Journal of International Commercial Law and Technology
Print ISSN: 1901-8401

Website: https://www.jiclt.com/

Article

Machine Learning in Financial Markets: A Performance Comparison of Basic and Stacked LSTM Models

Article History:

Name of Author:
Kiranmayi. P[1]*, Dr. K. S. Harish[2], Dr. V. Annapurna[3], Dr. V. Jayalakshmi [4]

Affiliation:
[1]Assistant Professor, Department of Data Science, Siva Sivani Institute of Management, Hyderabad.
[2]Professor, Department of Data Science, Siva Sivani Institute of Management, Hyderabad
[3]Professor, Department of Finance, Siva Sivani Institute of Management, Hyderabad.
[4]Professor, Department of Finance, Siva Sivani Institute of Management, Hyderabad

Corresponding Author:
Kiranmayi. P

Email: *kiranmayip@ssim.ac.in*

How to cite this article:
Kiranmayi P, *et al.* Machine Learning in Financial Markets: A Performance Comparison of Basic and Stacked LSTM Models. *J Int Commer Law Technol.* 2025;6(1):261–269.

Received*: 01-08-2025*
Revised*: 20-08-2025*
Accepted*: 02-09-2025*
Published*: 21-09-2025*

Abstract: Stock price prediction plays a crucial role in financial markets, enabling investors and analysts to make data-driven decisions. The effectiveness of Long Short-Term Memory (LSTM) models, specifically the Basic LSTM Model and the Stacked LSTM Model, is evaluated for forecasting stock prices using 10 years of daily Nifty 50 index data (2015–2024). A time-series analysis approach is applied, where the dataset undergoes preprocessing using MinMax Scaling, and predictions are generated for 30-day, 60-day, and 90-day forecasts. The models are assessed based on key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2) values, to determine prediction accuracy. The findings indicate that the Stacked LSTM Model consistently outperforms the Basic LSTM Model, particularly in 30-day and 90-day forecasts, by demonstrating higher accuracy and lower error rates. In contrast, the Basic LSTM Model exhibits higher deviations in 60-day forecasts, making it less reliable for medium-term predictions. Despite the effectiveness of LSTM-based models in capturing stock price trends, challenges such as market volatility, computational complexity, and hyperparameter sensitivity remain. Future advancements, including hybrid deep learning models, sentiment analysis, and real-time forecasting, could enhance predictive accuracy, making LSTM-based models a valuable tool for financial forecasting.

Keywords— Stock Price Prediction, Long Short-Term Memory (LSTM), Time-Series Forecasting, Nifty 50 Index, Deep Learning, Financial Market Analysis.

INTRODUCTION

Financial markets play a crucial role in economic growth by facilitating capital formation, investment opportunities, and wealth creation. Among these, stock markets serve as a key component, enabling businesses to raise funds while providing investors with avenues for financial growth. The performance of stock markets is influenced by macroeconomic factors such as interest rates, inflation, fiscal policies, and corporate earnings, along with investor sentiment, which significantly impacts price movements. With advancements in financial technology, machine learning and artificial intelligence (AI) techniques have been integrated into stock price forecasting, improving decision-making for investors. Among these, Long Short-Term Memory (LSTM) networks have gained prominence due to their ability to process sequential data and capture long-term dependencies, making them effective for financial time-series forecasting.

India's stock market, among the fastest-growing globally, operates primarily through the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). The NIFTY 50 Index, maintained by the NSE, represents the 50 largest and most liquid companies across various sectors, serving as a key indicator of India's economic health. Given its broad market representation, the NIFTY 50 accounts for over 65% of the total market capitalization of NSE-listed stocks and plays a crucial role in investment performance evaluation, portfolio management, and derivatives trading. Accurate forecasting of NIFTY 50 movements is essential for optimizing investment strategies, risk assessment, and economic analysis.

