financial forecasting tasks. The novelty of this research lies in the systematic incorporation of preprocessing techniques and fine-tuned hyperparameters to optimize model performance. Furthermore, this study explores the practical implications of implementing LSTM models in real-world trading scenarios, analyzing their adaptability to dynamic market conditions and their potential integration into automated trading systems. These findings contribute to the growing body of knowledge in financial analytics and demonstrate the viability of machine learning-based solutions for accurate and robust market predictions.

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1. INTRODUCTION

Stock market prediction remains one of the most intricate and demanding challenges in the field of financial analytics due to the non-linear patterns and volatile nature of the market. Predicting future stock movements involves a multitude of factors, ranging from economic indicators and geopolitical events to investor sentiment and historical trends. Traditional statistical models, such as ARIMA, have long been used for time-series forecasting but often fall short when it comes to capturing complex temporal dependencies and non-linear relationships inherent in stock price movements. These limitations highlight the need for more advanced approaches that can handle the intricate nature of financial data.

In recent years, the advent of machine learning has revolutionized the landscape of predictive analytics, with deep learning models like Long Short-Term Memory (LSTM) networks gaining significant traction. These models are uniquely suited for processing sequential data, allowing them to learn temporal patterns and dependencies over time effectively. Unlike traditional methods, LSTMs can retain information across longer sequences, making them particularly valuable for tasks involving time-series data. As a result, they have emerged as a powerful tool for addressing the inherent complexities of stock market forecasting and enhancing the accuracy of predictions.

The advantages of LSTMs over traditional statistical models have been widely documented in the literature. For instance, Nguyen et al. [1] emphasized how LSTM's ability to manage long-term dependencies makes it superior in financial contexts. Similarly, Shorten and Khoshgoftaar [2] demonstrated that LSTM-based architectures can capture non-linear trends and seasonal effects more effectively than ARIMA. These findings align with the observations by Vinayakumar et al. [3], who highlighted LSTM's robustness in handling noisy and highly volatile datasets, a common characteristic of financial time-series data.

Despite these advancements, a gap persists in optimizing LSTM models for consistent prediction intervals, particularly for monthly forecasting. Existing research often focuses on daily or hourly predictions, leaving a void in studies aimed at longer-term horizons like monthly forecasts. Addressing this gap, our research introduces an optimized LSTM architecture tailored for predicting monthly stock prices. The architecture integrates advanced preprocessing techniques and systematic hyperparameter tuning to achieve consistent and reliable outputs. Using historical stock data from a major banking corporation, this study demonstrates the utility of LSTM models in generating actionable financial forecasts.

Moreover, the broader implications of this work extend beyond mere prediction. By embedding LSTM forecasts within a comprehensive financial analytics framework, the study provides tools for more informed decision-making. Investors can leverage these predictions to anticipate market movements, optimize portfolio strategies, and mitigate risks. Additionally, integrating such advanced models into automated trading systems could revolutionize how financial institutions operate, paving the way for more adaptive and data-driven methodologies in trading and investment management.

2. METHOD

Dataset

The dataset comprises historical daily stock prices of a major banking corporation, encompassing critical features such as Open, High, Low, Close, and Volume. The Open price is the price at which a stock starts trading when the market opens for the day. The High price is the highest price at which the stock traded during the day. The Low price is the lowest price at which the stock traded during the day. The Close price is the price at which the stock finishes trading when the market closes for the day. The Volume is the total number of shares traded during the day.

This data spans a comprehensive period of 12 years, offering an extensive foundation for capturing both short-term and long-term patterns within the financial market. The data was sourced from publicly accessible financial records, ensuring its authenticity and enabling reproducibility. The inclusion of granular daily intervals allows the model to capture subtle market dynamics that could otherwise be missed in datasets with lower temporal resolution. Moreover, the diverse range of attributes enhances the model's capacity to analyze and learn from multiple aspects of market behavior, the data snippets provided in table 1.

