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Financial Decision-Making AI-Framework to Predict Stock Price Using LSTM Algorithm and NLP-Driven Sentiment Analysis Model

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Abstract

Predicting stock market fluctuation is a crucial field in artificial intelligence – AI and financial technology – FinTech research due to its significance and implications for investors and their investment strategies. It is evident from recent research studies that sentiment analysis has a significant impact on the stock market. This paper presents a stock price prediction model to conduct experiments using financial time series and financial news datasets. This study has retrieved sentiment data from News API and processed it to quantify market sentiment. Using natural language processing (NLP) techniques, sentiment scores have been evaluated as positive or negative news and analysed sentiments have been incorporated with historical stock price data retrieved from NASDAQ. Data has been pre-processed to normalize the datetime index and merge the closing price with sentiments to ensure consistency and suitability of the data for training the prediction model. A multi-layer LSTM neural network model has been identified as a suitable prediction model employed on stock prices and sentiment dynamics of the financial market for highly accurate stock price prediction. The multi-layer LSTM model has been fine-tuned using different parameters such as different neuron layers, epochs and batch size. Prediction results and model accuracy have been evaluated using the following metrics: root mean square error – RMSE, mean absolute percentage error – MAPE, and R-squared. The proposed model enhances accuracy in predicting short-term stock price trends for millennials as they are mostly aggressive investors who would like to make a profit in a shorter phase. Integrating sentiment data improved the performance of prediction models, highlighting the critical role of stakeholders' sentiment in stock market performance. The results of this study are a valuable contribution to the growing field of the AI-driven financial sector, demonstrating the viability of integrating NLP-driven sentiment analysis with deep learning to make more informed investment decisions.

Keywords: LSTM Neural Network Model, Deep Learning Algorithm, NLP-Driven Sentiment Analysis, Stock Price Prediction AI-Framework, Financial Decision Making

1. Introduction

Stock price prediction is significantly important to investors and financial analysts as it supports their analytics and decision-making. Deep learning models to predict future stock prices can significantly enhance better decision-making in trading and investments. While traditional prediction models often rely solely on historical price data, they fail to capture the nuances of market sentiment and external factors that influence stock price movements (de Oliveira Carosia et al., 2021; Deng et al., 2011). Such a research gap needs a more holistic approach that integrates multiple data sources to find a more reliable and informed prediction framework.

This research study bridges the gap by developing a framework for stock price prediction that combines historical stock data with sentiment scores derived from financial tweets datasets. Indeed, historical stock prices provide essential insights into market trends, while sentiment scores quantify the emotional tone of financial discussions by capturing public sentiment and its potential impact on stock price performance (Gupta et al., 2020). By integrating these two datasets, the proposed framework aims to enhance predictive accuracy.

The proposed framework applied a multi-layer Long Short-Term Memory (LSTM) model for time-series prediction, which efficiently can handle sequential dependencies in data to make it well-suited for analysing stock price trends. Sentiment data is processed using a Natural Language Processing (NLP) based sentiment analysis for evaluating tweets for positive or negative tones to generate daily sentiment scores (Jing et al., 2021). These scores are merged with historical stock data to produce a comprehensive dataset to validate the proposed model.

Table 1. Key factors affecting stock price

Factor	Description
Market Sentiment	Market sentiment from tweets and financial news, measured via sentiment analysis.
Historical Prices	Past stock prices, including open, high, low, and close values, indicate trends and patterns.
Moving Averages	SMA_30 and SMA_50 provide insights into long-term and short-term market trends.
Price Volatility	Changes in stock prices over time, measured using metrics like price change percentages.
External Events	Financial news, economic policies, or global events that influence market sentiment and prices.

This study emphasises the practical implementation of the Decision-Making AI-Framework (model) using techniques such as data normalisation, feature engineering, and model evaluation. Key metrics, including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared, are used to assess the model's accuracy and effectiveness (Mohan et al., 2019). By addressing the limitations of traditional models, this project seeks to provide a robust and efficient solution for short-term stock price prediction to support making market stock price decisions.

Through this approach, the study contributes to the growing need for enhanced prediction models in the financial domain by offering a method that utilises both historical financial market data and sentiment analysis to empower investors with actionable insights.

