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RESEARCH PAPER

Advanced Deep Learning System for Financial News-Based Sentiment Analysis in Stock Price Prediction

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***Abstract*—The complex connection between news-driven mood and macroeconomic factors, as well as the intrinsic volatility of financial markets, makes stock price prediction a tough undertaking. This study recommends a Bi-direcstional Long Short-Term Memory (Bi-LSTM) model for analyzing the tone of financial news as a means to improve stock price prediction. The Financial Phrase Bank dataset, which contains 4,848 news headlines categorized as positive, negative, or neutral financial, is a good place to start when developing the approach. Before dividing the dataset into training and testing subsets, data must undergo preprocessing operations such as text cleaning, tokenization, normalization, and label encoding. From what can tell from the experiments, the Bi-LSTM gets an F1-score of 90.62%, a recall of 90.11%, and a precision of 91.13%. When compared to standard models like FinBERT and Random Forest, the Bi-LSTM performs far better. The results show that the suggested method is suitable for practical uses in financial forecasting since it combines sentiment analysis with sophisticated deep learning architectures to give a solid foundation for dealing with market unpredictability.**

Keywords—Stock Price Prediction, Financial News, Bi-LSTM, Deep Learning, Financial Phrase Bank.

I. INTRODUCTION

The capacity of publicly listed companies to raise capital through the stock market increases innovation, tasks, and GDP, making it a vital component of the global economic system [1]. It is truly challenging to predict the movement of stock prices due to the complicated and unpredictable nature of the market. Stock prices move in patterns that are hard to predict using conventional approaches because they are affected by economic indicators, geopolitical events, and investor sentiment. More dynamic forecasting methods are required due to the market's sensitivity to real-time events, even though trends in past data do have some predictive value. The shortcomings of more conventional methods like technical and fundamental analysis have prompted researchers to seek out new alternatives, with sentiment analysis emerging as a prominent contender [2]. Sentiment, which captures public opinion and emotional reactions, has shown increasing relevance in predicting market behavior. Financial news, in particular, serves as a key source of structured and unstructured information that reflects institutional perspectives and expert analyses. When processed effectively, this news can reveal valuable insights into market sentiment, offering a complementary dimension to purely numerical stock data [3][4]. However, capturing the subtlety of sentiment in financial language requires more than basic statistical or rule-based techniques [5][6].

Deep Learning (DL), a subfield of ML, has shown superior performance in modeling sequential and non-linear data relationships [7]. CNNs, LSTM architectures, and transformer-based models like BERT and FinBERT excel at extracting temporal and contextual patterns from text [8]. These models automatically learn hierarchical features and representations, allowing them to understand both local sentiment signals and broader narrative themes within financial news [9][10]. DL models like this can greatly enhance the accuracy of prediction systems when fed with stock price history data. These developments are not enough to fill the knowledge vacuum in creating integrated frameworks that successfully combine financial news sentiment analysis with time-series forecasting based on DL [11][12]. Many existing studies either rely on social media sentiment, neglect domain-specific financial terminology, or fail to incorporate temporal market dynamics [13].

A. Motivation and Contribution of Study

Stock price volatility forecasting is extremely difficult because of the complexity and volatility of financial markets. These markets are impacted by economic indicators, geopolitical events, and investor mood. Market behaviour is very dynamic and driven by sentiment, which is difficult for traditional forecasting approaches like technical and fundamental analysis to capture. However, advanced modelling techniques are needed to extract meaningful insights from this domain-specific language in financial news, despite the fact that this data source is rich in both structured and unstructured information reflecting institutional viewpoints and investor reactions. This study improves sentiment-based stock price prediction using deep learning, specifically a Bi-LSTM architecture, by effectively capturing financial writing's temporal patterns, contextual meaning, and long-term dependencies. In doing so, hope to circumvent the problems that have plagued rule-based and statistical sentiment analysis. The key contributions are:

- The suggested model's resilience in dealing with actual financial sentiment data is demonstrated through experimental validation on the Financial Phrase Bank dataset.
- A comprehensive framework for financial news sentiment analysis, integrating advanced preprocessing, normalization, and label encoding for robust data preparation.