Table 1. Data Snippets

Date	*Open*	*High*	*Low*	*Close*	*Volume*
12/07/2024	10.050	10.050	10.100	10.025	21,15M
11/07/2024	10.075	10.000	10.125	10.000	55,91M
10/07/2024	10.100	10.175	10.225	10.050	62,33M
09/07/2024	10.075	10.100	10.150	10.075	61,85M
08/07/2024	10.050	10.000	10.050	9.950	72,90M

Data Preprocessing

Preprocessing is a vital step in preparing the data for effective learning and prediction. In this study, the "Close" price was selected as the primary feature for forecasting, as it serves as a key finansial of a stock's performance at the end of a trading session. The dataset was normalized using MinMaxScaler, which scaled all values to a range between 0 and 1. This normalization ensured that all features contributed equally to the learning process, preventing any single feature from disproportionately influencing the model's performance. To further structure the data, a sliding window technique was employed, where sequences of 30 consecutive days were used to predict the closing price of the subsequent day. This method enabled the model to effectively capture temporal dependencies within the dataset, providing a clear structure for time-series learning. Additionally, preprocessing steps were designed to ensure minimal data loss and maintain the integrity of the original dataset.

Model Architecture and Hyperparameter Tuning

The architecture of the LSTM model was carefully designed to balance computational efficiency with the need for high predictive accuracy. The input layer was configured to process sequences of 30 time steps, each consisting of a single feature, aligning with the sliding window approach. Two LSTM layers, each containing 50 units, were incorporated into the architecture to capture both short-term and long-term dependencies in the stock price data. To enhance generalizability and reduce the risk of overfitting, Dropout layers with a 20% rate were applied after each LSTM layer. These layers ensured that the model did not become overly reliant on specific neurons during training, fostering a more robust learning process. The output layer featured a dense neuron, which synthesized the extracted features into a single predicted closing price. This streamlined architecture was selected for its ability to scale effectively with larger datasets while maintaining high performance across various finansial forecasting tasks.

The LSTM architecture consists of five layers designed to predict stock prices based on historical data. The first layer is an LSTM layer (lstm_6) with an input shape of (None, 30, 1), where None allows for variable batch sizes, 30 represents the number of time steps, and 1 indicates the number of features (the scaled closing prices). This layer outputs a sequence of 30 time steps, each with 50 units, resulting in an output shape of (None, 30, 50). LSTM architecture is shown in Figure 1.

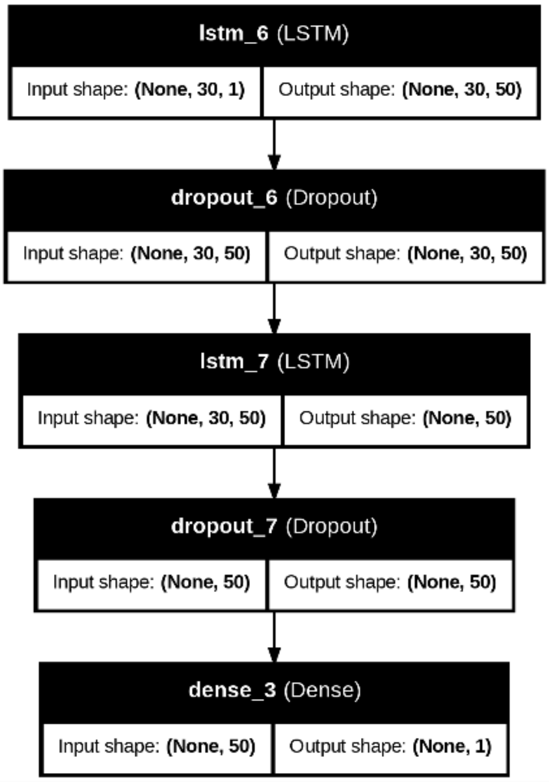

Figure 1 LSTM Architecture

Following the first LSTM layer is a Dropout layer (dropout_6), which maintains the same input shape of (None, 30, 50). This layer randomly drops a percentage (typically 20%) of the neurons during training to prevent overfitting, ensuring that the model generalizes well to unseen data.