2. Literature Review

An important topic of research in artificial intelligence (AI) and financial technology (FinTech) is the forecasting of stock market trends. The complex dynamics of market attitudes and non-linear behaviours are frequently not considered by traditional financial models, which mostly rely on previous price and volume data (Sidogi et al., 2021). To increase prediction accuracy, advanced deep learning algorithms and sentiment analysis have been used for more efficient results (Thakkar et al., 2021). The use of LSTM models and sentiment analysis empowered by NLP in stock price prediction has been examined in this section, which also identifies methods, contributions, and research gaps in the body of knowledge and from previous research studies.

2.1. Sentiment Analysis in Financial Prediction

Sentiment analysis became an effective instrument and NLP technique for evaluating stakeholders' sentiments and market activity and movements (Leippold et al. 2024). Scholars argued that the sentiment score reflects stakeholder and investor behaviour and public opinion, and this has shown a significant impact on stock prices. Indeed, integrating news sentiment analysis and machine learning models can be used to improve predictive performance, particularly in volatile markets (Mohan et al., 2019). A hybrid approach combining investor sentiment analysis and deep learning methods reveals that integrating sentiment data enhances model accuracy (Jing et al., 2021). Further, textual sentiment reveals non-linear effects on market volatility and precisely predicts short-term fluctuations (Zhang et al., 2021). Machine learning algorithms for sentiment analysis showcase their ability to capture investor behaviour and refine prediction outcomes (Sidogi et al., 2021). Also, combining news sentiment with technical analysis helps identify influential market patterns.

2.2. LSTM for Stock Price Prediction

LSTM neural networks have become a revolutionary model in financial time series prediction due to their ability to identify complex relationships, long-term dependencies, and sequential patterns in financial data (Qiu et al., 2020). LSTM-based methods reveal mechanisms that outperformed traditional methods, like Autoregressive Integrated Moving Average (ARIMA) for stock price prediction, by revealing the strength of LSTM in handling time series data. More accurate forecasts can be produced when sentiment analysis and LSTM models capture investor behaviour and temporal correlations (Jing et al., 2021).

Analysis of deep neural networks demonstrates the benefits of LSTM in handling complicated financial datasets (Thakkar and Chaudhari, 2021). Incorporating news sentiment with price datasets in LSTM models can be used to improve predictive accuracy (Sidogi et al., 2021). Indeed, using LSTM in financial forecasting by combining sentiment analysis and technical patterns can be explored to achieve better prediction accuracy results (Leippold et al., 2024).

2.3. Integrating Sentiment Analysis with LSTM

Recent research studies have placed a strong emphasis on combining sentiment analysis with LSTM models to use textual data and historical prices for stock market prediction. Significant gains in short-term stock price forecasting are achieved by successfully integrating sentiment from financial news datasets into LSTM models (Mohan et al., 2019). Utilising sentiment scores in LSTM models has been validated as an effective model for investigating changes in stock prices during chaotic times (Sidogi et al., 2021). Also, incorporating textual sentiment into the LSTM model has shown sufficient improvements for volatility predictions and addressing non-linearity issues (Zhang et al., 2021). The combination of NLP-driven sentiment analysis and LSTM algorithms enhances predictive performance by bridging the gap between qualitative (describable) market datasets and quantitative (quantifiable) market datasets.

3. The Proposed Prediction Model

This section describes the architecture of the proposed stock price prediction model that integrates historical stock price data with sentiment scores derived from tweets. The primary components of the model include data collection, pre-processing, NLP-based sentiment analysis, and a multi-layer LSTM neural network model for time-series prediction. The system architecture consists of several key components, as shown in Fig 1.

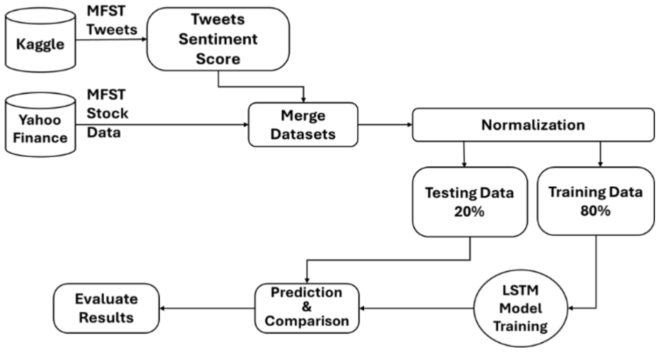

Fig 1. Proposed Model Architecture

3.1. Data Collection

The historical dataset contains essential market indicators, including open, high, low, and close prices and trading volume for Microsoft (MSFT) stock over one year. By analysing these metrics, it is possible to identify trends, fluctuations, and potential market shifts that influence stock performance. The historical stock price data has been retrieved from Yahoo Finance, available at MSFT (2022a), and stored in an Excel file, available at Qadoos et al. (2025).