Stock price prediction is critical for investors, traders, and financial analysts, helping to optimize portfolio performance and mitigate risks. Traditional forecasting methods, such as fundamental and technical analysis, have limitations in volatile markets, making machine learning models like LSTMs a preferred approach. This research evaluates the performance of Basic LSTM and Stacked LSTM models in predicting NIFTY 50 Index movements over different timeframes (30-day, 60-day, and 90-day forecasts). The Basic LSTM model, with a single-layer structure, optimizes computational efficiency, whereas the Stacked LSTM model, with multiple layers, enhances feature extraction and pattern recognition. Performance is assessed using key metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). The findings contribute to the growing role of AI-driven predictive models in financial markets, shaping the future of investment strategies, algorithmic trading, and risk management.

LITERATURE REVIEW

Stock price forecasting has been a significant area of research in financial markets, with machine learning and deep learning models proving to be effective in capturing complex market trends. The NIFTY 50 Index, one of India's leading stock market indices, has been widely used as a benchmark for financial studies due to its representation of the 50 most liquid and actively traded stocks on the National Stock Exchange (NSE). Several studies have explored various methods for predicting stock prices using historical closing prices, trading volume, and financial indicators to enhance forecasting accuracy.

The use of closing prices as the primary variable in stock price prediction has been extensively studied. Ghosh et al. (2019) and Xiao (2023) emphasized that historical closing prices play a crucial role in capturing price trends, as they reflect the final market consensus at the end of a trading session. Yenireddy et al. (2024) further supported this by demonstrating that models trained on sequential closing prices perform better in capturing short-term fluctuations compared to those relying on other financial indicators. Similarly, Bansal, Goyal, and Choudhary (2022) compared different machine learning models, including LSTM, KNN, and SVR, concluding that LSTM models significantly outperform traditional statistical models in processing sequential data for stock price forecasting.

The NIFTY 50 Index has been widely used in stock market research due to its market representation and liquidity. Li (2024) and Demirel et al. (2021) analyzed the impact of market volatility on index-based forecasting, indicating that deep learning models, particularly LSTMs, demonstrate superior performance over conventional forecasting methods such as ARIMA and MLP. Zhao et al. (2024) extended this research by introducing a hybrid CNN-LSTM model that integrated both convolutional layers for feature extraction and LSTM layers for long-term dependency learning, resulting in improved forecasting accuracy for NIFTY 50 stocks.

The application of LSTM models for stock market forecasting has gained considerable attention. Raut & Shrivas (2024) explored stacked LSTM networks and highlighted their ability to capture long-term dependencies, outperforming traditional SVM models. Liu (2024) incorporated sentiment analysis into LSTM models, demonstrating that integrating market sentiment data with stock price history enhances prediction accuracy. Bhanuse et al. (2023) and Deshpande (2023) further emphasized the importance of feature engineering in LSTM-based forecasting, suggesting that including technical indicators such as moving averages, RSI, and MACD improves model robustness.

Financial indicators such as trading volume and volatility measures have been extensively studied in stock price prediction. Bharathi & Ilavarasan (2024) examined how trading volume influences price movement predictions, finding that higher trading volumes lead to more accurate forecasts due to increased market participation. Dhokane & Agarwal (2023) analyzed the role of Exponential Moving Averages (EMA) and Relative Strength Index (RSI) in enhancing LSTM performance, showing that integrating these indicators significantly reduces prediction error.

The effectiveness of Stacked LSTM models over single-layer architectures has been explored in multiple studies. Behura, Pande, and Ramesh (2023) developed a Multi-Layer Sequential LSTM (MLS-LSTM) model, addressing the vanishing gradient issue common in RNNs and proving that deeper networks enhance predictive stability. Wang (2025) conducted a comparative analysis of LSTM and

Bidirectional LSTM (Bi-LSTM), finding that Bi-LSTM improves prediction accuracy by capturing both forward and backward dependencies in stock price trends. Similarly, Vaish et al. (2024) validated that Stacked LSTMs perform better in multi-step forecasting by extracting deeper representations of financial time-series data.

