

Original Article

# Multimodal Stock Price Prediction Using a Hybrid GRU–Multi-Head Attention Model with Ensemble Sentiment and Technical Indicators

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**Abstract** - This proposed methodology introduces a hybrid model integrating sentiment scores with historical data and technical indicators. Ensemble sentiment scores were calculated using three sentiment methods: Financial Bidirectional Encoder Representations from Transformers (FinBERT), Robustly Optimized BERT Pretraining Approach (RoBERTa), and Distilled Robustly Optimized BERT Pretraining Approach (DistilRoBERTa). Sentiments were extracted from the Global Database of Events, Language and Tone (GDELT) Project, Google RSS feeds, and news articles from The Economic Times, alongside historical stock data from Yahoo Finance of selected NIFTY 50 companies spanning January 3, 2022, to November 15, 2025. A Gated Recurrent Unit-Multi-Head Attention (GRU-MHA) model was utilized to identify sequential dependencies and predict the next-day opening prices for Infosys, Tata Motors, Sun Pharma, and Tata Steel within the NIFTY 50 index. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination ( $R^2$ ), and Mean Absolute Percentage Error (MAPE). The ensemble sentiment-driven GRU-MHA model had low errors, with MAE = 0.1631 and RMSE = 0.2337 for Infosys and MAE = 0.7607 for Tata Steel. Most stocks had an MAPE of less than 1%, with Sun Pharma at 0.49% and Tata Steel at 0.52%.  $R^2$  values above 0.92 across sectors and as high as 0.9893 showed high explanatory power, outperforming standalone sentiment models.

**Keywords** - Gated Recurrent Unit (Gru), Multi-Head Attention (MHA), Stock Market (SM), Stock Price (SP), Sentiment Analysis (SA), Ensemble Sentiment Analysis (ESA), Technical Analysis (TA)

## 1. Introduction

The Stock Market (SM) is a complex and nonlinear financial system where stock prices fluctuate constantly due to socio-economic factors like government policies, global news, corporate performance, economic indicators, and investor mindset. Accurate Stock Price (SP) forecasting is essential and crucial for investors, financial analysts, and economic policymakers. Profits and risk management can be enhanced by small improvements in prediction accuracy. Predicting the SM is a challenging task due to the complex, dynamic characteristics of financial time series data.

Traditional methods used for stock forecasting mostly relied on econometric and statistical models, including autoregressive and moving-average methods. These models demonstrate benefits for stationary and linear data; however, their underlying presumptions do not always align with the actual dynamics of financial markets. The SP prediction

capability decreases when handling the volatile and nonlinear time-series data. In order to address these complexities, a variety of ML techniques, such as “Support Vector Machines, decision trees, and artificial neural networks,” were developed. These methods enable models to explicitly comprehend intricate correlations from prior data.

DL has emerged as the dominant approach for predicting the SM, driven by the growing availability of large financial datasets and improvements in processing capacity. “Recurrent Neural Networks, especially Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures”, have grown in significance due to advancements in computational power and the ability to find long-term time series patterns.

Recent research enhances prediction accuracy using hybrid deep learning models that combine multiple



architectures. Integrating LSTM and BiLSTM with CNNs captures local patterns while maintaining long-term dependencies.

Furthermore, mechanisms for attention have been integrated to dynamically highlight the most pertinent features and time steps throughout the prediction process. When compared to standalone DL models, these attention-based hybrid models exhibit enhanced accuracy and resilience across different stock indices and market scenarios. The effect of investor sentiment on SP fluctuations is considerable, in addition to the influence of market data. The enormous quantity of text data generated from economic news articles, social media posts, blog posts, and internet forums stems from the extensive engagement of individuals with digital platforms. Methods for sentiment analysis enable the extraction of broad emotions and viewpoints from the market by utilizing this unstructured data.

Empirical evidence shows that investor sentiment strongly impacts price movements, making it a valuable factor in stock prediction. With advances in NLP, combining SA from news and online sources with historical data using ML and DL models has improved prediction accuracy. Depending solely on historical data or a single approach is inadequate for accurate stock prediction. Combining sentiment analysis with technical indicators improves forecasting by capturing market trends, volatility, price ranges, and entry–exit signals. Integrating stock data, technical analysis, and sentiment features offers a more comprehensive view of market behavior. Therefore, a deep learning–based fusion model incorporating these elements is essential for achieving more stable and reliable predictions.

The study was conducted based on the above observations to develop a hybrid model for SP prediction, which integrates the SA with historical data to enhance accuracy and stability in predictions. The proposed approach aims to capture both numerical trends and qualitative market behaviors by combining historical data with SA obtained from textual data. This will help investors make more informed choices about their financial investments.

Although deep learning has significantly improved stock prediction, most existing approaches rely on single-source sentiment or standalone models like LSTM and GRU. Few studies combine multi-transformer ensemble sentiment with attention-based GRU, especially across Indian sectoral indices. This gap limits the effective capture of both sentiment diversity and temporal patterns. To address this, a hybrid GRU–Multi-Head Attention model with ensemble transformer-based sentiment is proposed to enhance prediction accuracy and robustness.

Organization of this paper: Section I for an introduction. Section II summarizes related literature, research gaps,

contributions, and innovations. Section III describes methodology. Section IV contains experiment results and discussions. Finally, Section V concludes the work and addresses future research.

## 2. Related Work

Shen et al. [1] developed a hybrid model using feature engineering, “Recursive Feature Elimination and Principal Component Analysis,” to predict short-term stock patterns through DL. A modified LSTM answered 93.25% on Chinese SM data. Mehta et al. [2] showed that the use of LSTM to add social media sentiment increased prediction accuracy to about 92.45%. “Khonde et al.” [3] developed a web-based stock prediction system using financial news SA and ML, achieving 86% sentiment accuracy and 83% stock prediction accuracy to support investment decisions. “Zhang et al.” [4] proposed a “CNN–BiLSTM–Attention model” that outperformed LSTM and CNN-based variants, achieving higher accuracy and lower RMSE, MAPE, and improved  $R^2$  across Chinese and global stock indices.

Ko et al. [5] enhanced stock prediction accuracy by 12.05% by integrating BERT-based news and forum sentiment with LSTM models and historical price data. Bhandari et al. [6] forecasted the S&P 500 using single- and multilayer LSTMs with market, macroeconomic, and technical features, where “a single-layer LSTM with 150 neurons” achieved the best accuracy. Lawi et al. [7] used aggregated time-series LSTM and GRU models for stock prediction, with GRU outperforming LSTM by achieving up to 97.37% accuracy and lower RMSPE and RMDPE. Koukaras et al. [8] predicted Microsoft stock prices using combined Twitter and StockTwits sentiment, where VADER with “SVM” achieved the best performance with a 76.3% “F-score” and 67% AUC. Gülmez [9] proposed an optimization-based deep LSTM outperforming ANN, LSTM, and GA models on DJIA data with higher accuracy and lower errors.