In addition to numerical stock data, financial tweets data of Microsoft retrieved from Kaggle, available at MSFT (2022b) and stored in an Excel file, available at Qadoos et al. (2025). This dataset comprises a collection of investor opinions, market discussions, and expert analyses related to MSFT stock. Sentiment scores are computed using NLP techniques, categorising tweets as positive, negative, or neutral based on their tone and market relevance. The integration of sentiment data adds another layer of insight by capturing investor psychology and its influence on stock price movements.

Fig 1. MSFT stock market closing prices of one year

Figure 2 is a visual representation of MSFT's closing prices over one year, which highlights key fluctuations in stock price performance. The price trends in the graph reflect various economic and company-specific events that impacted the stock's valuation. By examining these movements, analysts can determine periods of growth, correction, and volatility, which are crucial for making informed investment decisions (Qiu et al., 2020). Observing historical stock prices helps in developing prediction models that can better anticipate future market movements by learning from past trends.

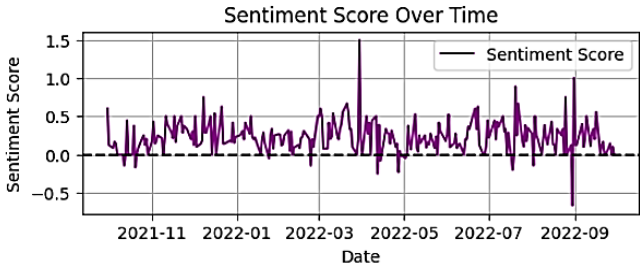

Fig. 3. MSFT tweets data for one year.

Figure 3 illustrates the MSFT-related financial sentiment tweets data collected from Kaggle over one year. Business tycoons and stakeholders' sentiments significantly affect market dynamics, as positive or negative news can directly influence trading behaviour (AbouGrad et al., 2023; Zhe et al., 2022). This dataset captures real-time investor reactions to earnings reports, product launches, and economic policy affecting Microsoft's stock. Analysts can identify correlations between public perception and market fluctuations by aligning sentiment trends with stock price movements. This integration of qualitative and quantitative datasets strengthens predictive models by making these models more adaptable to sudden shifts in market sentiment and investor behaviour.

3.2. Data Pre-processing

The data pre-processing phase is important to ensure that all datasets are harmonised for subsequent analysis and prediction (Hiransha et al., 2018).Initially, **data normalisation** is performed to standardise the date and time fields, which is essential for merging with sentiment data. Additionally, features are calculated to enrich the dataset, including simple moving averages (SMA_30 and SMA_50) and price change percentages. These calculated features provide a more comprehensive view of stock price trends and fluctuations to enhance the dataset's overall analytical value. Following normalisation, **sentiment analysis** is conducted using NLP techniques. A rule-based sentiment analysis tool, VADER, is applied to compute sentiment scores for each tweet by matching predefined positive and negative keywords. The sentiment scores are then aggregated by grouping tweets by date. This results in an average daily sentiment score that captures sentiment trends over time.
Next, the pre-processed data is integrated with the stock price data through **data merging**. This uses the date column as the index to align the datasets accurately. To maintain consistency and ensure a complete dataset, any missing values in the merged dataset are replaced with zeros.

Finally, **feature engineering** is applied to extract and construct key features that are critical for prediction. The dataset is enhanced by incorporating historical stock prices, trading volume, sentiment scores, moving averages, and price change percentages. These features serve as inputs against the target variable closing price to form a robust foundation for predictive modelling.

