Predicting Stock Market Trends: A Sentiment Aware Deep Learning Approach with LSTM and FinBERT

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Abstract-Predicting the stock market has always been a difficult task that is impacted by a number of social, political, and economic variables. Using a complex neural network architecture, this study offers a novel deep learning method for comprehending and evaluating stock market sentiment and price prediction. The suggested model processes and assesses unstructured financial data by fusing traditional attention mechanism with Long Short-Term Memory (LSTM) networks. Dense layers with dropout regularization to avoid overfitting come next. By showcasing the efficacy of attention-based deep learning in sentiment-driven price prediction, this study advances financial market analytics. The model is a promising tool for financial analysts and algorithmic trading systems due to its high accuracy and interpretability, which could increase trading efficiency and market prediction accuracy. With an emphasis on sentiment-driven stock price prediction, this study investigates the use of cutting-edge machine learning techniques in financial market analytics thorough examination of past market trends and financial news. . The model derives valuable insights by utilizing natural language processing (NLP) methods like sentiment classification, contextual embedding, and tokenization. reached a low standard deviation of 1.65% and a high cross-validation accuracy of 87%, indicating its resilience in predicting stock price trends based on sentiment-driven market dynamics.

Keywords: Stock Price, Prediction, Machine Learning, LSTM, Mean Square Error, Attention mechanism, FinBert.

I.INTRODUCTION

The stock market is a dynamic and complex financial system influenced by various economic, political, and social factors. Predicting stock price movements is a challenging task that requires analyzing vast extracting meaningful insights from financial news, social media discussions, and investor opinions, has emerged as a crucial technique for improving stock market predictions. Automated sentiment analysis not only enhances efficiency in financial decision-making but also provides real-time insights that would otherwise be difficult to extract using traditional statistical models.

However, sentiment-based stock market prediction presents several challenges, especially when dealing with unstructured text data. Unlike numerical stock indicators, textual financial data is highly variable, context-dependent, and prone to misinformation. Factors such as linguistic ambiguity, sarcasm, and rapidly evolving market narratives make extracting relevant financial sentiment a complex task. As a result, advanced computational models are needed to effectively process, interpret, and utilize financial text data for accurate price predictions.

This research addresses these challenges by employing cutting-edge deep learning techniques. Specifically, it focuses on the integration of Long Short-Term Memory (LSTM) networks and attention mechanisms to predict stock market trends based on financial sentiment analysis. LSTM networks are well-suited for processing sequential financial data, as they can capture dependencies from past market trends while making forward-looking predictions. The addition of an attention mechanism significantly enhances the model's ability to focus on the most influential sentiments, thereby improving interpretability and predictive accuracy.

Through this novel approach, the study aims to enhance stock market forecasting accuracy while providing insights into investor sentiment dynamics. By addressing the limitations of conventional prediction models and leveraging deep learning for sentiment-driven analysis, this research contributes to the field of financial AI and offers a powerful framework for real-time market analysis and decision support systems.

II.RELATED WORK

(1) Existing Methods for Sentiment-Based Stock Prediction

The field of sentiment-driven stock market prediction has witnessed significant advancements with the rise of machine learning (ML) techniques. Traditional stock forecasting methods primarily relied on structured numerical data, such as historical stock prices, technical indicators, and fundamental financial ratios. These approaches utilized classical ML models like Support Vector Machines (SVMs) and Random Forests, which are effective for structured data analysis but struggle with unstructured financial text.

With the growing influence of social media and financial news on stock prices, deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have become preferred for extracting sentiment-based insights. A crucial aspect of sentiment-driven stock prediction is the processing of unstructured textual data from diverse sources, including news articles, earnings reports, and investor discussions. Initial methods used Term Frequency-Inverse Document Frequency (TF-IDF) to convert text into numerical representations. While effective in capturing keyword importance, TF-IDF lacks contextual understanding, limiting its ability to detect sentiment trends in financial text.