- The study offers clear visual insights into popular mood and opinion patterns in political and financial events through sentiment distribution charts and word clouds.
- Developing and deploying a Bi-LSTM model to enhance sentiment categorization in financial literature by capturing both forward and backward contextual dependencies.
- This study sets a strong foundation for future research in financial text analytics by proving the model's usefulness using standard evaluation criteria (accuracy, precision, recall, and F1-score).

B. *Justification and Novelty*

Financial markets are very responsive to sentiments expressed in the news, and conventional statistical or machine learning algorithms have a hard time understanding text due to its sequential dependencies and contextual subtleties. This is why this study is necessary. The suggested Bi-LSTM model enhances the extraction of temporal and semantic characteristics necessary for sentiment classification by utilizing bidirectional learning, which analyzes financial news in both forward and backward contexts. This novel strategy tackles this limitation. The Bi-LSTM offers a more reliable depiction of long-term dependencies and also solves the issue of vanishing gradients that is intrinsic to RNNs, in contrast to traditional models. This novelty enables the model to achieve superior predictive performance in sentiment-based stock price prediction, offering a reliable and adaptable framework for handling volatility and uncertainty in real-world financial forecasting applications.

C. *Structure of Paper*

The following is the outline of the paper: Section II provides a literature review, Section III describes the method, Section IV presents the results and evaluation, and Section V discusses potential future research.

II. Literature Review

This section presents research on Financial News-Based Sentiment analysis in Stock Price Prediction utilizes diverse DL techniques, the summary of these studies is provided in Table I.

Agrawal and Mukherjee (2025) stock market is famously hard to anticipate since financial markets are unpredictable and complex. The results of experiments show that sentiment data-infused models perform better than the more conventional price-based ones. Achieving the best accuracy (98.92%) was the BERT-based sentiment model, which proved that deep-learning-driven sentiment extraction was effective. In the meanwhile, SVM handled high-dimensional sentiment variables effectively, making it the best-performing traditional model with a 98.48% performance statistic [14].

Ishica et al. (2024) process of predicting future stock values using emotional analysis of today's financial news stories as a framework for analyzing market activity. This research aims to construct a model for stock price prediction by utilizing a combination of ML and NLP to analyses the sentiment of news headlines as input. Along with an accuracy of 85.97%, a Random Forest Classifier was used to achieve good precision and recall metrics due to the model's ability to accurately forecast stock price increases and its ability to discern how market sentiment impacts stock behaviour [15].

Annalakshmi et al. (2024) managing stock prices is still difficult because there are a lot of elements that cause market volatility. Historically, investors and businessmen have relied on antiquated methods of forecasting, which mostly considered data from the distant past. As an example, a 95% prediction accuracy was achieved by combining Fin BERT for sentiment analysis with LSTM. Notable performance has also been demonstrated by XGBoost, Gated Recurring Unit (GRU), and DeepAR [16].

Churi et al. (2023) A stock price forecasting model that incorporates DL and sentiment analysis from the media. First, the LSTM architecture was used to find the best batch/epoch parameters for the NIFTY 50 data that was imported from Yahoo Finance (spanning March 2017 - March 2022). Primary results show that the 100-epoch, 6-layer LSTM model outperformed Random Forest and other models when it came to predicting stock values using historical financial data and news sentiment, while the CAT Booster model was somewhat more effective [17].

Mathanprasad and Gunasekaran (2022) machine learning categorization technique to facilitate the prediction of stock market price and movement. By analyzing performance changes and obtaining job suggestions and recommendations, users may easily find out which stocks stay in the market for longer. The stock exchange's prediction accuracy has been enhanced to 94.17% through the use of ML techniques [18].

Chou et al. (2021) extremely stochastic character of the stock market makes it difficult to forecast, and the uncertainty caused by the COVID-19 outbreak just adds to the dilemma. Even though the pandemic's outcome is unpredictable, experimental results show that LSTM can still forecast closing prices by tapping into investors' emotional tendencies and the attention mechanism. Financial backers and shareholders better equipped to comprehend market dynamics and priorities long-term growth and investment with the help of precise forecasts [19].

ML and DL have made a lot of progress in predicting the stock market. However, current studies have some major flaws, such as relying too much on social media sentiment, not properly handling financial terms, and not properly incorporating temporal dependencies within financial text. Many approaches either achieve high accuracy on short-term data without capturing long-term dependencies or neglect the contextual influence of macroeconomic indicators on stock trends. To address these gaps, this work proposes a Bi-LSTM based framework for financial news sentiment analysis, which leverages bidirectional sequential learning to extract deeper contextual and temporal features from financial text. By incorporating advanced preprocessing, label encoding, and normalization, alongside robust evaluation metrics, the proposed solution enhances sentiment classification and improves predictive accuracy, offering a reliable and adaptable model for sentiment-driven stock price forecasting.