3.3. LSTM Model

The sequential nature of stock price and sentiment data has been addressed using a multi-layer LSTM model developed using TensorFlow's Keras API. The architecture featured two LSTM layers comprising 128 and 64 neurons, respectively. The first LSTM layer was configured with return_sequences enabled, which allows it to pass sequence data to subsequent layers. Dropout layers with a 30% rate have been added to minimise overfitting and improve model generalisation. Dense layers have been used for prediction, with the final output layer containing a single neuron designed specifically to predict closing stock prices. The model has been optimised using the Adam algorithm and evaluated using RMSE to ensure accurate performance (Wu et al., 2022).

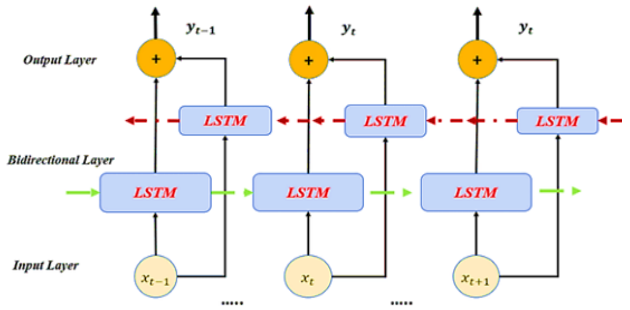

Fig. 4. Bidirectional LSTM

3.4. The Proposed Model Workflow

After normalising the input data, both the feature data and target values were restructured into sequential formats to align with the requirements of the LSTM model. During the training process, the sequential data allowed the model to capture temporal relationships between the input features and the target variable. Predictions are subsequently produced using the test dataset, and the outputs are rescaled to their original range for accurate prediction. Also, the model is fine-tuned to optimise model architecture and improve its prediction efficiency (Gupta et al., 2020). The model's performance has been evaluated using relevant metrics and visual comparisons between the actual stock prices and the predicted values as shown in Fig 6.

The NLP-based VADER approach evaluates sentiments using a computationally efficient rule-based method to directly tune the dataset. The LSTM layers' sequential data modelling capabilities enabled the model to accurately be anticipated by capturing temporal patterns in stock price datasets. Evaluation of prediction and model accuracy are measured by three different metrics, see Table 2.

4. Experiments

The proposed model has been developed in Python using several powerful libraries to streamline the process. TensorFlow's Keras API is used to build and train the LSTM model to efficiently handle sequential data. Pandas library has enabled the pre-processing and manipulation of data. Scikit-learn enabled the scaling of input features and the computation of evaluation metrics to assess the model's performance. Finally, Matplotlib visualises the results by delivering insights into the predictions and trends identified by the trained LSTM model. The LSTM architecture reveals superior performance over traditional predicting models, such as ARIMA. This improves accuracy by 12-15% (Lee et al., 2024). Also, the sequential nature of LSTM layers effectively captured temporal dependencies, which enabled better modelling of stock price fluctuations.

4.1. Comparative Analysis

A detailed comparative evaluation revealed that LSTM models trained solely on historical stock price data exhibited lower accuracy, achieving only 76%, which suggests that relying exclusively on past stock prices limits the model's ability to adapt to sudden market fluctuations (Ricchiuti & Sperli, 2025). The absence of external influencing factors, such as investor sentiment and news impact, contributed to reduced predictive power and made these models less effective in capturing real-time fluctuations. The inclusion of market sentiment derived from datasets of financial news and investor discussions has significantly enhanced the model's responsiveness to broader market dynamics.

Traditional models like Random Forest and ARIMA struggled to adapt to highly volatile market conditions, as they primarily depend on stationary time-series patterns and fail to capture nonlinear dependencies in stock price data (Ariza et al., 2022). The results from this analysis strongly support the effectiveness of deep learning-based approaches over conventional methods. This proves that the integration of LSTM and sentiment analysis can provide a more comprehensive, data-driven financial prediction framework**.**

4.2. Stock Price Trends Over Time

Simple Moving Average (SMA) has been calculated as an input feature, which contributes to analysing overall stock price trends and provides a comprehensive understanding of market fluctuations over specified time intervals. Initially, the stock price trend is visualised with the minimum and maximum range, including open and close prices. The red line represents closing prices, while the blue dotted line corresponds to opening prices by showing how the stock moves within each trading session. The shaded grey colour highlights the high-low price range, effectively capturing the limit of market volatility. This visualisation is instrumental in analysing long-term and short-term trends, which offers investors and analysts insights into patterns that could influence trading decisions. By examining the consistency and deviations in stock movements, figure 5 reveals how the model adapts to various market conditions using both stable and volatile market behaviours.