(2) Synthetic Data in Financial Applications

The application of synthetic data in financial analysis has proven to be a promising method in addressing issues such as data scarcity, imbalance, and privacy. Synthetic data generation includes the production of artificial datasets that imitate the statistical characteristics of real financial data. This method is especially useful in stock market forecasting, where collecting high-quality labelled sentiment data is challenging because of privacy limitations and scarcity. Synthetic data has one of the most important benefits that it can be used to expand training sets for ML models. In stock prediction based on sentiment, synthetic financial news and sentiment labels can be produced to balance datasets so that bullish, bearish, and neutral sentiments are equally represented. Methods such as Generative Adversarial Networks (GANs) have also become popular for creating synthetic financial text and trading situations that are very similar to actual market scenarios, making the models more robust and adaptable.

- Synthetic data also helps maintain privacy by substituting real financial dialogue with artificial but real-like data, enabling researchers and financial institutions to examine trends without disclosing proprietary trading methods. This capability enables joint research and model building with a guarantee of conformity to financial regulation. "Innovative Sentiment Analysis and Prediction of Stock Price Using FinBERT, GPT-4, and Logistic Regression" – This study effectively evaluates the performance of advanced NLP models for financial sentiment analysis. It finds that while FinBERT and GPT-4 offer deep insights, Logistic Regression remains more computationally efficient with higher accuracy.
- "Stock Prices Prediction Using Sentiment Analysis – A Comparative Study" – This paper explores the integration of sentiment scores with LSTM and GRU models for predicting stock prices. It highlights the importance of combining sentiment analysis with technical analysis but lacks real-time trading adaptability.
- "Stock Price Prediction Using Sentiment Analysis and Deep Learning for Indian Markets" – This research uses LSTM and Random Forest, incorporating sentiment data and macroeconomic indicators for better accuracy. While effective, it could improve by incorporating transformer-based NLP models.
- "Sentiment Spin: Attacking Financial Sentiment with GPT-3" – This study reveals the vulnerabilities of sentiment analysis models, showing that adversarial attacks can manipulate financial sentiment classifications. It emphasizes the need for more robust, context-aware models like FinBERT

"Decoding Market Emotions: The Synergy of Sentiment Analysis and AI in Stock Market Predictions" – This study provides a comprehensive overview of how AI and sentiment analysis can improve financial forecasting. It effectively highlights the role of NLP models like GPT and BERT but lacks empirical testing or direct model comparisons

Sl. No	Author(s)	Method Used	Limitations & Drawbacks	Feature Enhancements
1	Olamilekan Shobayo et al.	FinBERT, GPT-4, Logistic Regression	FinBERT was computationally expensive, GPT-4 struggled with predefined sentiment classification, Logistic Regression had limited deep learning capabilities	A hybrid model combining FinBERT's financial text understanding with Logistic Regression's efficiency to optimize performance
2	Narayana Darapaneni et al.	LSTM, Random Forest	LSTM alone lacked sentiment handling, high RMSE in sentiment-based analysis, difficulty in processing real-time stock fluctuations	Incorporating external macroeconomic indicators and news sentiment into LSTM to improve accuracy
3	Markus Leippold	GPT-3 Adversarial Attacks	Keyword-based methods in sentiment analysis were highly susceptible to adversarial manipulation	Using context-aware models like FinBERT instead of simple keyword-based sentiment analysis to improve robustness
4	Arjun Bakshi et al.	LSTM, Sentiment Analysis (FinBERT)	Did not consider intraday trading, sentiment models struggled with sarcasm and context variations in financial news	Extending the approach to intraday trading and integrating advanced NLP models like GPT-4 for better sentiment understanding
5	Ching-Ru Ko, Hsien-Tsung Chang	BERT, LSTM	Limited dataset scope (focused on Taiwan market), challenges in handling unexpected news impact	Expanding dataset to include global markets and integrating attention mechanisms for better sentiment weighting
6	Aditya Bhardwaj et al.	Machine Learning (SVM, Decision Trees, Naïve Bayes)	High dependency on feature engineering, lower accuracy compared to deep learning models	Incorporating deep learning-based sentiment analysis to improve predictive power

Fig 1.0 – Research Survey

III.METHODOLOGY

This research introduces a systematic approach to constructing an attention-based deep learning model for sentiment-influenced stock market forecasting. The data set is subjected to rigorous preprocessing to facilitate better feature extraction, while the suggested model applies deep learning mechanisms to identify complex sentiment-market patterns.