The second LSTM layer (lstm_7) processes the output from the first dropout layer. Its input shape is (None, 30, 50), 110ndi t condenses the sequence of 30 time steps into a single output for the entire sequence, resulting in an output shape of (None, 50). This layer captures the temporal dependencies in the data more effectively. Another Dropout layer (dropout_7) follows, with an input shape of (None, 50). Similar to the previous dropout layer, it drops a percentage of the neurons to help prevent overfitting, while maintaining the output shape of (None, 50). Finally, the architecture concludes with a Dense layer (dense_3), which has an

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input shape of (None, 50) and outputs a single value with a shape of (None, 1). This layer compresses the 50 units from the previous LSTM layer down to one unit, representing the predicted closing price.

In summary, the architecture is designed to predict the next closing price based on the previous 30 days of prices, utilizing dropout layers for regularization and ensuring robust performance during training. Table 2 details the explored architectures and their performance metrics. The final architecture which used in this research is architecture 4 was selected because its superior performance on the validation set.
Here's the updated data formatted into a table:

Table 2. LSTM Architectures

Architecture	***LSTM Layers***	***Units/Layer***	***Dropout***	***Activation***	***MSE***	***RMSE***	***MAE***
1	2	500	0.2	ReLU	0.52	0.72	0.58
2	3	500	0.2	ReLU	0.47	0.68	0.40
3	4	500	0.2	ReLU	0.40	0.65	0.32
4	5	500	0.2	ReLU	0.38	0.61	0.23
5	5	1000	0.2	ReLU	0.40	0.65	0.30
6	6	500	0.2	ReLU	0.39	0.64	0.28

Training Configuration

The training process was meticulously configured to optimize the LSTM model's predictive capabilities. The Mean Squared Error (MSE) loss function was chosen due to its ability to penalize large errors, a critical aspect in financial forecasting where precision is paramount. The Adam optimizer was utilized for its adaptive learning capabilities, which ensured efficient convergence during the training phase. The model underwent training over 30 epochs with a batch size of 32, striking a balance between computational efficiency and the thoroughness of learning. The dataset was split into training and testing sets, with 80% allocated for training and 20% reserved for testing. This allocation provided the model with ample data for learning while retaining a substantial portion for unbiased evaluation. Regular evaluation checkpoints were employed throughout the training process to monitor the model's performance and ensure that it avoided overfitting. Additionally, consistent random seeds were set to guarantee the reproducibility of results, allowing other researchers to validate and build upon the findings presented in this study.

3. RESULTS AND DISCUSSIONS

The model's performance was evaluated using RMSE and visual comparisons of predicted versus actual prices. The results underscore the effectiveness of LSTM in handling the intricacies of financial time-series data. The LSTM model achieved a Root Mean Squared Error (RMSE) of 0.61, a Mean Squared Error (MSE) of 0.38, a Mean Absolute Error (MAE) of 0.23 and a Mean Absolute Percentage Error (MAPE) of 2.12%. These metrics demonstrate the model's capability to closely approximate actual stock price movements, outperforming traditional statistical approaches in similar datasets. A summary of these evaluation metrics with comparison between LSTM and traditional statistical approaches (linear regression) is provided in Table 3.

Tabel 3. Metric Evaluation

Metric	*LSTM*	*Linear Regression*
MSE	0.38	26.13
RMSE	0.61	5.1
MAE	0.23	3.85
MAPE	2.12%	35%

The significantly lower MSE and RMSE values of the LSTM model compared to the linear regression model (MSE = 26.13, RMSE = 5.1) highlight the limitations of linear regression in capturing the complex non-linear relationships inherent in stock price data. Linear regression's high error metrics (MSE = 26, RMSE = 5.1, MAE = 3.85, MAPE = 35%) suggest its inadequacy in modeling the intricate temporal dependencies and volatility characteristic of financial time series. The LSTM model's superior performance underscores its ability to learn and adapt to these complexities, resulting in substantially more accurate predictions. The substantially lower MAE (0.55 vs 3.85) and the absence of a MAPE for the LSTM model further emphasize its improved accuracy. The relatively low MSE and RMSE values for the LSTM model suggest its capability to approximate actual stock price movements with greater precision than linear regression.