TABLE I. COMPARATIVE ANALYSIS FOR FINANCIAL NEWS-BASED SENTIMENT ANALYSIS IN STOCK PRICE PREDICTION

Author	Methodology	Data	Key Findings	Limitation	Future Work
Agrawal and Mukherjee (2025)	BERT-based sentiment analysis, SVM for traditional ML	Financial market data + sentiment data	BERT-based model achieved 98.92% accuracy; SVM best among traditional models (98.48%)	Limited generalization across different markets; only tested with specific datasets	Expand to multi-market and multi-lingual sentiment data; integrate real-time prediction
Ishica et al. (2024)	NLP with CountVectorizer + Random Forest Classifier	Daily financial news headlines and stock results	Achieved 85.97% accuracy, strong in predicting stock price rise	Focused only on binary classification (rise/fall); limited dataset	Apply deep learning for multi-class forecasting; expand dataset coverage
Annalakshmi et al. (2024)	FinBERT for sentiment + LSTM; also tested XGBoost, GRU, DeepAR	Public media sentiment data + historical stock prices	FinBERT + LSTM achieved 95% accuracy; external sentiment improves predictions	Performance may vary with noisy/unstructured media data	Incorporate multimodal data (tweets, blogs, global news) for robustness
Churi et al. (2023)	LSTM (6 layers, 100 epochs) + CATBoost vs. Random Forest	NIFTY 50 data (2017–2022) + financial news	LSTM best for time-series; CATBoost slightly better than Random Forest with sentiment	LSTM requires heavy computation; limited to NIFTY 50 index	Explore hybrid DL-ML frameworks; optimize hyperparameters for broader indices
Mathanprasad and Gunasekaran (2022)	Comparative ML classification approach	Stock market movement data	Improved prediction accuracy to 94.17%	Lack of deep learning integration; methodology not deeply explained	Extend to deep learning and ensemble methods; enhance interpretability
Chou et al. (2021)	LSTM with attention mechanism + investor sentiment	Stock market data during COVID-19	Attention-based LSTM improved prediction despite uncertainty	Performance affected by sudden global events (pandemic)	Apply transfer learning to adapt to crises; combine economic indicators

III. METHODOLOGY

Financial Phrase Bank is one dataset that is used for sentiment analysis of financial news in order to predict stock values. Data preprocessing involves text cleaning, tokenization, min-max normalization, and label encoding using scikit-learn to convert categorical labels to numeric. Data is then split (80% train, 20% test). A Bi-LSTM model is suggested for capturing long-term dependencies. This model has four gates: forget, input, cell update, and output. Comprehensive comprehension of classification effectiveness in forecasting financial emotion is achieved by evaluating model performance using accuracy, precision, recall, and F1-score. The flow diagram of the stock price prediction using sentiment analysis based on financial news is shown in Figure 1.

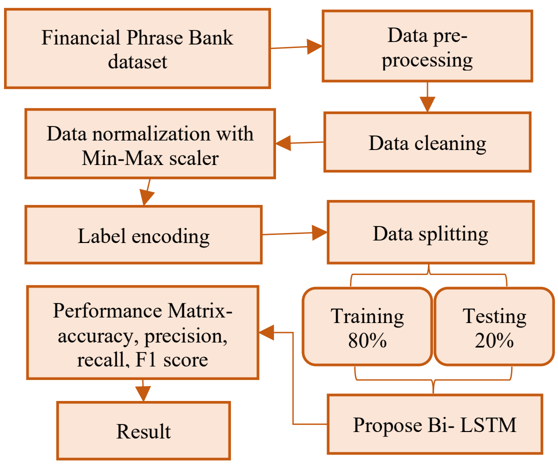

Fig. 1. Flowchart of the Financial News-Based Sentiment analysis in Stock Price Prediction

The following sections provide each step description that also shows in methodology and proposed flowchart:

A. Data Collection

Financial news headlines tagged with sentiment from a retail investor's perspective make up the Financial Phrase Bank Sentiment Analysis. Two columns labelled "Sentiment" and "News Headline" indicate if the sentiment is good, negative, or neutral. Included in this collection are 4,848 English sentences culled from various financial news sources. Its sentiment analysis capabilities make it a go-to tool for evaluating market mood from textual data in the financial sector.