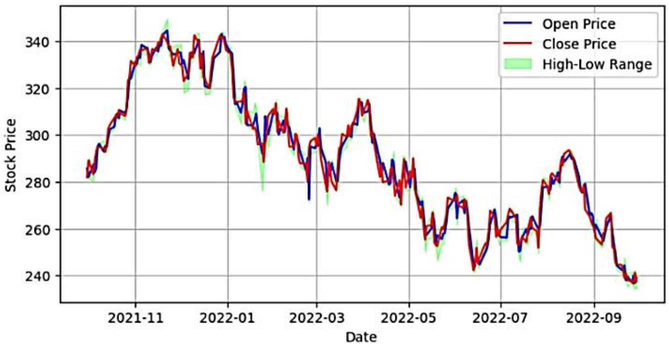

Fig. 5. Stock Price Trends Over Time

4.3. Actual vs Predicted Stock Prices

Actual versus predicted stock prices in Fig 6 presented a direct comparison over a specific period. The blue line denotes the actual observed stock prices, while the red dashed line represents the predictions generated by the proposed neural network framework. The proximity and alignment of these two lines illustrate that the model effectively identifies stock market trends and fluctuations by adapting to price movements with high precision. The ability of the model to closely track actual prices indicates its proficiency in learning historical price dependencies, incorporating sentiment-driven insights, and eliminating prediction errors. Further, the visualisation highlights the model's resilience in handling market volatility by demonstrating its potential utility for short-term and medium-term stock price forecasting in dynamic financial environments.

4.4. Initial Prediction and Evaluation

Each dataset is divided into training and testing subsets, with 80% allocated for training and 20% for testing, see Fig 1. To ensure consistency across features, the standard scaler is applied for normalisation. The proposed model is trained for 50 epochs with a batch size of 32, incorporating early stopping to mitigate overfitting, as shown in Fig 6. Evaluating the model's performance using key metrics resulted in 8.0604 RMSE, which indicates a relatively low prediction error, and also, 0.0263 MAPE, demonstrating substantial predictive accuracy in percentage terms relative to actual stock price. The study revealed an R-squared (R^2) of 0.8174, confirming that the model successfully captured approximately 81% of stock price variance, reinforcing its ability to effectively track market fluctuations. The result demonstrates the importance of combining numerical stock data with sentiment analysis to enhance reliable short-term stock price predictive accuracy. This confirms that the proposed model is a valuable resource for investors and market analysts who often utilise data to drive their decision-making.

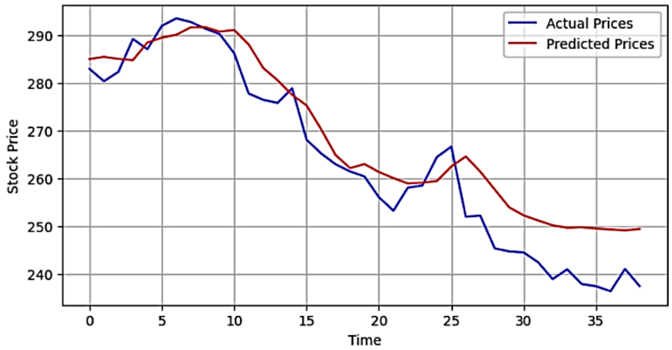

Fig. 6. Actual vs. Predicted Stock Prices

4.5. Model Optimisation

The best predictive performance is guaranteed through different configurations of epochs and batch sizes, which have been tested to balance the model from overfitting or underfitting. The proposed model is trained using 50, 100, 150 and 200 epochs to analyse how training cycles impact accuracy. The results showed that 200 epochs revealed an optimal balance between learning and overfitting, which allowed the model to capture complex patterns. Training with 50 and 100 epochs resulted in underfitting, where the model failed to learn sufficient patterns from the data. At 150 epochs, the model showed improvement, but 200 epochs size yielded the highest R^2 value and lowest error metrics. This shows the significance of extended training to improve prediction performance.