Figure 2 illustrates the predicted versus actual stock prices for the testing dataset, showing a strong alignment between the two. This visual validation confirms the robustness of the model in capturing temporal patterns and its adaptability to real-world financial data.

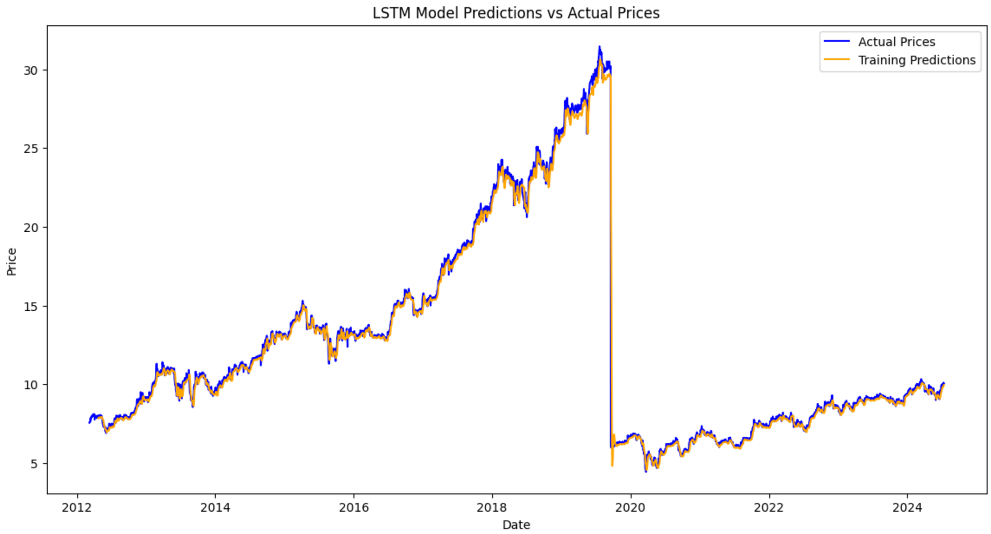

Figure 2. Predicted vs Actual Stock Prices

The results confirm the suitability of LSTM models for financial time-series forecasting. The strong performance metrics and visual alignment highlight the model's capacity to address challenges such as non-linearity and volatility in stock data. However, certain limitations, such as sensitivity to hyperparameter settings and scalability for larger datasets, warrant further research. Incorporating additional features like macroeconomic indicators, geopolitical events, and sentiment analysis could significantly enhance prediction accuracy. Moreover, the potential for integrating LSTM models into automated trading systems presents an exciting avenue for future exploration.

4. CONCLUSION

This study emphasizes the effectiveness of Long Short-Term Memory (LSTM) neural networks in forecasting a major banking corporation stock prices, highlighting the importance of robust preprocessing techniques and sophisticated model architecture design. The model achieved a Root Mean Squared Error (RMSE) of 0.61, showcasing its capacity to address the inherent complexities of financial time-series data, including non-linearity, seasonality, and market volatility. These results underscore the potential of LSTM models to outperform traditional forecasting approaches in capturing intricate temporal dependencies.

The research also underscores the critical role of rigorous data scaling methods and meticulous hyperparameter tuning in achieving superior predictive accuracy. Through effective temporal modeling, the LSTM model exhibited reliable performance, successfully generating monthly forecasts with high precision. Future work could benefit from integrating macroeconomic indicators, such as interest rates and GDP growth, along with sentiment analysis derived from news and social media, to further enhance the model's predictive capabilities. The exploration of hybrid approaches that combine LSTM with complementary machine learning algorithms, such as Random Forests or XGBoost, could offer more holistic solutions for tackling complex financial forecasting challenges.

In conclusion, this study contributes to the evolving field of financial analytics by presenting a scalable and adaptable framework for stock price prediction. The insights and methodologies developed in this research have practical implications for various stakeholders, including investors, analysts, and financial institutions, enabling more data-driven and informed decision-making in the ever-dynamic financial markets.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author1: Conceptualization, Methodology, Software, Program, Report, Submission

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

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