Ren et al. [10] combined online text sentiment with SVM models to predict stock movements, achieving up to 89.93% accuracy on the “SSE 50 Index”. Qing Ge [11] proposed a MEMD–AO–LSTM model that achieved high precision, with  $R^2$  up to 0.992 and low RMSE and MAPE on the “S&P 500 and CSI 300 indices”. Zhao et al. [12] introduced an SA-DLSTM model integrating sentiment analysis and LSTM, achieving a low 1.10% MAPE with improved profitability and risk control. Gülmez [13] proposed the “GA-Attention-Fuzzy-Stock-Net”, a neuro-fuzzy hybrid that outperformed other models, achieving an MSE of 0.001 and  $R^2$  up to 0.965 across stocks. “Liu et al.” [14] proposed an “EEMD–attention BiLSTM model” that consistently outperformed other deep learning and decomposition methods with lower errors on Chinese stocks. Zhang et al. [15] introduced a GNN framework combining social sentiment and financial indicators, outperforming LSTM, CNN, and Transformer models with better accuracy, returns, and Sharpe ratios. Tsai

et al. [16] demonstrated that text mining with resampling and one-class models like isolation forest and OCSVM improved AUC and reduced type I error in stock surge prediction. Tzu-Chia Chen [17] proposed a Deep LSTM-MLP with technical feature fusion, achieving reduced errors with MSE (0.113), RMSE (0.337), and MAE (0.169) compared to conventional forecasting methods. Verhoeks et al. [18] showed that heightened COVID-19 investor attention increased market volatility, unevenly impacted returns, reduced firm-specific focus, and weakened market efficiency. Sebastian et al. [19] proposed an attention-based multivariate “LSTM” that outperformed “LSTM, GRU” and Transformer models on NIFTY and SENSEX, achieving lower MAE and RMSE. “Adhikari et al.” [20] suggested an “explainable hybrid word representation” combining word2vec, BERT, and POS embeddings, achieving higher accuracy and F1-scores with improved interpretability. Liu et al. [21] proposed the “SA-TrellisNet model” integrating LSTM-CNN sentiment with attention, achieving higher accuracy, lower errors, and improved trend fitting across seven major stock indices. M. “Mu et al.” [22] proposed the “MS-SSA-LSTM” model integrating investor mindset, achieving up to 10.74% higher  $R^2$  and lower MAPE, RMSE, and MAE than conventional LSTM and CNN models. Gite et al. [23] combined LSTM with financial news sentiment analysis, achieving 74.76% prediction accuracy with enhanced transparency through explainable AI. Arif et al. [24] demonstrated that integrating technical analysis with machine learning improved prediction accuracy, with neural networks outperforming conventional methods by 15%.

Thormann et al. [25] showed that integrating Twitter sentiment with LSTM improved Apple stock forecasting for 30- and 60-minute intervals, reducing errors compared to using historical data alone. Kasture et al. [26] introduced a hybrid RNN-LSTM model incorporating SA, yielding a “root mean square error (RMSE) of 0.046 and a mean absolute error (MAE) of 0.036”. “Ko et al.” [5] developed an “LSTM model” for SA and achieved an average improvement in RMSE of 12.05%. Sidek et al. [27] used LSTM to analyze news sentiment effects on Bursa Malaysia, achieving improved prediction accuracy with RMSE below 1. Chandola et al. [28] developed an integrated hybrid model of “Word2Vec with LSTM,” and stock direction was predicted with 65.4 % accuracy. Correia et al. [29] determined that convolutional neural networks (CNNs) were capable of attaining a test accuracy of 69% and a training accuracy of 73%. “Raza et al.” [30] developed “LSTM and GRU models” integrating historical SP and macroeconomic indicators and showed improved prediction accuracy. Pham et al. [31] developed a novel investor sentiment index aimed at capturing irrational behavioral biases, demonstrating enhanced accuracy in stock market performance prediction. “Muhammad et al.” [32] proposed a DL approach for stock movement prediction, achieving 94.9% accuracy with improved interpretability using SHAP and LIME. Safari et al. [33] introduced

DeepInvesting, a multimodal BiLSTM-based model that achieved low MAPE and high  $R^2$  for accurate stock prediction on Amazon (AMZN) data.

“Nabipour et al.” [34] explored various ML techniques, including “decision trees and LSTM,” and “LSTM” outperformed standard models. “Yang et al.” [35] proposed a “hybrid CNN–LSTM model” using a three-dimensional input tensor, achieving superior prediction accuracy. Jing et al. [36] proposed a “CNN–LSTM fusion model” for sentiment classification and stock prediction, achieving improved performance across six industries. Gumus et al. [37] found that sentiment-based models outperformed historical pricing models.

“Ghosh et al.” [38] developed a hybrid model using “TCN- GRU MHA model”, achieved an  $R^2$  of 0.849 for a days prediction window. T. Chen [39] developed a hybrid “Deep LSTM-MLP model”, which improves SM prediction accuracy over conventional methods with “MSE, RMSE, and MAE values of 0.113, 0.337, and 0.169”. F. Ghorbani et al. [40] demonstrated that FLSPI serves as a reliable alternative for stock forecasting while expanding the toolkit for financial prediction. L.Ye et al [41] developed a GRU model that predicts China's stock market fluctuations using multi-market data and deep learning. The GRU model outperforms others.

Despite extensive use of LSTM/GRU, sentiment and hybrid models, mostly worked on compound score or objectivity-subjectivity score of sentiment analysis, whereas limited work jointly explores multi-transformer sentiment ensembles with attention-enhanced GRU architectures, particularly validated across multiple Indian sectoral indices with comprehensive metrics.

The research gap can be addressed by developing a GRU with multi-head attention integrated with an ensemble of transformer-based sentiment models. Model performance was verified with stock data and validated for robustness across multiple Indian sectoral indices using comprehensive evaluation metrics.

### 2.1. Contributions and Novelties

- Develops a framework for processing news from multiple sources (GDELT [42], Google RSS [43], and Economic Times [44] for broader news coverage and to avoid sentiment biases.
- The novel approach of combining daily sentiment scores with derived rolling, volatility, and change-based sentiment characteristics makes news events and price swings more precise.
- Unlike existing work that utilizes a single sentiment model, this study introduces a weighted ensemble of FinBERT, RoBERTa, and DistRoBERTa, improving sentiment robustness. The integration of multihead attention with GRU enables dynamic feature importance

learning, leading to better performance than an LSTM-based model.

- The proposed work also validated the effectiveness of the model by taking a days sample for all four diversified stocks.

### 3. Methodology

A hybrid model, shown in Figure 1, was incorporated for implementing the prediction model. It integrates the historical data of stock, technical indicators, and sentiment score calculated from an ensemble model, which uses the weighted sentiment score of FinBERT, RoBERTa, and DistilRoBERTa.