Several studies have also investigated hybrid deep learning models to improve stock price prediction. Mahboob et al. (2023) applied a Stacked LSTM model to the KSE-100 stock exchange, confirming that deeper architectures provide higher accuracy in volatile markets. Gu (2023) transformed stock price fluctuations into a multi-class classification problem, integrating technical indicators with LSTM networks, achieving a 78% prediction accuracy. Chary et al. (2024) explored the combination of LSTM models with feature engineering, hyperparameter tuning, and ensemble learning, demonstrating that optimizing LSTM architectures significantly improves financial forecasting.

Advanced deep learning techniques have also been explored to refine stock price prediction. He (2024) developed an SSA-LSTM model, combining Singular Spectrum Analysis (SSA) with LSTM networks to reduce noise in financial data, leading to a 6% improvement in R^2 scores. Josey & Amrutha (2024) conducted a comparative study between LSTM, Random Forest, and Linear Regression, concluding that LSTM consistently outperforms traditional models in capturing sequential market trends. Nie (2024) examined the impact of window size selection on LSTM models, proving that using an optimal sliding window enhances forecasting accuracy without overfitting.

The integration of attention mechanisms and transformer-based models in stock price forecasting has been a recent area of exploration. Kulkarni et al. (2024) proposed an LSTM-Transformer hybrid model, leveraging transformers to improve sequence learning, achieving higher accuracy than standalone LSTMs. Wang (2024) further analyzed LSTM vs. ARIMA models, confirming that deep learning models reduce error rates by 92% in high-volatility stocks.

The overall literature suggests that deep learning models, particularly LSTM-based architectures, provide superior stock price prediction accuracy compared to traditional methods. The use of closing prices, trading volume, financial indicators, and deep neural networks enhances predictive performance, making LSTM models highly effective for financial forecasting. The comparison between Basic LSTM and Stacked LSTM models highlights the advantages of deeper architectures in capturing long-term dependencies. However, studies also emphasize the need for hybrid models and advanced optimization techniques to further refine forecasting accuracy in dynamic financial markets.

Research Methodology

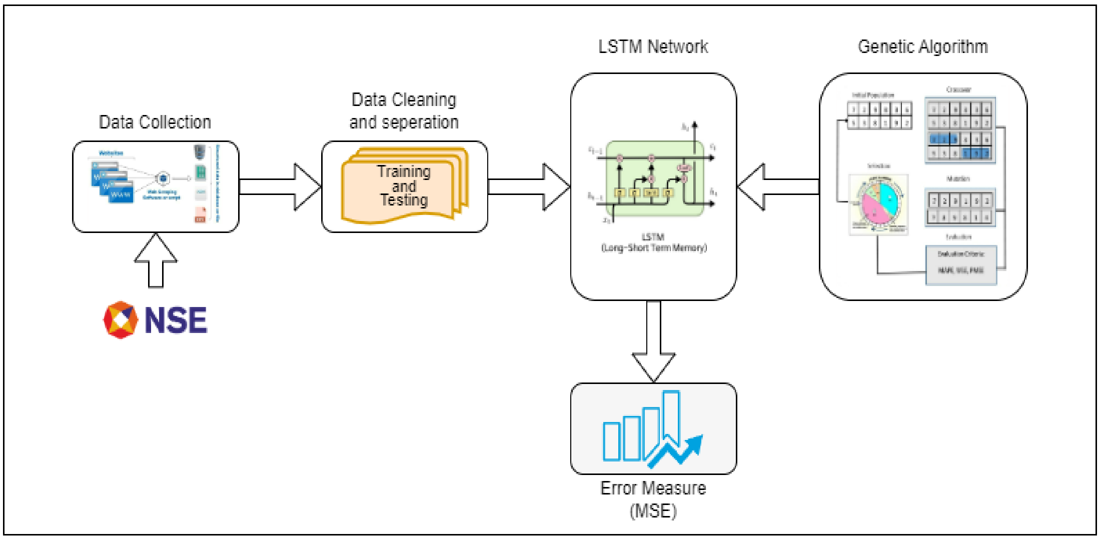
Research Objectives

- To compare the predictive accuracy of Basic LSTM and Stacked LSTM models for NSE Nifty 50 stock price forecasting (2015–2024).
- To evaluate both models over 30-day, 60-day, and 90-day forecasts using MAE, RMSE, MAPE, and R^2 as performance metrics.
- To assess the ability of deep learning models in capturing market trends and patterns in financial time-series data.
- To determine if Stacked LSTM improves accuracy over Basic LSTM by enhancing feature extraction and long-term dependency learning.