The visualization graph is provided below.

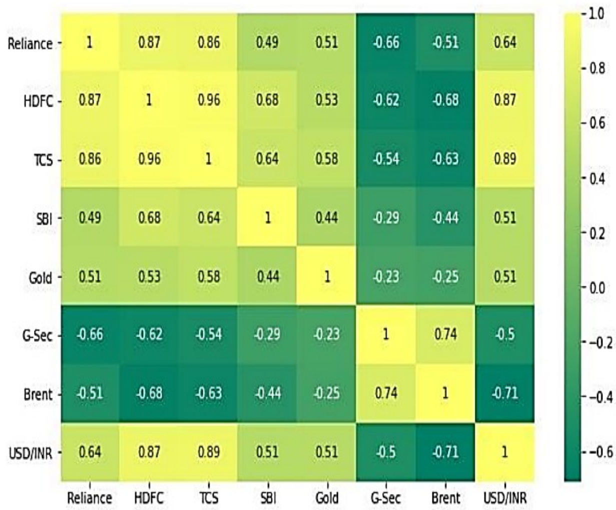

Fig. 2. Correlation - Macro Parameters and Stock Prices

Figure 2 presents the correlation matrix between selected macroeconomic indicators (such as Gold, G-Sec, Brent Crude, and USD/INR) and the stock prices of major Indian companies (Reliance, HDFC, TCS, SBI). The matrix reveals strong positive correlations between HDFC and TCS (0.96), as well as between TCS and USD/INR (0.89), indicating that these stock prices tend to move in tandem and may be influenced similarly by macroeconomic factors. Conversely, Brent Crude shows a negative correlation with most stocks, particularly with G-Sec (-0.74) and USD/INR (-0.71), suggesting that rising oil prices may adversely affect these indicators.

Fig. 3. Positive Sentiment Words

Figure 3 presents a word cloud representing positive sentiment words extracted from financial or political news content. Prominent terms such as "modi," "india," "narendra," "bjp," "people," and "country" appear in larger fonts, indicating higher frequency and association with favorable sentiment. The presence of words like "good," "vote," "will," and "leader" further emphasizes a constructive and optimistic tone in the underlying text.

Fig. 4. Negative Sentiment Words

Figure 4 presents a word cloud highlighting negative sentiment words derived from financial or political discourse. Key terms such as "modi," "india," "people," "bjp," "congress," and "united" appear prominently, suggesting they frequently occur in contexts expressing discontent or criticism. Unlike the positive word cloud, this one includes words like "poor," "now," "even," "hate," and "dont," which carry negative or skeptical connotations. Overall, this visualization reflects themes of political tension, public dissatisfaction, and criticism in the analyzed content.

Fig. 5. Neutral Sentiment Words

Figure 5 presents a word cloud depicting neutral sentiment words derived from political and financial news content. Dominant terms like "modi," "narendra," "india," "bjp," "congress," and "people" indicate their frequent appearance in news articles without a strongly positive or negative tone. Words such as "vote," "say," "now," "country," "election," and "time" suggest factual or descriptive usage rather than opinion-driven sentiment. This visualization reflects the balanced or objective reporting style typical of neutral news coverage.

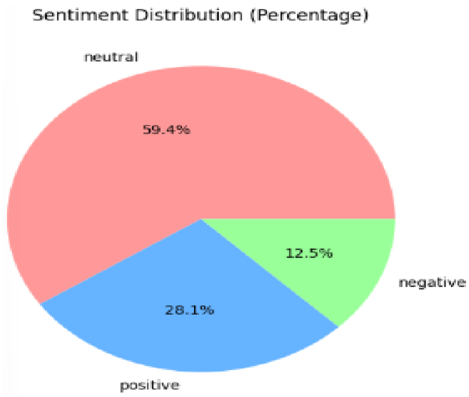

Fig. 6. Sentiment Distribution of Percentage

In Figure 6 the three divisions of positive, neutral, and negative sentiment are shown in the pie chart. The overwhelming majority of the sentiment falls into the "neutral" category, accounting for 59.4%. "Positive" sentiment represents a significant portion at 28.1%, while "negative" sentiment makes up the smallest share at 12.5%.