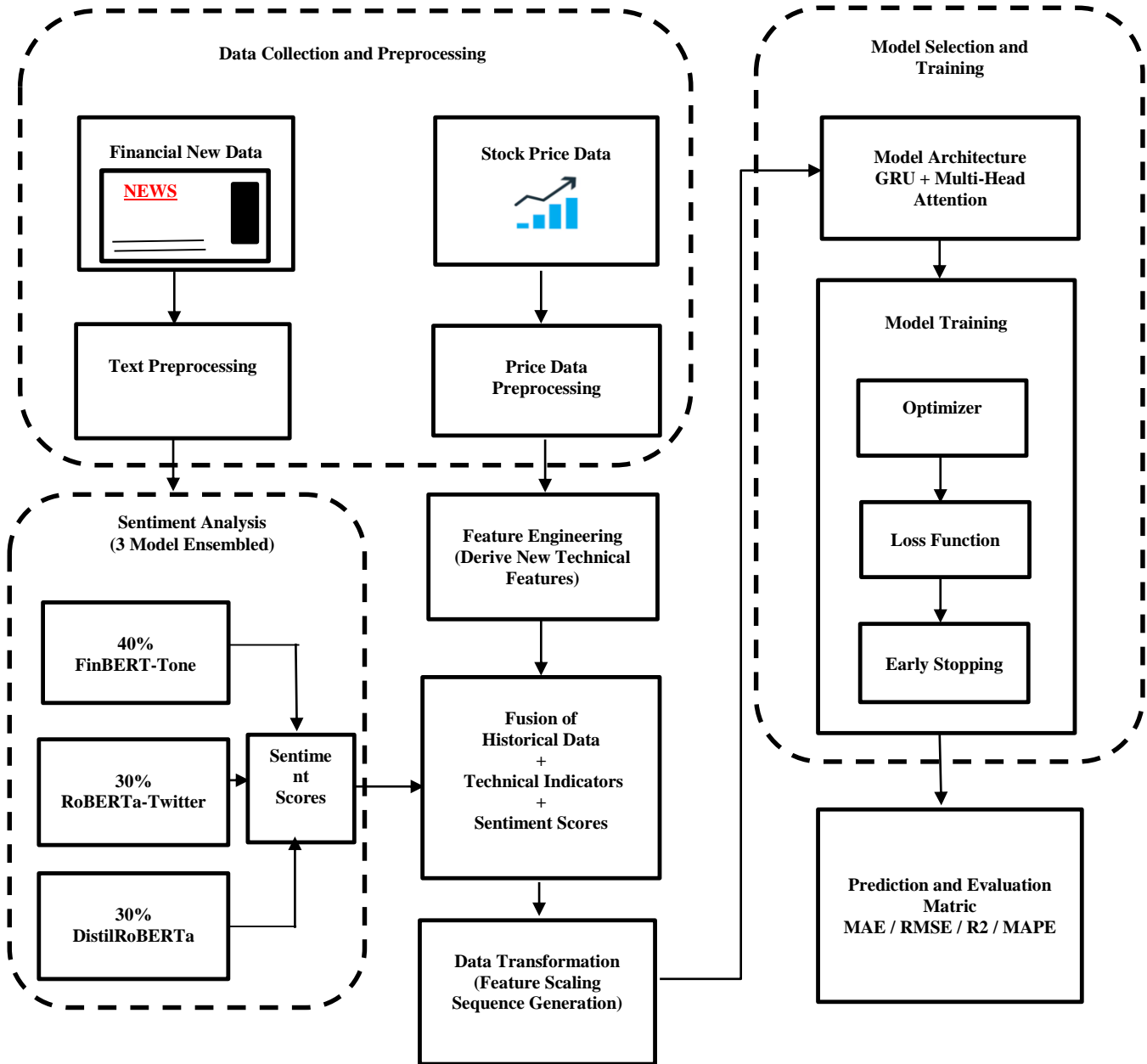


Fig. 1 Prediction model process flow

The framework was used to extract and analyze sentiment data of news articles from GDELT, Google News, and “The Economic Times” for selected companies of “NIFTY 50”, from January 3, 2022, to November 15, 2025. Stock data of “Infosys, Sun Pharma, Tata Steel, and Tata Motors” from different sectoral indices of NIFTY 50 were considered.

#### 3.1. Data Acquisition and Preprocessing

##### 3.1.1. Data Collection

The data collection phase integrates financial market data with news-based sentiment data to capture both quantitative and qualitative drivers of SP movements.

### Financial News Data

- **Primary Source:** GDELT was used as the primary source for discovering news articles. GDELT monitors news media worldwide and provides article metadata, including URLs. GDELT provides article URLs but not full content. The actual news text was scraped from the source websites using BeautifulSoup and requests.

GDELT was chosen because it provides real-time global news with structured event metadata, sentiment scores, location details, and source reliability. It aggregates thousands of international news sources, reducing bias, and offers historical data via API suitable for machine learning. This is justified since global macro-level sentiment influences stock markets more strongly than local news.

- **Secondary News Sources:** Google News RSS and Economic Times - Google News RSS feeds were used to acquire the most recent, trending, and time-critical headlines, providing contemporaneous updates and elevated news fluctuations that augment GDELT's extensive reporting. For the Indian stock market, specifically for the NSE and BSE stock exchanges, the most reliable financial news source is The Economic Times, which provides Indian corporate news, government policies, regulations, market outlooks, and global market review.

All financial news of the Indian Market is covered in-depth in The Economic Times, which provides a much clearer picture and is a reliable source for SA.

#### 3.1.2. Data Processing

The raw data obtained from diverse sources were preprocessed to ensure uniformity and reliability.

#### Price Data Processing

From raw data, missing values in the data and NaN entries were removed. Date formats were arranged in chronological order for standardization. To ensure uniformity in feature extraction, column names were normalized.

#### Text Data Processing

News headlines from sources were aggregated on a daily basis to align with the trading days. News articles published in the English language were collected. Special characters, symbols, and extra spaces were removed from text data. This procedure resulted in a synchronized and noise-free dataset, thereby enhancing the efficacy of subsequent feature generation processes.

### 3.2. Feature Selection and Engineering

#### 3.2.1. Feature Selection

Feature selection emphasized the preservation of variables that exhibit substantial financial significance and predictive efficacy. The chosen features are classified into

three principal categories:

**Technical Indicators (18 features):** "Momentum, Trend, Volatility, Volume, And Price-Return Indicators" such as "Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple Moving Average (SMA), Exponential Moving Average (EMA), Average True Range (ATR), Bollinger Bandwidth, On Balance Volume (OBV) and Money Flow Index (MFI)".

- **Sentiment Features:** An ensemble of transformer-based language models was used to extract sentiment evaluations from daily financial news.
- **Derived Statistical Features:** Attributes including moving averages, moving standard deviations,
- measurements of volatility, and overnight price disparities.

The particular selection achieved expressiveness of the model and the efficiency of its dimensionality.