Research Design

This research adopts a rigorous empirical and quantitative methodology to forecast NIFTY 50 stock prices for the period 2015–2024, utilizing both Basic LSTM and Stacked LSTM models. A comparative analysis framework is employed to evaluate the performance of these models under consistent conditions, focusing on their predictive accuracy across short-term, mid-term, and long-term horizons. The evaluation metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the R^2 Score. To enhance model precision, preprocessing techniques such as normalization and the transformation of data into a supervised learning format are applied. This study presents a data-centric approach to stock price prediction, aiming to identify the more effective model for delivering accurate future forecasts.

Fig. – 1: Research Model Architecture



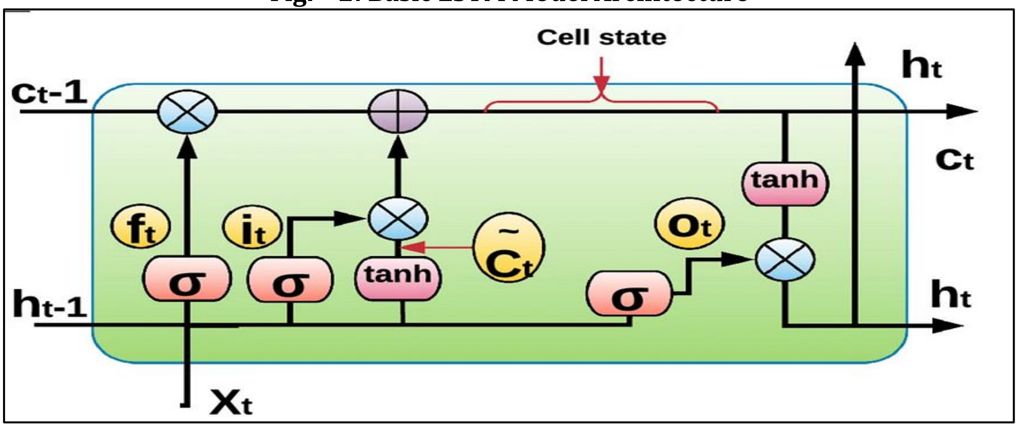
Data Collection

Historical NIFTY 50 Index data (2015–2024) from the National Stock Exchange (NSE) is utilized to develop and evaluate Basic LSTM and Stacked LSTM models for stock price forecasting. The dataset includes Open, High, Low, Close Prices, and Trading Volume, capturing market trends, volatility, and liquidity over a 10-year period. Various market conditions, including bullish and bearish trends, are considered to enhance predictive accuracy. Preprocessing techniques such as normalization and missing value handling improve data quality. Leveraging high-quality stock data ensures robust and data-driven forecasting, supporting informed financial decision-making.