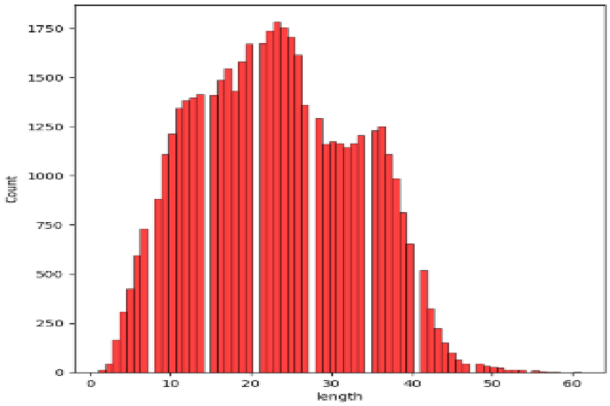

Fig. 7. Plotting the percentage of different sentiments of all the tweets

Figure 7 presents a histogram representing the distribution of tweet lengths in terms of word count. The x-axis denotes the length of tweets, while the y-axis indicates the frequency (count) of tweets for each length category. The distribution appears to follow a right-skewed pattern, with most tweets ranging between 10 and 40 words, and a peak around the 20–25-word mark. This suggests that users tend to express their thoughts in moderately sized messages, likely balancing clarity with brevity.

B. Data Preprocessing

The Financial Phrase Bank dataset underwent preprocessing steps including text cleaning (removing whitespaces, punctuation, and lowercasing), tokenization, and min-max normalization to scale features. Sentiment labels were encoded into numerical values using Label Encoder. The following steps of pre-processing are listed in below:

C. Data Cleaning

The raw dataset contains sentences sourced from financial news articles, which are typically well-formatted. However, basic text cleaning is still necessary. This includes:

- Removing unnecessary white spaces
- Converting all text to lowercase for normalization

- Eliminating special characters and punctuations not essential for semantic meaning (e.g., unnecessary symbols)
- Removing HTML tags or escape sequences, if present

D. Data Normalization with Min-Max Scaler

A crucial process known as normalisation is keeping the numerical values of features within a regular range, often between 0 and 1. In this study, the data is converted according to the minimum and maximum values of each feature using min-max normalisation, which is derived from Equation (1):

$$Normalize(X) = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

The inclusion of this stage in the model training process guarantees that all features have an equal impact and prevents features with greater numerical ranges from being overshadowed. Consequences include faster convergence and better model correctness.

E. Label Encoding

The scikit-learn Label Encoder is a must-have for most machine learning models since it numerically represents categorical sentiment labels. Specifically, the fit transform method is applied to the 'sentiment' column of the dataset, transforming the text labels 'negative', 'neutral', and 'positive' into integer values, typically 0, 1, and 2, respectively. The encoder. Classes attribute confirms the original class labels and their corresponding encoded values.

F. Data Splitting

An efficient way to evaluate the performance of the model was to split the dataset in half: 80% for training and 20% for testing.

G. Proposed Bi-LSTM Model

A Bi-LSTM model can be thought of as an RNN variant that uses an LSTM. The problem of gradient disappearance in conventional RNN can be solved by adding a gating unit to the LSTM [20]. This makes the RNN better at detecting and using dependencies in long-distance data, and it makes the LSTM better at capturing long-term dependencies. The new structure of an LSTM cell unit primarily consists of four gates: the input gate i_t, the output gate o_t, the forget gate f_t, and the storage unit c_t. Figure 8 shows the internal construction of one cell in the Bi-LSTM module.

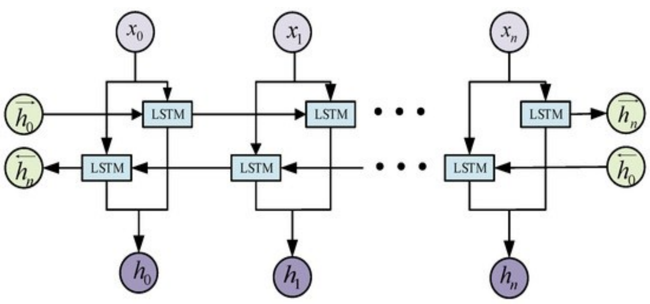

Fig. 8. Bi-LSTM network model.