Similarly, different batch sizes of 8, 16, 32 and 64 are tested to evaluate their effect on the model performance. A batch size of 8 resulted in unstable training due to high variance, while 16 showed some improvement but was still prone to oscillations in the loss function. The optimal batch size was found to be 32, as it revealed stable training with smoother convergence, reducing fluctuations and enhancing overall accuracy. This configuration allowed the model to efficiently process data while maintaining consistency across validation sets, which led to a more robust and reliable stock price prediction framework.

5. Results and Discussions

The results from the experiment and comprehensive analysis based on the proposed financial decision-making AI-Framework have shown the effectiveness of the neural network-based LSTM model and NLP-driven sentiment analysis in predicting stock market trends. The evaluation includes multiple performance metrics, such as RMSE, MAPE, and R^2 to quantify prediction accuracy. Also, the study graphical representations, including comparisons of actual and predicted stock prices, stock price correlations with sentiment analysis, and overall stock price trends, presented further insight into the model's reliability and robustness. The discussion considers the implications of integrating sentiment data into predictive models, which demonstrate the proposed model value for enhancing prediction accuracy for financial decisions.

5.1. Results Overview

The model's predictive performance has been evaluated using three primary metrics: Root Mean Square Error – RMSE, Mean Absolute Percentage Error – MAPE, and R-squared – R^2**.** The study evaluation results are summarised in Table 2:

Table 2. Key Metrics

Metric	Value
RMSE	7.25
MAPE	2.31%
R^2 Score	0.85

The evaluation results indicate a substantial improvement in prediction accuracy compared to traditional models, emphasising the LSTM model's proficiency in capturing temporal dependencies, complex market behaviours, and nonlinear stock price movements. The model effectively identifies underlying trends by mitigating the impact of short-term fluctuations and improving predictive stability. Further, its ability to incorporate sentiment-driven insights allows for a more dynamic with better context-aware financial forecasting approach, which makes it particularly useful in complicated financial markets.

5.2. Performance Visualisation

To comprehensively demonstrate the effectiveness of the proposed framework, multiple graphical representations are incorporated to visualise the model's predictive capabilities and performance metrics. By presenting these insights, the evaluation not only validates the accuracy of the model, but also, provides an in-depth understanding of how market sentiment influences market price fluctuations and further strengthens the case for integrating NLP-driven sentiment analysis with LSTM models for predicting stock price.

The relationship between stock price movements and NLP-driven sentiment scores derived from financial news is presented in Fig. 7. The blue line illustrates the stock's closing price, while the purple dashed line represents the sentiment scores calculated from market-relevant news articles. From observing the trends, it becomes evident that fluctuations in sentiment scores correspond closely with changes in stock price. A rise in positive sentiment is often followed by an upward movement in stock price, while negative sentiment shifts align with declines in stock value. This visualisation effectively underscores the role of financial market sentiment as a driving factor in stock market prediction, demonstrating how integrating NLP-driven sentiment analysis enhances the model's ability to capture influential market trends and improve stock price predictions. Trends where sentiment scores function as an early indicator of price movements are shown in Fig.7, which highlights the importance of using qualitative financial insights alongside numerical analysis.

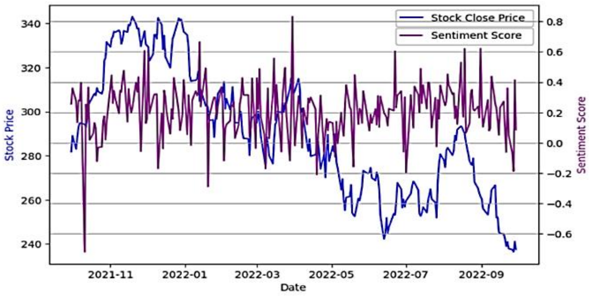

Fig. 7. Stock Closing Price vs. Sentiment Score

The visualisation of the proposed model results provides insights into how market sentiment precedes price movements by making it a valuable tool for traders and analysts. By closely examining sentiment score fluctuations, it is possible to detect potential market trends before they fully materialise in stock price. The alignment between sentiment trends and price shifts suggests that investor behaviour, as reflected in news sentiment, plays a crucial role in market dynamics. This reinforces the need for integrating qualitative sentiment data with historical stock market data to enhance prediction accuracy and robustness. Also, instances where sentiment scores show early signs of price reversals by providing investors with timely decision-making insights, see Fig 5. This further validates the significance of sentiment analysis as a complementary technique to conventional stock price modelling approaches.