3.4 Selection of Models and their Functioning

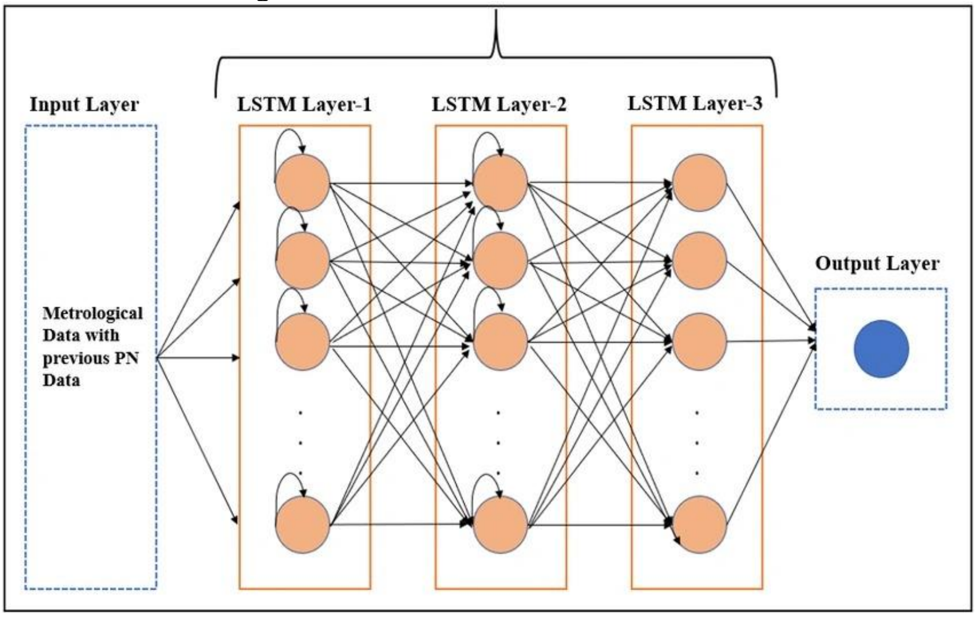
Long Short-Term Memory (LSTM) networks, a specialized type of Recurrent Neural Networks (RNNs), are designed to handle sequential data by overcoming the vanishing gradient problem. Unlike traditional RNNs, LSTMs use memory cells and gating mechanisms to selectively retain relevant information, making them effective for time-series forecasting, where historical trends influence future predictions. Two key implementations include the Basic LSTM Model and the Stacked LSTM Model, each offering unique advantages in stock price forecasting. The Basic LSTM Model consists of a single LSTM layer followed by a Dense output layer, capturing short-term dependencies in stock movements. It processes normalized time-series data, using forget, input, and output gates to filter and retain essential information. The model is optimized using the Adam optimizer and trained using the Mean Squared Error (MSE) loss function. Performance is evaluated with Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared (R^2) Score. While computationally efficient, its ability to capture long-term dependencies is limited, reducing accuracy in extended forecasting.

Fig. – 2: Basic LSTM Model Architecture



The Stacked LSTM Model enhances the Basic LSTM architecture by incorporating multiple LSTM layers, allowing it to extract deeper patterns and learn long-term dependencies. Each LSTM layer refines sequential information before passing it forward, making it more effective for mid-term and long-term predictions. Training requires higher computational resources and longer processing times, but it significantly improves forecasting accuracy. Despite its advantages, careful hyperparameter tuning is essential to prevent overfitting. The Stacked LSTM Model is well-suited for financial market predictions, where capturing complex stock trends is crucial.

Fig. – 3: Stacked LSTM Model Architecture



Model Training and Performance Evaluation

To ensure accurate stock price predictions, Basic LSTM and Stacked LSTM models were trained using 80% of the dataset, while 20% was reserved for testing. Mean Squared Error (MSE) was chosen as the loss function for penalizing large errors, and the Adam optimizer was used to enhance convergence and prevent local minima issues.

Model performance was assessed using Mean Absolute Error (MAE) for average prediction error, Root Mean Squared Error (RMSE) for error variance, Mean Absolute Percentage Error (MAPE) for relative accuracy, and R-Squared (R^2) Score to measure how well predictions align with actual stock prices. Lower MAE, RMSE, and MAPE, along with a higher R^2, indicate better model performance.

By analyzing these metrics, the study determines which model—Basic LSTM or Stacked LSTM—offers superior predictive accuracy for financial forecasting. The findings contribute to the optimization of deep learning approaches in stock price prediction, aiding investment decision-making.

DATA ANALYSIS

The performance of Basic LSTM and Stacked LSTM models in forecasting NIFTY 50 stock prices is analyzed using daily data from 2015 to 2024. Key indicators such as Open, High, Low, Close prices, and Trading Volume are used to capture market trends. The models are developed in Google Colab using Python libraries including TensorFlow, Keras, NumPy, Pandas, and Scikit-Learn. The dataset is split into 80% training and 20% testing. Model accuracy is evaluated using MAE, RMSE, MAPE, and R^2 Score to determine the better-performing approach. The findings support AI-driven financial forecasting, aiding data-informed investment decisions.