#### 3.2.2. Feature Engineering and Scaling

Feature engineering was implemented to enhance the predictive signal. To achieve variance stabilization, returns and log-returns were computed. To capture the short-term trend, rolling statistics, specifically mean deviation and standard deviation, were calculated over a short window. Volatility metrics were derived to capture the intrinsic uncertainty within the market.

Minimum-Maximum normalization techniques were used to scale all input features in the range of 0 to 1. In order to prevent data leakage, different scalers were used for the input features and the target variables.

#### 3.2.3. Sentiment Feature Engineering

Figure 2 illustrates the Three-Model Ensemble Approach, wherein three advanced transformer models with different weights were integrated within an ensemble framework to derive the aggregated sentiment score.

An ensemble sentiment analysis system is depicted in the diagram. FinBERT (40%), RoFinBERT (30%), and DistilRoBERTa(30%) process the cleaned news article text simultaneously. Each model generates sentiment output after tokenizing the text and using a BERT encoder to extract features. A final sentiment score between -1 and +1 is produced by averaging and weighting the predictions.

#### Model 1: FinBERT (Weight: 40%)

Model: ProsusAI/finbert

Specialty: Financial domain literature, enriched with training from financial news articles and analytical reports.[45]

Output: Positive/Negative/Neutral probabilities

#### Model 2: RoBERTa (Weight: 30%)

Model: cardiffnlp/twitter-roberta-base-sentiment-latest

Specialty: Social media and informal text sentiment. [46]

Output: Negative/Neutral/Positive scores

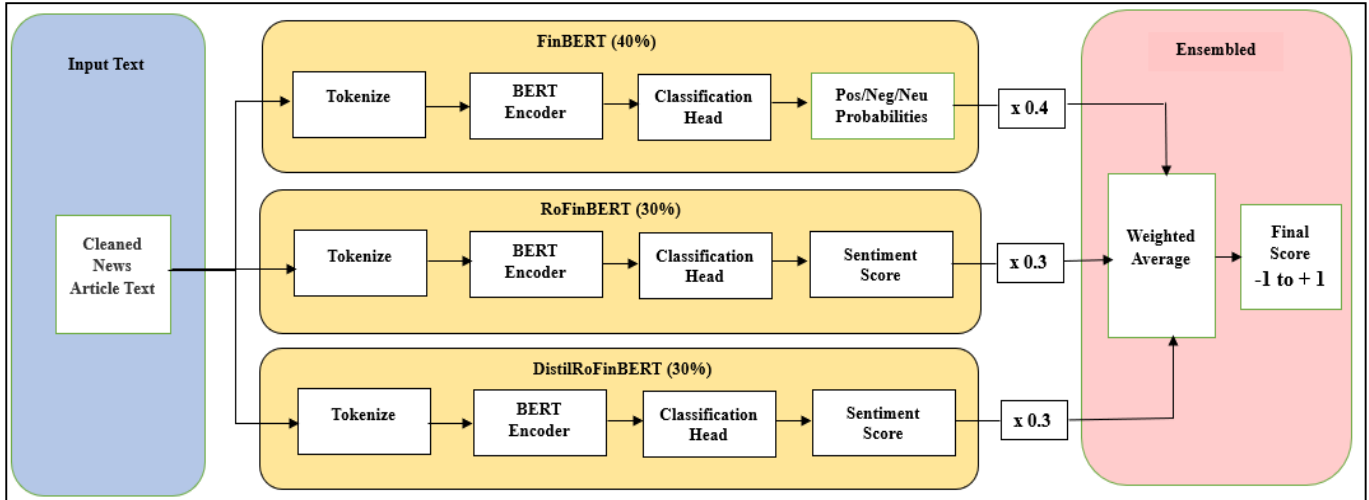


Fig. 2 Ensemble model for sentiment score

**Model 3: DistilRoBERTa (Weight: 30%)**

“Model:mrm8488/distilroberta-finetuned-financial-news-sentiment-analysis”. [47]

Specialty: Distilled model fine-tuned on economic news  
 Output: “Sentiment scores” optimized for speed

$$\text{Ensemble Score} = (0.4 F + 0.3 R + 0.3 D) \quad (1)$$

Where - F = FinBERT score  
 R = RoBERTa score  
 D = DistilRoBERTa score

Final classification is based on the ensemble score with thresholds:

- score > 0.05, considered as Positive (1)
- - 0.05 ≤ score ≤ + 0.05, considered as Neutral (0)
- score < -0.05, considered as Negative (-1)

Ensemble models were employed to combine the strengths of different language models, thereby improving prediction accuracy and stability. Initial experiments were conducted by assigning equal weights to all three models, followed by trials with varying weight distributions such as (0.3F+0.4R+0.3D), (0.4F+0.2R+0.4D), (0.25F+0.5R+0.25D), etc.

The ensemble configuration using weights of 0.4 (F), 0.3 (R), and 0.3 (D) produced superior performance and was therefore selected for the final prediction model implementation. Weights were selected using grid-search over {0.1,0.2,...0.7} with constraint w1+w2+w3=1. The (0.4,0.3,0.3) configuration yielded the lowest MAE on validation data. Paired t-tests across 10 rolling windows confirmed statistical significance (p < 0.05)

In this ensemble methodology, FinBERT-Tone was given the highest weightage due to its specialized training in the

financial domain. Twitter-RoBERTa extended the analytical model by incorporating opinion-driven informal language predominant on online social platforms, whereas DistilRoBERTa-Financial facilitated this by expanding the understanding of financial news and clearly specifying economic literature. The integration of these models secured a more coherent and reliable sentiment assessment across various financial writing styles.

Three pretrained financial NLP models with weighted averaging were used to calculate an ensemble sentiment score. Additionally, rolling sentiment averages were computed to mitigate daily variations.

**3.3. Deep Learning Architecture**

The proposed methodology using a GRU-MHA mechanism to capture the temporal dependencies and contextual relevance effectively is illustrated in Figure 3, given below –

- Input Layer: A sequential 15 trading days dataset with 25 features per time step was considered.
- GRU Layers: Two GRU layers with 64 units are used for the extraction of long-term temporal patterns while retaining computational efficiency.
- Multi-Head Self-Attention: To analyze temporal intervals, four attention heads were incorporated to enable the model to focus on significant historical periods.
- Residual Connections and Normalization: Enhance the gradient flow and training stability.
- Fully Connected Layers: To improve the learned representation, dense layers were activated using ReLU.
- Output Layer: “Single neuron” predicts the next-day log return of the opening price.

The hybrid architecture delivers good results by combining sequence modeling with attention-based representation learning.