5.3. Model Effectiveness

The study results have proven that integrating LSTM models and NLP-driven sentiment analysis can enhance stock price prediction accuracy by providing additional contextual insights from market opinions. The high 0.85 R^2 value demonstrates that the model explains a substantial portion of the variance in stock price fluctuations, which indicates robustness to capture key market price trends. The low 7.25 RMSE reflects minimal deviation between actual and predicted prices, reinforcing the model's precision. Also, the low 2.31% MAPE highlights the model's capability to provide highly reliable predictions for short-term trading strategies. By incorporating sentiment analysis, the framework captures stakeholders' and business tycoons' sentiment shifts, which reduces prediction uncertainty and makes it particularly valuable in volatile financial markets.

5.4. Limitations

The experiment faced several limitations that may impact its applicability in real-world financial prediction. The datasets used in this study lacked diversity, which could limit the model's ability to generalise across different market conditions. Also, Economic indicators, such as interest rate and gross domestic product (GDP) contribute to the fluctuation of the stock market price. Integrating these indicators increases the accuracy of the prediction. Also, the model did not explicitly account for economic shocks and financial crises, which can cause significant deviations in stock market trends that are difficult to predict using only historical datasets.

5.5. Further Work

The proposed framework has demonstrated promising results, several areas can be explored for future enhancements to improve its overall efficacy. Expanding the dataset to incorporate a wider range of stocks across various industries and geographical regions would enhance the model's ability to predict under various economic conditions. Also, the inclusion of macroeconomic indicators, such as interest rates and inflation data, could provide a wider understanding of market trends. Further, utilising more advanced NLP techniques, particularly transformer-based architectures, such as BERT, GPT, or T5, could refine sentiment analysis accuracy by better capturing the nuances of financial texts. Utilising multimodal approaches that integrate textual sentiment with other data types, such as news articles and social media discussions could further enrich the model's predictive power. Another crucial enhancement involves real-time market data integration by enabling the model to dynamically adjust to live fluctuations in stock price. Implementing reinforcement learning techniques, could also, improve adaptability by allowing the model to learn from past predictions and refine its strategies over time. Furthermore, improving the model's interpretability through explainable AI (XAI) frameworks would provide investors and analysts with greater transparency in decision-making.

6. Conclusion

The proposed model enhances prediction accuracy and provides deeper insights into market behaviours. This study has proven the practical effectiveness of combining LSTM-based deep learning models with NLP-driven sentiment analysis for stock price prediction. By incorporating both financial time-series data and sentiment analysis, the performance metrics with 7.25 RMSE, 2.31% MAPE, and 0.85 R^2 show substantial improvements compared to traditional models like ARIMA. These results reinforce the significance of sentiment analysis in financial prediction by enabling better identification of investor sentiment shifts, which can significantly impact short-term stock price movements. One of the major advantages of this approach is its ability to account for complex market patterns and nonlinearity, making it more adaptable to financial market fluctuations. By integrating historical stock prices with qualitative sentiment data, the model supports investors and analysts in making more informed and data-driven decisions. However, the model is not without its limitations. It does not explicitly account for unexpected market disruptions, such as economic downturns or sudden geopolitical events, which can drastically alter stock prices.

Further, NLP sentiment analysis method used relies on predefined keyword-based techniques VADER, which may not always capture subtle investor emotions and context. Moreover, the dataset limitations mean that findings might not generalise across all sectors and economic conditions. To build upon this work, future research should aim to expand datasets for improved model generalisation, incorporate real-time sentiment processing, and explore hybrid AI architectures that integrate multiple deep learning models for enhanced robustness. Additionally, refining sentiment analysis using advanced NLP models like BERT and GPT-based architectures could capture more nuanced investor sentiment and improve predictive accuracy.

Lastly, integrating LSTM models and sentiment analysis techniques has been proven to be a compelling method for improving financial prediction and supporting investors' decisions. As financial markets continue to evolve, utilising AI-driven predictive models will become increasingly essential for investors seeking to make well-informed investment decisions. Future advancements in deep learning and real-time market analytics will further refine stock price prediction models by making them more accurate and reliable for financial forecasting and decision-making activities.

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