Table – 1: Loss Evaluation Metrics Result of Basic and Stacked LSTM Models

LOSS EVALUATION METRICS RESULT						
	Basic LSTM Model			**Stacked LSTM Model**		
	30 Days	**60 Days**	**90 Days**	**30 Days**	**60 Days**	**90 Days**
MAE	306.3816	387.4679	241.2415	180.854	364.4056	182.8013
RMSE	357.317	485.8458	312.7658	232.3992	432.2199	235.2529
MAPE	1.48%	1.72%	1.08%	0.83%	1.63%	0.83%
R-SQUARED	0.9808	0.9642	0.9851	0.9915	0.9668	0.9886

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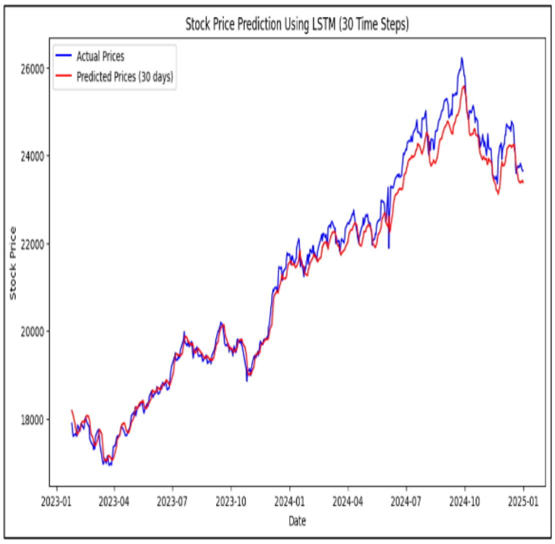
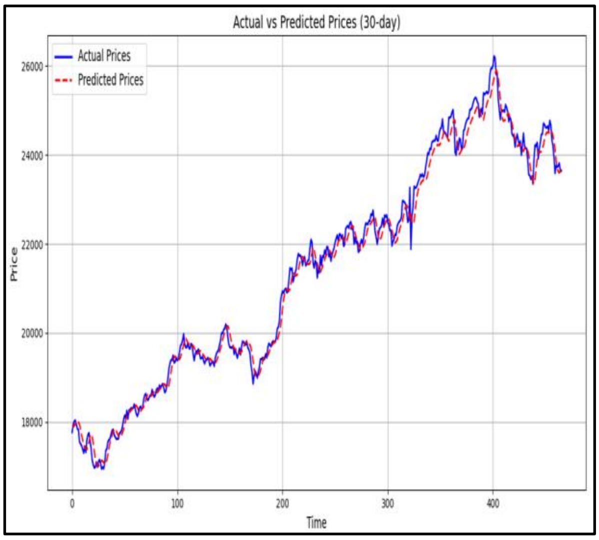
<tr><td>30 Days</td><td>
</td><td>