The LSTM update formula is as follows:

1) Forget Gate Mechanism:

The forget gate f_t is a type of rewritable memory cell. There is a weight matrix $W_{(f)}$ and the input is represented by x_t at time Z. σ is the Sigmoid activation function. It formulates Equitation (2):

$$f_t = \sigma\left(W_{(f)}x_t + u_{(f)}h_{t-1} + b_{(f)}\right) \quad (2)$$

2) Input Gate Mechanism:

The input gates that regulate the memory cell's input are represented by the input gate i_t. Sigmoid activation function is represented by σ. Equation (3) is formulated using it:

$$i_t = \sigma\left(W_{(f)}x_t + u_f\, h_{t-1} + b_{(f)}\right) \quad (3)$$

3) Current Unit Status:

$\tilde{c}$ stands for potential memory cell. Reset memory cells include the forget gate f_t. "Cell state" is defined as c_{t-1}. It generates the Equation (4):

$$\tilde{c} = f_1 \odot c_{t-1} \quad (4)$$

4) Update Unit Status:

The cell state c_t stands for long-term memory, while the candidate memory cell $\tilde{c}$ is represented by it. A representation of the input to the memory cell, as dictated by the input gates, is i_t it. The Equation (5) is expressed as:

$$c_t = \tilde{c} + i_t \odot tanh\left(W_{(c)}x_t + u_c\, h_{t-1} + b_{(c)}\right) \quad (5)$$

5) Output Gate Mechanism:

The memory cell's output is controlled by the output gates, denoted as o_t. At time Z, the input is x_t, the Sigmoid activation function is denoted by σ, and a weight matrix is $W_{(o)}$. It formulates the Equation (6):

$$o_t = \sigma\left(W_{(o)}x_t + u_o\, h_{t-1} + b_{(o)}\right) \quad (6)$$

6) The current state of the hidden layer:

h_t represents the concealed state. For the Sigmoid activation function, tanh stands. The long-term memory is represented by the cell state, c_t. Equation (7) is formulated using it:

$$h_t = 0_t * tanh(C_t) \quad (7)$$

H. Performance Evaluation Matrix

The following statistical measures were used to construct the classification metrics: accuracy, precision, recall, and F1-score:

Accuracy: The frequency with which the model's predictions came true. The Equation (8) for**:**

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \quad (8)$$

Precision: Evaluation of the accurate positive predictions using Equation (9).

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

Recall: Accurate positive occurrences predicted by the model quantified. with respect to Equation (10):

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

F1 Score: The harmonic means of recall and precision, which bring the two measures into harmony with one another used in Equation (11):

$$F1 = \frac{2*(precision*recall)}{precision+recall} \quad (11)$$

IV. Results and Discussion

The proposed model is implemented in Python Version 3.7 on the computational system with specifications of processor Intel Core i7 12th generation with clock speed 3.2 GHz of16GB RAM and 512 GB SSD. The experimental setup, results analysis, and dataset utilized to assess the suggested model are detailed in this section. The suggested Bi-LSTM model's performance evaluation metrics on the Stock-Market News Sentiment Dataset are presented in Table II. This model's impressive accuracy (90.63%), precision (91.13%), recall (90.11%), and F1-score (90.62%), which strikes a good balance between the two, proves that the Bi-LSTM model is up to the challenge of sentiment classification using financial news data, and it's ready for use in stock market analysis in the real world.

TABLE II. PERFORMANCE OF PROPOSE MODEL ON SENTIMENT ANALYSIS FOR FINANCIAL NEWS

Performance Matrix	Bi-LSTM
Accuracy	90.63
Precision	91.13
Recall	90.11
F1-score	90.62

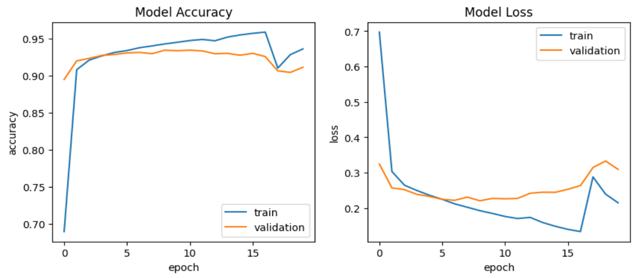

Fig. 9. The accuracy/loss curve of Bi-LSTM model

Figure 9 shows the Bi-LSTM model's accuracy and loss curves over all training epochs. The accuracy plot on the left shows that both training and validation accuracy improve significantly during the initial epochs, with training accuracy surpassing 95% and validation accuracy stabilizing around 90%, indicating effective learning and generalization. Training loss continues to reduce consistently during the early epochs, as shown on the right side of the loss curve, but validation loss drops significantly later on. A little increase in validation loss following epoch 10 indicates the beginning of overfitting, in which the model becomes more proficient at learning the training data than the unseen validation data. Although there is some overfitting in the later phases, the model still performs admirably overall.