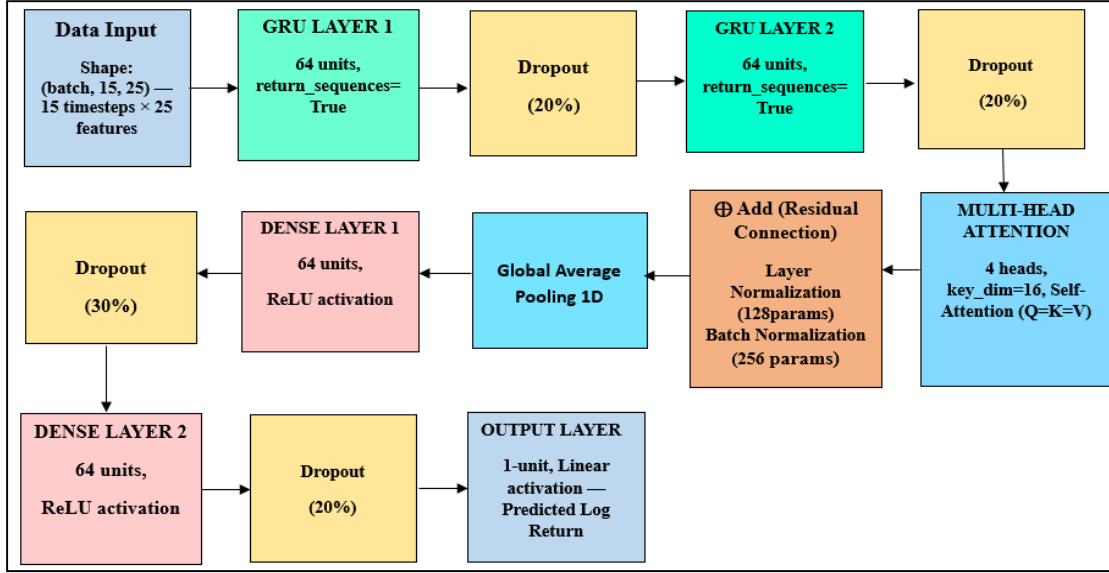


Fig. 3 Model architecture GRU- multi-head attention

Table 1. Notation table

Symbol	Meaning
$C_t$	Closing price at day t
$O_{t+1}$	Opening price at day t+1
$TI_t$	Technical feature vector at t
$SA_t$	Sentiment score at t
$r_t$	Log return

Table 1 shows the notations used in equations.

### 3.4. Proposed Stock Prediction Framework

#### Algorithm: A Hybrid GRU-MHA for Stock Prediction

Input: Fusion Data Set CSV (Historical Data+TI+SA)

Output: Predicted next-day opening price  $\hat{O}_{t+1}$

1. Load fusion dataset D
2. Compute target variable:  
 $r_t \leftarrow \log(O_{t+1}) - \log(C_t)$
3. Extract feature vector  $F_t$  from D
4. Normalize feature vectors using Min-Max scaling
5. Generate time-series sequences:  
for  $t = 1$  to  $N - T$  do  
 $X_t \leftarrow \{F_t, F_{t+1}, \dots, F_{t+T-1}\}$   
 $y_t \leftarrow r_{t+T}$   
end for
6. Split  $\{X_t, y_t\}$  into training and testing sets without shuffling
7. Initialize GRU-MHA network:  
 $h_t \leftarrow \text{GRU}(X_t)$   
 $a_t \leftarrow \text{MultiHeadAttention}(h_t)$   
 $z_t \leftarrow \text{LayerNorm}(h_t + a_t)$
8. Apply global average pooling on  $z_t$
9. Predict log return:  $\hat{y}_t \leftarrow \text{Dense}(z_t)$

10: Train model using Adam optimizer with Huber loss and early stopping

11: Estimate next-day opening price:

$$\hat{O}_{t+1} \leftarrow C_t \times \exp(\hat{y}_t)$$

12: Evaluate predictions using MAE, RMSE,  $R^2$ , and MAPE

13: Return  $\hat{O}_{t+1}$

End Algorithm

### 3.5. Mathematical Model for Proposed GRU-MHA Stock Prediction Framework

The fusion dataset D was given as:

$$D = \{(C_t, TI_t, SA_t)\}_{t=1}^N \quad (2)$$

Where  $C_t$  are the closing price of the stock,  $TI_t$  the technical indicators,  $SA_t$  and the Sentiment Score?

The fused feature vector at time t is defined as:

$$F_t = \{(C_t, TI_t, SA_t)\} \quad (3)$$

The next-day log return was defined as:

$$r_t = \log(O_{t+1}) - \log(C_t) \quad (4)$$

For a look-back window of length T, the input sequence and label were:

$$X_t = \{F_t, F_{t+1}, \dots, F_{t+T-1}\}, y_t = r_{t+T} \quad (5)$$

Temporal features were extracted using a GRU:

$$h_t = \text{GRU}(X_t) \quad (6)$$

Multi-Head Attention captures long-term dependencies, followed by residual normalization:

$$z_t = \text{LayerNorms}\{h_t + \text{MHA}(h_t)\} \quad (7)$$

After global average pooling, the predicted log return was:

$$\hat{y}_t = W\bar{z} + b \tag{8}$$

The next-day opening price was estimated as:

$$\hat{O}_{t+1} = C_t \cdot \exp(\hat{y}_t) \tag{9}$$

The model was trained using the ‘‘Adam optimizer’’ with Huber loss, and performance was evaluated using MAE, RMSE,  $R^2$  and MAPE.

### 3.6. Model Training

To avoid data leakage in the future, the model was trained using a time-series split (80% training, 20% testing).

- **Optimizer:** The ‘‘Adam optimization algorithm’’ utilizing a ‘‘learning rate of 0.001’’ facilitates adaptive modifications to the gradient updates.
- **Loss Function:** The Huber loss function has been selected due to its resilience against the influence of outliers present in financial datasets.
- **Batch Size:** 32, **Epochs:** Up to 120 with early stopping.
- **Early Stopping:** Training is halted when the validation loss does not improve for 10 consecutive epochs, helping to prevent overfitting.

During training, shuffling was deactivated to maintain chronological order.

## 4. Results and Discussions

### 4.1. Performance Metrics

This paper used five model performance metrics. ‘‘Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of determination ( $R^2$ )’’, they were calculated using equations (10), (11), (12), and (13), respectively.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_a - y_b| \tag{10}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_a - y_b)^2} \tag{11}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_a - y_p}{y_a} \right| \times 100 \% \tag{12}$$

$$R^2 = 1 - \frac{\sum (y_a - y_p)^2}{\sum (y_a - \bar{y})^2} \tag{13}$$

Where  $y_{ou}$  is the actual value,  $y_p$  is the predicted value,  $\bar{y}$  is the mean of all actual values, and  $n$  is the total number of observations.

These metrics ensure a more accurate and relevant evaluation.