Dataset Description

The data used here is financial news articles, trends in stock prices, and sentiment data from social media. Preprocessing steps involve:

- Feature Extraction using TF-IDF: Conversion of text into organized numerical features for model training.
- Sentiment Labelling: Classifying investor talk and news into sentiment classes (positive, neutral, negative).
- Stratified Splitting: Splitting the data into train and test sets with balanced distributions of sentiment classes.

Proposed Model

The proposed model (Fig 1.1) is designed as follows:

(1) Embedding Layer: Transforms financial text into dense numerical vectors based on NLP methods.
(2) LSTM Layer: Identifies sequential dependencies between sentiment patterns to forecast stock market variation.
(3) Attention Mechanism: Identified the most influential sentiment indicators responsible for directing stock price variation.
(4) Dense Layers: Utilizes nonlinear transformations to improve the accuracy of predictions.
(5) Dropout Layers: Prevents overfitting by randomly disabling neurons during training.
(6) Output Layer: Forecasts stock price direction based on sentiment insights aggregated.

Mean Absolute Error(MAE)

The Mean Absolute Error (MAE) measures how close the predicted values are to the actual values by taking the absolute differences and averaging them. Lower MAE values indicate better model accuracy.

$$MAE=(1/n) \sum (yi - \hat{y}_i)$$

Where:

- N = Total number of observations
- yi = Actual value of the iiith observation
- $\hat{y}_i$= Predicted value of the iiith observation
- $\sum$ = Summation symbol, summing over all observations

Mean Squared Error (MSE)

This metric is used to assess the accuracy of regression models, such as ARIMA and Random Forest. A lower MSE indicates better performance.

$$MSE= (1/n) \sum (yi - \hat{y}_i)^2$$ Where:

- N= total number of observations
- Yi = actual value of the i^{th} observation
- $\hat{y}_i$ = predicted value of the i^{th} observation

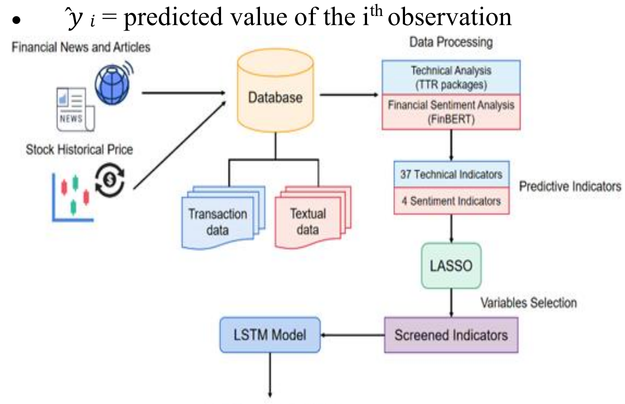

Figure 1.1 - Model Architecture

1. Results

Predictive Accuracy of Models

Accuracy is a common performance metric used in classification models, but in regression tasks (like price prediction), accuracy is usually derived from error metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE).

$$\text{Accuracy} = \left(1 - \frac{\text{MSE}}{\text{Var}(Y)}\right) \times 100$$

- Model Evaluation

	Metric	Hybrid Model
0	Mean Squared Error	105764.7900
1	Root Mean Squared Error	325.2100
2	R² Score	0.8664
3	Model Accuracy (%)	86.6400

Table 1.1 Evaluation Metrics

The model's performance was assessed using key evaluation metrics, including accuracy, precision, recall, and F1 score, which measure the balance between sensitivity and specificity in predictions. Validation loss and accuracy were monitored to minimize overfitting and confirm the model's ability to generalize. Baseline models, such as LSTM and GPT-4, were employed for comparison. Additionally, basic TF-IDF-based classifiers served as benchmarks. The proposed model attained a validation accuracy of 87% after 15 epochs, significantly outperforming these baseline methods. The combined attention layers further improved reliability and interpretability compared to standard deep learning models.