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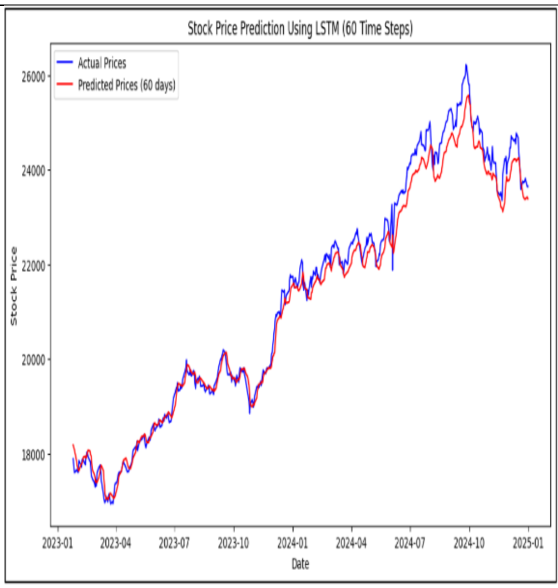
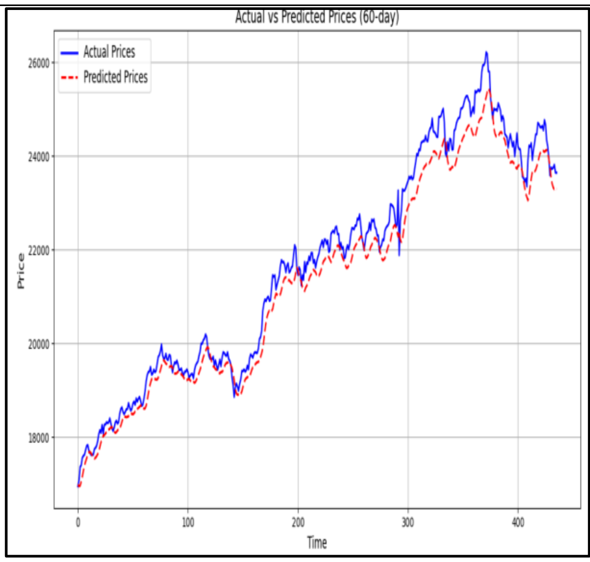
<tr><td>60 Days</td><td>
</td><td>
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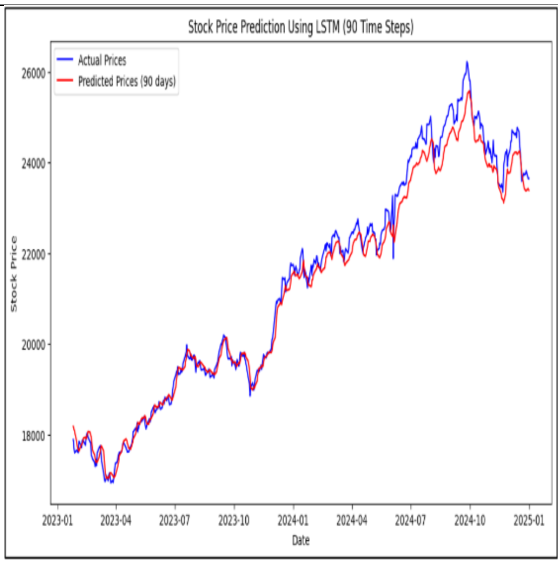
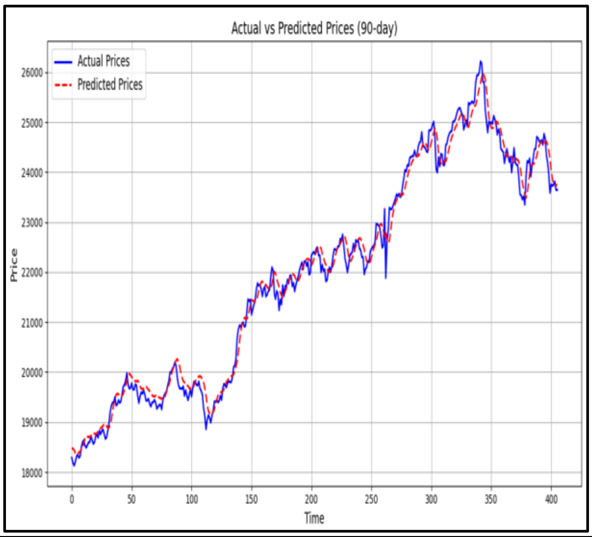
<tr><td>90 Days</td><td>
</td><td>
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Table – 2: Graphical Comparison of Actual vs Predicted Values for Selected Timestamps

