Enhancing Stock Market Predictions Using Hybrid Deep Learning Models with Sentiment Analysis and Feature Engineering

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Stock price prediction remains a complex yet crucial task in financial markets, requiring robust methodologies to capture intricate dependencies in stock price movements. This study proposes the Hybrid Deep Learning for Stock Market Prediction (HDL-SMP) model, integrating Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM), and an Attention Mechanism to enhance predictive accuracy. The model processes three key data sources: historical stock prices, technical indicators, and sentiment analysis scores from financial news and social media. The CNN layer extracts spatial patterns in price movements, while the BiLSTM layer learns long-term dependencies and captures both past and future trends. The Attention layer assigns dynamic weights to features based on their significance, optimizing prediction outcomes. Experimental evaluations on benchmark stock market datasets demonstrate the superiority of HDL-SMP over traditional machine learning models and existing deep learning architectures. The model achieves higher prediction accuracy, lower error rates, and improved robustness against market volatility. A comparative analysis with Support Vector Regression (SVR), CNN-BiLSTM, and other hybrid deep learning models confirms the effectiveness of HDL-SMP in financial forecasting. These findings highlight the potential of deep learning-based models in stock market prediction, aiding investors and financial analysts in making informed decisions.

Povzetek: Članek predstavi hibridni HDL-SMP model (CNN, BiLSTM, Attention) s tehničnimi indikatorji in sentimentno analizo, ki presega obstoječe pristope pri napovedovanju delnic z nižjimi napakami in višjim R^2*.*

1 Introduction

Stock market prediction has been a subject of extensive research due to its significance in financial decision-making, risk assessment, and investment strategies. Accurate stock market forecasting can provide investors with critical insights to optimize their portfolios and mitigate risks. However, predicting stock prices remains a challenging task due to the highly volatile, dynamic, and non-linear nature of financial markets, which are influenced by a complex interplay of historical price patterns, macroeconomic factors, market sentiment, and global events [1-4]. Traditional statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been widely used for stock price forecasting, but they often struggle to capture the intricate dependencies and latent patterns present in large-scale financial data. With the advent of machine learning and deep learning, researchers have explored the potential of artificial intelligence-driven models in enhancing prediction accuracy. Among these, deep learning techniques such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have gained prominence due to their ability to model temporal dependencies and extract meaningful features from complex datasets. Despite their effectiveness, standalone deep learning models often face limitations in handling noisy data and external influencing factors such as investor sentiment and news-driven market movements [5-7]. To address these challenges, this study proposes a hybrid deep learning framework that integrates sentiment analysis and feature engineering to enhance stock market predictions.

Sentiment analysis plays a crucial role in financial forecasting by incorporating market sentiment derived from news articles, social media, and financial reports. Investor sentiment, which reflects public perception and emotions toward specific stocks or market trends, has been shown to impact stock price movements significantly.

Sentiment analysis techniques leverage natural language processing (NLP) and machine learning algorithms to quantify sentiment scores from textual data, allowing models to incorporate qualitative information alongside traditional numerical indicators. The integration of sentiment analysis into stock prediction models has gained traction in recent years, as studies suggest that market sentiment can serve as a leading indicator for stock price fluctuations [8-11]. However, effectively capturing and integrating sentiment information remains a challenge due to the subjective nature of textual data, varying linguistic structures, and the presence of misinformation. In this study, a sentiment analysis module is incorporated into the hybrid model to extract meaningful sentiment-driven features from financial news and social media discussions [12-17]. The sentiment scores are then utilized as additional input features to enhance predictive performance. Feature engineering is another critical aspect of stock market prediction that involves transforming raw data into informative and structured representations that improve model performance. Traditional feature selection methods rely on predefined technical indicators such as moving averages, Bollinger Bands, Relative Strength Index (RSI), and MACD (Moving Average Convergence Divergence). While these indicators provide valuable insights, deep learning models can further benefit from automated feature extraction and selection techniques. The proposed hybrid approach leverages deep learning-driven feature engineering to extract high-dimensional feature representations from historical stock prices, trading volumes, and external sentiment data. By combining domain-specific feature selection with deep learning-based automated feature extraction, the model enhances its ability to capture intricate dependencies and reduce redundant or irrelevant information. The hybrid architecture employed in this study combines LSTM and CNN models to exploit both sequential and spatial characteristics in stock market data. LSTM networks are particularly effective in handling time-series data by preserving long-term dependencies, while CNNs excel in capturing local patterns and feature correlations. The fusion of these architectures enables the model to learn hierarchical representations and improve forecasting accuracy.