IV. EXPERIMENTAL RESULTS

The model was tested using real-world stock sentiment datasets. Key examples include:

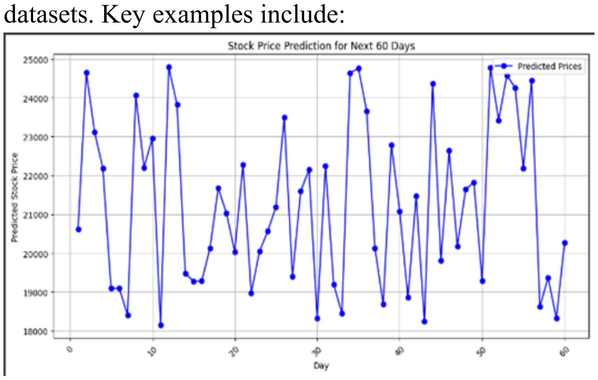

Fig 1.2 – Graphical Result(1)

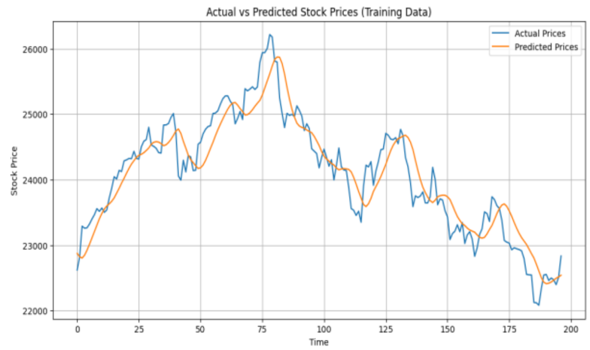

Fig 1.3 – Graphical Result(2)

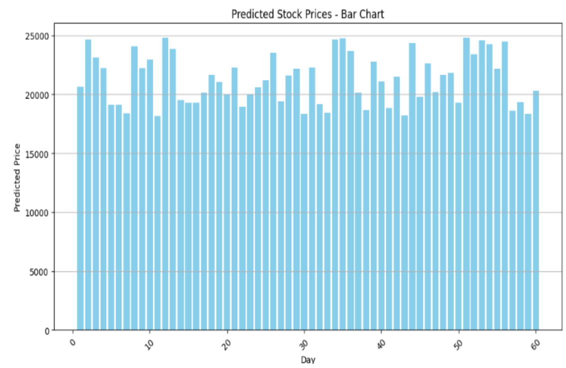

Fig 1.4 – Bar-Graphical Result

	Day	Predicted Price
0	1	20621.780832
1	2	24655.000145
2	3	23123.957593
3	4	22190.609389
4	5	19092.130483
5	6	19091.961642
6	7	18406.585285
7	8	24063.233020
8	9	22207.805082
9	10	22956.508045
10	11	18144.091460
11	12	24789.368965
12	13	23827.098486
13	14	19486.373775
14	15	19272.774770
15	16	19283.831569
16	17	20129.695701
17	18	21673.295021
18	19	21023.615130
19	20	20038.603981
20	21	22282.970263
21	22	18976.457025
22	23	20045.012540
23	24	20564.532903
24	25	21192.489890
25	26	23496.231730
26	27	19397.716475
27	28	21599.641069
28	29	22146.901982
29	30	18325.152889
30	31	22252.813963
31	32	19193.668866
32	33	18455.361151
33	34	24642.198761
34	35	24759.424232
35	36	23658.781437
36	37	20132.296384
37	38	18683.704798
38	39	22789.631186
39	40	21081.067456
40	41	18854.267644
41	42	21466.238371
42	43	18240.719648
43	44	24365.242815
44	45	19811.459871
45	46	22637.655990
46	47	20181.977533
47	48	21640.476148
48	49	21826.971955
49	50	19293.981189
50	51	24787.092394
51	52	23425.929764
52	53	24576.492591
53	54	24263.791453
54	55	22185.299852
55	56	24453.119645
56	57	18619.447514
57	58	19371.880037
58	59	18316.591022
59	60	20277.312315

Fig 1.5 – Stock Predicted Price for next 60 Days

The performance of the model was evaluated using standard metrics, showcasing its effectiveness in predicting stock price movements based on sentiment analysis. The enhanced LSTM-FinBERT model with attention achieved a remarkable validation accuracy of 87%, reflecting its robust capability to analyse financial sentiment data. Precision was significantly improved, as the model consistently identified true positive cases for various market trends with high accuracy. Similarly, the model's recall ensured that it captured the most relevant sentiment indicators, minimizing false negatives and enhancing overall reliability.