From the above table1, the Loss Evaluation Metrics Result presents a detailed comparative analysis of the Basic LSTM Model and the Stacked LSTM Model across three forecast horizons: 30 days, 60 days, and 90 days, using standard evaluation metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the R-Squared (R^2) Score. The MAE results indicate that the Stacked LSTM Model consistently produces lower error values across all time horizons (180.85 vs. 306.38 for 30 days, 364.41 vs. 387.47 for 60 days, and 182.80 vs. 241.24 for 90 days), signifying improved predictive accuracy. Similarly, the RMSE values reinforce this outcome, with the Stacked LSTM Model demonstrating reduced error magnitudes in all scenarios (232.40 vs. 357.32 for 30 days, 432.22 vs. 485.85 for 60 days, and 235.25 vs. 312.77 for 90 days), highlighting its enhanced robustness in handling stock price fluctuations. The MAPE scores further validate the superior performance of the Stacked LSTM Model, especially in the 30-day and 90-day forecasts, where it achieves significantly lower percentages of 0.83% and 1.08%, respectively, compared to the Basic LSTM Model's 1.48% and 1.82%. Furthermore, the R^2 Score, which quantifies the proportion of variance in actual stock prices explained by the model, remains consistently higher for the Stacked LSTM Model across all forecast ranges (0.9915 vs. 0.9808 for 30 days, 0.9668 vs. 0.9642 for 60 days, and 0.9886 vs. 0.9851 for 90 days), confirming its superior goodness-of-fit. In summary, the Stacked LSTM Model demonstrates greater effectiveness in minimizing prediction errors and enhancing overall forecast accuracy, making it a more reliable and suitable model for stock price prediction across multiple time horizons

Findings

The results indicate that the Stacked LSTM Model consistently outperformed the Basic LSTM Model across all forecast periods, effectively capturing complex stock price patterns. The 30-day and 90-day forecasts showed the highest accuracy, with R^2 exceeding 0.98 and MAPE as low as 0.83%, while the Basic LSTM Model struggled with 60-day predictions, exhibiting higher error values. The Stacked LSTM Model demonstrated strong predictive performance, particularly in short-term and long-term forecasts, while medium-term (60-day) predictions required further refinement. Overall, the study highlights the effectiveness of LSTM models in stock price forecasting, offering valuable insights for financial decision-making.

Limitations

The study focuses solely on historical stock prices, excluding macroeconomic factors, financial news, and investor sentiment, which impact stock movements. LSTM models struggle with sudden price fluctuations due to economic crises, policy changes, or global events, affecting prediction accuracy. Model performance is highly dependent on hyperparameter tuning, where improper adjustments can lead to overfitting or underfitting. Additionally, training deep learning models requires significant computational power, posing challenges for real-time stock predictions without advanced hardware. The 60-day forecast exhibited higher errors than the 30-day and 90-day predictions, emphasizing the need for improved medium-term forecasting.

Scope

Improving the accuracy of stock price predictions can be effectively accomplished by incorporating a combination of technical and fundamental indicators such as trading volume, the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD). The application of Natural Language Processing (NLP) techniques to analyze financial news articles, corporate disclosures, and prevailing sentiments on social media platforms offers an additional layer of insight that enhances forecasting reliability. Integrating Long Short-Term Memory (LSTM) networks with more advanced architectures, including Gated Recurrent Units (GRU), Transformer-based models, or hybrid approaches like CNN-LSTM, can substantially elevate predictive performance. Employing real-time data streams for forecasting enables the development of models with greater applicability in dynamic market environments. Moreover, refining model efficiency and enhancing predictive precision can be achieved by employing hyperparameter optimization methods such as Bayesian Optimization, Grid Search, or Genetic Algorithms.

Conclusion

The performance of Basic LSTM and Stacked LSTM models is evaluated using ten years of daily NSE Nifty 50 data (2015–2024). Findings show that the Stacked LSTM consistently outperforms the Basic LSTM across 30-day, 60-day, and 90-day forecasts, with key metrics confirming its higher accuracy. Short-term (30-day) and long-term (90-day) predictions are more reliable, while medium-term (60-day) forecasts exhibit higher error margins. LSTM models effectively capture temporal stock market patterns, supporting data-driven investment decisions. Incorporating variables such as technical indicators, macroeconomic factors, or sentiment analysis may enhance predictive precision, and future work could explore hybrid or attention-based models for improved adaptability.

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