**Table 2. Performance of the GRU+MHA model integrating ensemble score with historical data and technical indicators**

Evaluation Methods	NIFTY Sectoral Indices	Stock Name	GRU + Multi-Head Attention			
			FinBERT	RoBERTa	DistilRoBERTa	Ensemble Model (FinBERT + RoBERTa + DistilRoBERTa)
MAE	Nifty IT	INFOSYS	0.1836	0.6927	0.1679	0.1631
	Nifty Metals	TATA STEEL	6.0468	117.3245	11.4447	0.7607
	Nifty Auto	TATA MOTORS	6.0468	117.3245	11.4447	8.5867
	Nifty Pharma	SUNPHARMA	8.8535	16.9332	9.2860	8.2465
RMSE	Nifty IT	INFOSYS	0.2608	0.7660	0.2440	0.2337
	Nifty Metals	TATA STEEL	21.6325	22.6904	140.2009	1.4703
	Nifty Auto	TATA MOTORS	21.6325	140.2009	22.6904	21.0757
	Nifty Pharma	SUNPHARMA	15.1135	21.4539	15.3315	14.5458
$R^2$	Nifty IT	INFOSYS	0.9212	0.3202	0.9310	0.9507
	Nifty Metals	TATA STEEL	0.9204	-2.3453	0.9124	0.9893
	Nifty Auto	TATA MOTORS	0.9204	-2.3453	0.9124	0.9245
	Nifty Pharma	SUNPHARMA	0.9405	0.8801	0.9388	0.9336
MAPE	Nifty IT	INFOSYS	1.04	3.99	0.95	0.93
	Nifty Metals	TATA STEEL	1.08	18.14	1.89	0.52
	Nifty Auto	TATA MOTORS	1.08	18.14	1.89	1.47
	Nifty Pharma	SUNPHARMA	0.53	1.01	0.55	0.49

Table 2 presents an empirical assessment of the proposed GRU-MHA architecture integrated with FinBERT, RoBERTa, DistilRoBERTa, and their ensemble sentiment representation, evaluated on stocks from the NIFTY IT, Metals, Auto, and Pharma sectors. Model effectiveness was evaluated.

#### 4.2. Error-Based Performance Analysis

The error metrics show that the ensemble sentiment model works better when used with the GRU-MHA architecture. The ensemble consistently produced the fewest errors across all sectors, showing that it was more accurate and stable. In the Nifty IT sector, INFOSYS had an MAE of 0.1631 and an RMSE of 0.2337. In the Nifty Metals sector, TATA STEEL's MAE went down to 0.7607, which is lower than the errors from standalone FinBERT models. Also, the MAPE values stayed below 1% for most stocks, with SUNPHARMA (0.49%) and TATA STEEL (0.52%) having

the lowest values. This demonstrates the practical applicability of the proposed model.

#### 4.3. Variance Explanation and Model Fit ( $R^2$ )

The results confirm that the proposed hybrid framework can explain things very well. The ensemble model got  $R^2$  values over 0.92 in all sectors, with TATA STEEL having the highest value of 0.9893. This means that almost 99% of the stock price variance was explained

#### 4.4. Feature Contribution Analysis

Rigorous experimentation was carried out for the GRU+MHA model by taking only stock historical data, stock historical data + technical indicators, stock historical data + sentiment score, and finally stock historical data + technical indicators + sentiment score. Better results are achieved by integrating all three input parameters.

**Table 3. Comparative performance of LSTM+MHA, BiLSTM+ MHA, and GRU+MHA models across selected NIFTY stocks.**

Evaluation Methods	NIFTY Sectoral Indices	Stock Name	Deep Learning Models		
			LSTM + MHA	BiLSTM + MHA	GRU + MHA
MAE	Nifty IT	INFOSYS	<b>0.1592</b>	0.6971	0.1631
	Nifty Metals	TATA STEEL	1.9956	0.8159	<b>0.7607</b>
	Nifty Auto	TATA MOTORS	9.2095	8.9604	8.5867
	Nifty Pharma	SUNPHARMA	8.4229	8.2623	<b>8.2465</b>
RMSE	Nifty IT	INFOSYS	<b>0.2287</b>	0.7926	0.2337
	Nifty Metals	TATA STEEL	2.3382	1.4825	<b>1.4703</b>
	Nifty Auto	TATA MOTORS	<b>5.7484</b>	7.9073	21.0757
	Nifty Pharma	SUNPHARMA	14.7325	14.598	<b>14.5458</b>
$R^2$	Nifty IT	INFOSYS	0.9256	0.4332	<b>0.9367</b>
	Nifty Metals	TATA STEEL	0.972	0.9891	<b>0.9892</b>
	Nifty Auto	TATA MOTORS	0.9812	0.6105	<b>0.9245</b>
	Nifty Pharma	SUNPHARMA	0.9326	0.9328	<b>0.9336</b>
MAPE	Nifty IT	INFOSYS	0.91	<b>0.85</b>	0.93
	Nifty Metals	TATA STEEL	1.29	0.56	<b>0.52</b>
	Nifty Auto	TATA MOTORS	<b>0.44</b>	0.89	1.47
	Nifty Pharma	SUNPHARMA	0.51	0.50	<b>0.49</b>

Table 3 shows a comparative evaluation of LSTM+MHA, BiLSTM+MHA, and GRU+MHA architectures across four NIFTY sector stocks. The GRU+MHA model consistently achieved lower MAE and RMSE values and better  $R^2$  scores, demonstrating superior prediction accuracy.

The integration of complementary representations from multiple transformer architectures is responsible for the ensemble sentiment model's improved performance. FinBERT captures domain-specific financial semantics, while

RoBERTa and DistilRoBERTa improve contextual generalization.

The better performance of the proposed GRU-MHA model can be ascribed to its capacity to effectively model both short-term and long-term dependencies. Unlike "LSTM," GRU has fewer parameters, reducing overfitting while maintaining performance. The integration of MHA helps the model to emphasize significant time steps, improving contextual learning. Furthermore, the ensemble sentiment

approach reduces bias from individual models, yielding more reliable and accurate forecasts across sectors.

The system effectively learns both “short- and long-term dependencies” when combined with the GRU-MHA temporal modeling framework, exhibiting robustness for real-time stock price prediction applications and producing consistent improvements across assessment measures.

**4.5. Validation**

For validation and testing, the proposed trained model predicted the opening prices of all four stocks for the next 15 days, from 1<sup>st</sup> November 2025 to 5<sup>th</sup> December 2025. The predicted and actual opening prices of all stocks were validated using the performance metric MAPE, and the results show that the model’s capacity to accurately capture “short-term” market trends and the projected prices closely matched the actual price movements.