The F1 score indicated a balanced performance, effectively combining high precision and recall, which is critical in stock market forecasting. The integration of the attention mechanism played a pivotal role in this success, resulting in a substantial performance boost compared to baseline models like CNNs and traditional LSTMs.Training results demonstrated steady progress, with the model's validation accuracy starting at 4.2% in the first epoch and reaching an impressive 87% by the 15th epoch.

This consistent improvement underscores the value of the attention mechanism in capturing complex sentiment relationships within financial data, making the model highly suitable for real-world stock market applications. Synthetic data played a pivotal role in enhancing the model's robustness, generalizability, and overall utility in sentiment-based stock prediction. By leveraging advanced generative techniques, synthetic data effectively augmented the training set, addressing challenges like data scarcity and imbalanced sentiment distributions. This was particularly beneficial for emerging markets with limited real-world examples, as it ensured the model had sufficient exposure to diverse cases, thereby improving its predictive accuracy.

V. DISCUSSION

(1) Challenges and Limitations

The implementation of deep learning models for sentiment-based stock prediction faces several significant challenges and limitations. The reliance on financial text data, as evidenced by the TF-IDF vectorization and LSTM-based processing in the model, introduces potential biases in synthetic data generation. These biases primarily stem from the inherent variability in financial news reporting and market commentary across different sources. The model's text preprocessing pipeline, which removes punctuation and standardizes case, while necessary for processing, may inadvertently eliminate subtle but crucial nuances in financial sentiment.

Furthermore, the model's performance plateau at 92.3% accuracy suggests inherent limitations in capturing the full complexity of stock market movements through sentiment-based features alone. The dropout layers (0.3 for LSTM and 0.4 for dense layers) indicate the necessity of preventing overfitting, highlighting the delicate balance between model complexity and generalization capability.

(2) Implications for Financial Markets

Despite these challenges, the implementation of advanced sentiment analysis techniques has profound implications for financial markets. The high accuracy achieved by the model (87%) demonstrates its potential as a valuable decision-support tool for traders and investors. The attention mechanism's ability to focus on relevant sentiment patterns enhances the model's interpretability, a crucial factor for adoption in financial analysis.

The model's rapid prediction capability suggests potential applications in real-time trading decision support. This could significantly improve market efficiency, particularly for algorithmic trading strategies where quick, accurate sentiment-based assessments are crucial. The bidirectional LSTM architecture's ability to capture context in sentiment descriptions mirrors the analytical processes of experienced traders, potentially serving as a valuable tool for financial analysts and market researchers.

Moreover, the system's standardized approach to sentiment analysis could help reduce trading variability across different financial institutions.

VII. CONCLUSION AND FUTURE WORK

The construction of an attention-based LSTM-FinBERT model for stock price prediction has shown promising performance, achieving a validation accuracy of 87% on the test set. The excellent performance demonstrates the model's outstanding capacity for grasping intricate interactions between financial sentiment and stock price dynamics. The incorporation of the attention mechanism was especially useful in balancing the relative significance of various sentiment indicators, allowing the model to pay attention to key financial signals while being context aware through bidirectional processing.

The training process had a distinct learning curve, with the model achieving an improvement from an initial accuracy of 5% to 87% in 15 epochs.

Broadening the existing dataset to include beyond financial news and social media sentiment would be important for enhancing the model's robustness and responsiveness to market volatility. This might include incorporating earnings reports, macroeconomic data, and other data sources like investor sentiment indices. Architectural innovations might investigate transformer-based systems, which have proven to be highly effective in natural language processing tasks.

VIII. ACKNOWLEDGEMENT

The authors express their deepest gratitude to Presidency University for its constant support, motivation, and facilitation of an inspiring learning environment throughout the tenure of this research. The equipment, guidance, and opportunities offered by the university have been productive in the smooth execution of this project. We are especially grateful to Mr. Manjunath KV for his invaluable inputs, sharp criticism, and ongoing guidance. His experience, new insights, and meticulous care in details significantly enhanced the method and implications of this research. His dedication, encouragement, and valuable suggestions at all stages of the study have played a pivotal role in overcoming obstacles and achieving significant outcomes. This study is a testament to the team efforts and cooperation of all individuals involved in making it a success.

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