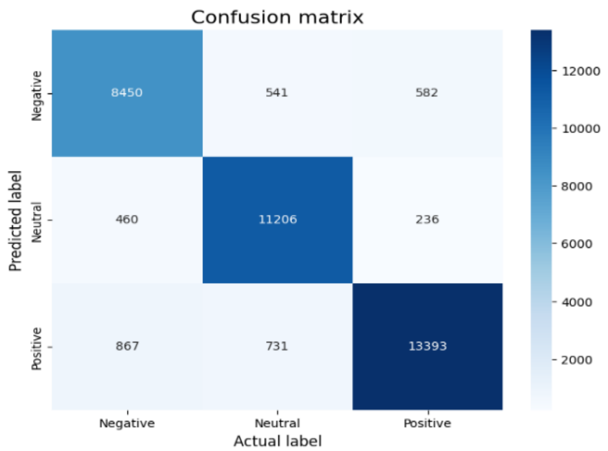

Fig. 10. Confusion matrix of BI-LSTM model

Figure 10 shows the Bi-LSTM model's confusion matrix, which shows how well it performed across three negative, neutral, and positive sentiment classes. The matrix indicates that the model correctly classified 8,450 negative, 11,206 neutral, and 13,393 positive instances, which are the diagonal values representing true positives. However, some misclassifications occurred for instance, 541 neutral and 582 positive tweets were incorrectly labeled as negative, and 867 negative tweets were wrongly predicted as positive.

TABLE III. COMPARISON BETWEEN BASE AND PROPOSE MODEL PERFORMANCE MATRIX FOR STOCK PRICE PREDICTION

Performance Matrix	Bi-LSTM	Fin Bert[21]	RF[22]
Accuracy	90.63	84.23	55.2
Precision	91.13	85.45	54.7
Recall	90.11	84.23	55.2
F1-score	90.62	84.39	55.1

The new Bi-LSTM model is compared to the baseline models FinBERT and Random Forest (RF) in Table III, which shows how well they forecast stock prices. The results show that Bi-LSTM achieves the highest accuracy (90.63%), precision (91.13%), recall (90.11%), and F1-score (90.62%) compared to both baseline techniques. In contrast, FinBERT demonstrates moderate performance with accuracy and recall values of 84.23%, while RF records the lowest performance, with accuracy of only 55.2% and similar values for other metrics.

The suggested Bi-LSTM model uses bidirectional learning to analyze data from both the past and the future, allowing it to capture sequential dependencies in time-series data. Because of this method, the model can better handle the ever-changing stock price movements by extracting more detailed temporal features and patterns. The primary advantage of this model lies in its robustness for forecasting, as it effectively manages volatility and uncertainty, making it a reliable framework for financial prediction tasks.

V. CONCLUSION AND FUTURE SCOPE

The technique of determining the value of a company's shares by examining past data and other market circumstances is known as stock price prediction. It comprises utilizing statistical models and DL algorithms to analyze financial data and forecast the performance of stocks. Investors can benefit from stock price prediction by getting a better idea of where equities are headed in the future. An impressive 90.63% accuracy, 91.13% precision, and a balanced F1-score of 90.62% were achieved by combining financial news sentiment with DL approaches, particularly a Bi-LSTM model, according to the study's findings. By effectively capturing contextual sentiment in financial headlines and combining it with advanced preprocessing and classification methods, the proposed model outperforms traditional techniques like Fin BERT and Random Forest.

Despite its promising results, future research can further enrich this framework by incorporating real-time sentiment data, macroeconomic indicators, and explainable AI mechanisms to enhance interpretability and support transparent investment decision-making. Expanding the model to handle multilingual financial texts and applying it across global stock indices also presents valuable directions for future exploration.

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