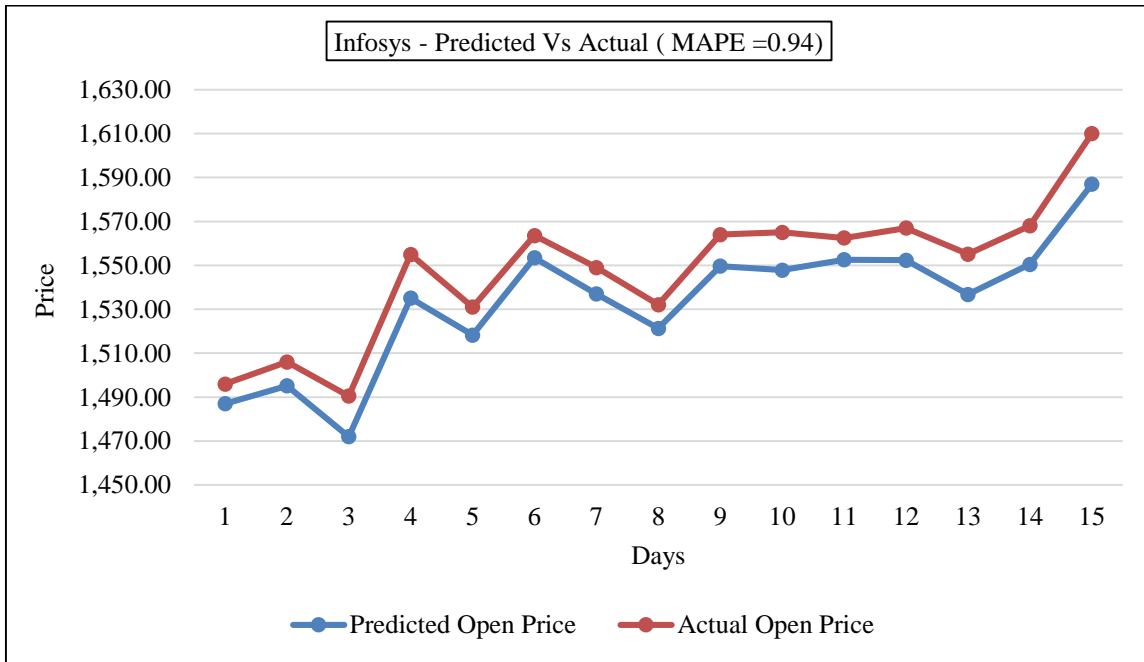


Fig. 4 Testing of infosys prediction plot

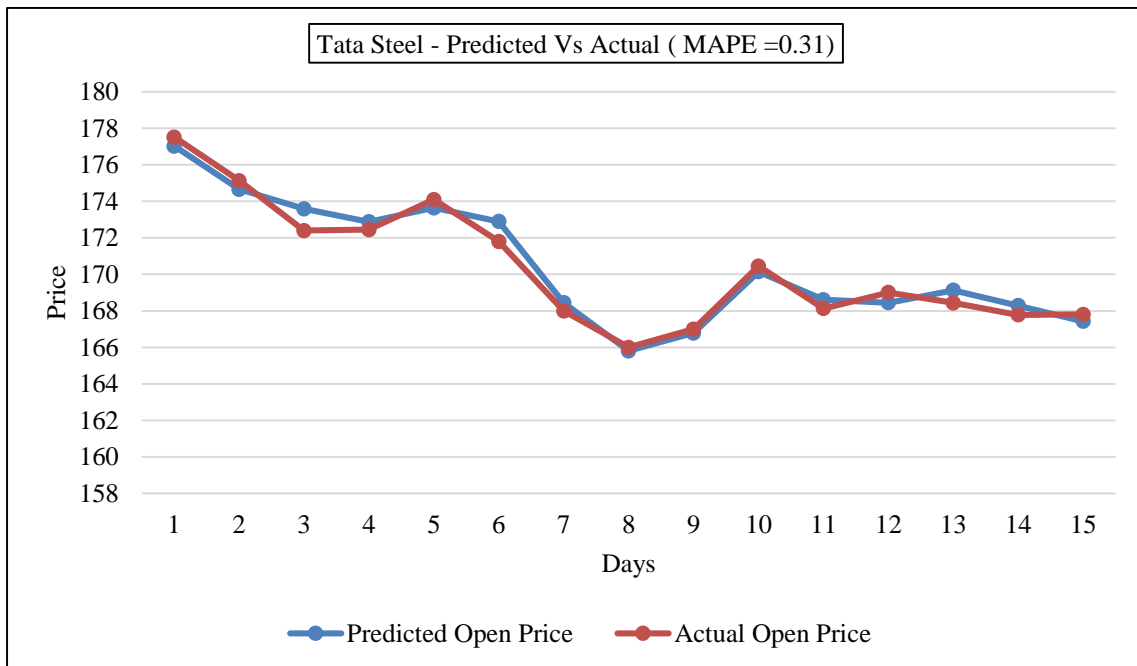


Fig. 5 Testing of Tata steel prediction plot

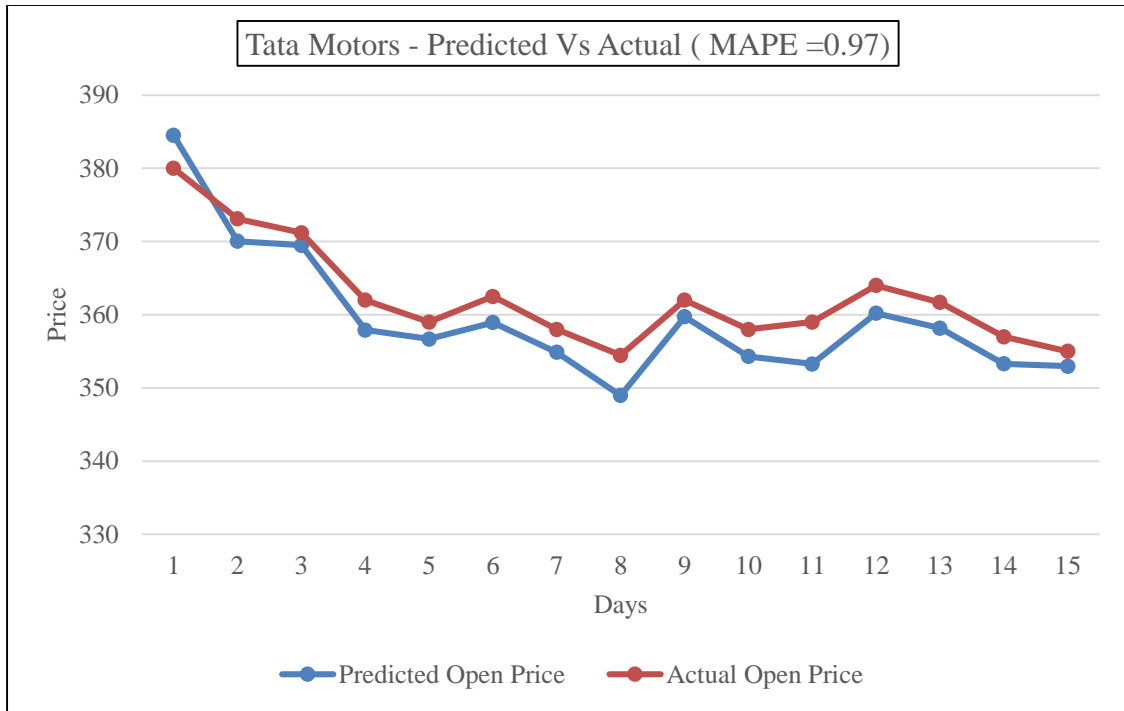


Fig. 6 Testing of Tata motors prediction plot

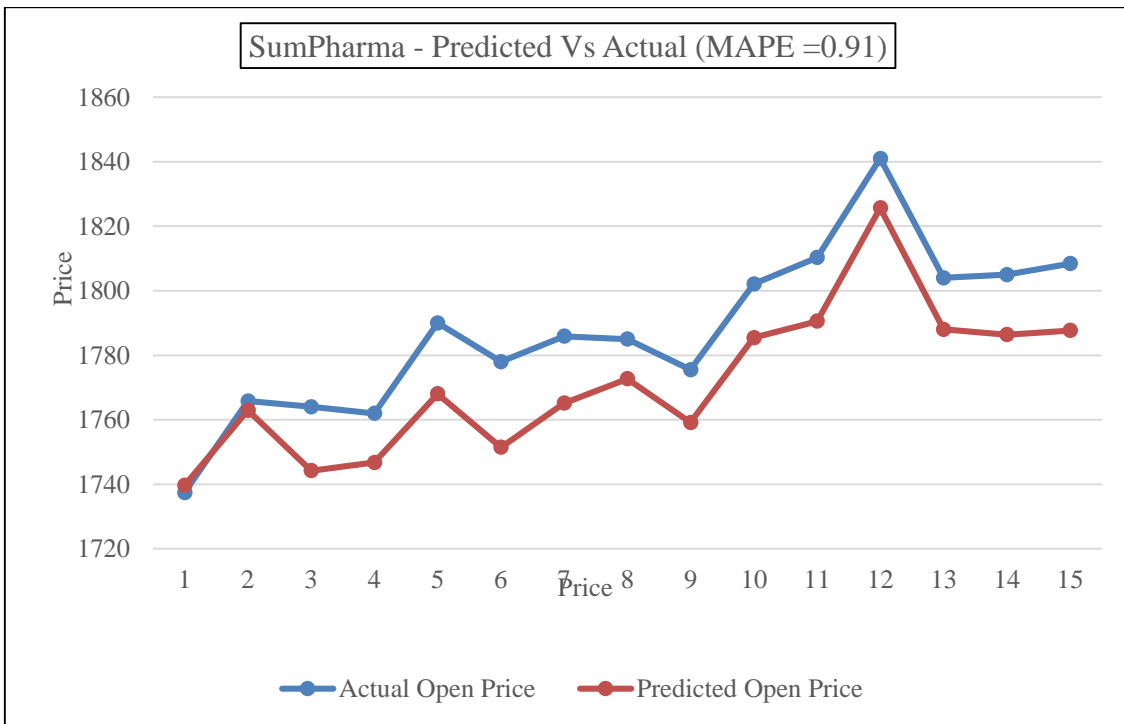


Fig. 7 Testing of Sun Pharma prediction plot

Figures 4, 5, 6, and 7 show the plot of predicted opening prices and actual opening prices of Infosys, Sun Pharma, Tata Motors, and Tata Steel from 17th November 2025 to 5<sup>th</sup> December 2025. MAPE values were calculated as 0.94% (Infosys), 0.31% (Tata Steel), 0.97% (Tata Motors), and 0.92% (Sun Pharma). The corresponding error percentages

indicate low and stable prediction errors, indicating strong forecasting accuracy and robustness of the suggested model across various sectors. (Tata Steel), demonstrating high forecasting accuracy and resilience of the proposed model across different sectors.

**Table 4. Comparative analysis of the proposed approach against state-of-the-art techniques**

Author and Year	Methodology	Results	Relevance to the present work
Zhang et al [4]	CNN–BiLSTM–Attention hybrid	RMSE =14.54, MAE =8.24, R <sup>2</sup> = 0.93–0.95, MAPE = 0.49%	Strong evidence for CNN + Attention hybrids
Bhandari et al [6]	Single & multi-layer LSTM	RMSE = 0.012–0.018, MAPE =1–2%	Establishes LSTM as baseline predictor
Lawi et al [7]	LSTM, GRU, LSTM–GRU hybrids	MAPE = 0.5–0.9%, RMSPE improved over standalone models	Justifies comparing LSTM, GRU, and hybrids
Gülmez [13]	GA–Attention–Fuzzy–Stock–Net	MSE as low as 0.001 and R <sup>2</sup> up to 0.965	Highlights attention + optimization benefits
Liu et al [21]	TrellisNet + Sentiment Attention	RMSE = 0.023, MAE = 0.017	Supports sentiment-attention integration
Kasture et al [26]	Hybrid RNN–LSTM + sentiment	MAE = 6.21, RMSE = 4.63, R <sup>2</sup> > 0.95	Supports hybrid RNN architectures
Nabipour et al. [34]	ANN, RNN, LSTM, tree-based ensemble models	LSTM achieved lowest MAE =1.94 & RMSE = 2.69, highest R <sup>2</sup> across all sectors	Confirms LSTM superiority for nonlinear stock data
R.K.Ghosh et al [38]	Hybrid TCN-GRU Multi-head Attention	RMSE = 0.072, an MAE =0.051, MAPE of 5.10%, and an R <sup>2</sup> of 0.849	Better results were achieved by the hybrid model (TCN-GRU) than by using an independent model.
<b>Proposed Work</b>	<b>Ensemble Sentiment and GRU MHA Model</b>	<b>Achieved R<sup>2</sup> up to 0.9893</b>	<b>A hybrid model with the fusion of transformer-based sentiment fusion with a DL model.</b>

Table 4 demonstrates the comparative analysis of the proposed methodology with existing literature work; the proposed methodology achieves an R<sup>2</sup> of up to 0.9893.

The improved performance is due to three main factors. First, combining FinBERT, RoBERTa, and DistilRoBERTa captures diverse sentiment information and reduces bias. Second, integrating Multi-Head Attention with GRU helps the model focus on important time steps and temporal patterns. Third, merging historical data, technical indicators, and sentiment features provides a comprehensive view of market behavior, enhancing overall prediction accuracy and generalization.

## 5. Conclusion

The study predicted stock prices using a hybrid GRU with a Multihead Attention model and ensemble transformer-based sentiment analysis. Experimental results across the NIFTY

sector showed steady performance gains, low prediction errors, MAE = 0.1631, RMSE=0.2337. MAPE < 1% and good explanatory power (R<sup>2</sup> >0.92, culminating at 0.9893. These results show that temporal attention methods and multi-source sentiment fusion improves forecasting accuracy and model stability over standalone sentiment models.

This approach can be expanded with frequency and intraday market data, social media and macroeconomics sentiment signals, and explainable AI algorithms to improve transparency. Validation on real-time trading systems and foreign stock markets would improve its practicality and scalability.

## Conflicts of Interest

The authors declare that they have no competing interests related to this work.

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