2 Literature review

In recent years, hybrid deep learning models have gained popularity in stock market prediction due to their ability to learn intricate patterns from large datasets. These models often integrate different neural network architectures, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based models, to improve predictive accuracy. Furthermore, sentiment analysis has emerged as a crucial factor in financial forecasting, as investor sentiment derived from social media, news articles, and financial reports significantly impacts stock prices.

Feature engineering plays a pivotal role in enhancing model performance by selecting the most relevant input variables. By incorporating a combination of technical indicators, fundamental analysis, and sentiment scores, hybrid models can offer improved forecasting capabilities. Despite these advancements, challenges remain, including data quality issues, overfitting, and the ability to generalize across different market conditions.

This section explores recent studies on stock market prediction, focusing on the advantages and limitations of various approaches, particularly hybrid deep learning models integrated with sentiment analysis and feature engineering.

Olawale et al. [9] explored the impact of combining sentiment analysis and historical price data in stock market predictions. Their study emphasized how integrating investor sentiment from financial news and social media enhances traditional forecasting models. Advantages of their approach include improved model accuracy due to the incorporation of real-time market sentiment, which captures investor behavior more effectively than historical prices alone. However, a notable disadvantage is the challenge of ensuring data reliability, as sentiment data from social media may be noisy, misleading, or subject to manipulation.

Ebrahimian et al. [10] applied Support Vector Regression (SVR) to forecast stock prices, highlighting its ability to handle nonlinear patterns effectively. Their findings suggest that SVR models perform well when combined with sentiment-related variables and technical indicators. Advantages of this approach include the robustness of SVR in capturing complex relationships between stock prices and influencing factors. However, a key disadvantage is that SVR models can be computationally expensive and require careful parameter tuning to avoid overfitting.

Das et al. [11] developed hybrid deep learning models that integrate an enhanced Twitter sentiment score with technical indicators for stock price prediction. Their approach demonstrated that incorporating deep learning with sentiment analysis significantly reduces prediction errors. Advantages of their model include improved accuracy and the ability to adapt to sudden market changes by analyzing real-time sentiment data. However, a disadvantage is the dependency on the quality and availability of sentiment data, which may not always reflect actual market movements.

Zhong and Enke [12] investigated the use of hybrid machine learning algorithms for predicting the daily return direction of stock markets. Their study found that combining multiple algorithms led to improved predictive performance. Advantages include enhanced robustness and generalization across different market conditions. However, a disadvantage is the increased complexity of model implementation and the need for substantial computational resources.

Zheng et al. [13] introduced an evolutionary framework incorporating bidirectional Long Short-Term Memory (BiLSTM) networks for stock price prediction. Their study demonstrated that BiLSTM networks effectively capture sequential dependencies in financial time series data. Advantages of this approach include improved long-term prediction accuracy and the ability to retain important historical trends. However, a disadvantage is the potential for overfitting, especially when training on limited data.

Wang et al. [14] proposed a hybrid model combining Convolutional Neural Networks (CNNs) with BiLSTM architectures to predict stock closing prices. Their results showed that CNNs help extract spatial features from stock data, while BiLSTMs enhance sequential learning. Advantages of this hybrid model include a more comprehensive understanding of market patterns and improved generalization. However, a disadvantage is the requirement for a large dataset to train both CNN and BiLSTM components effectively.

Kumar et al. [15] applied bootstrap aggregation ensemble learning for financial forecasting, illustrating the effectiveness of ensemble methods in improving model reliability. Advantages of their approach include increased stability and reduced variance, leading to more consistent predictions. However, a disadvantage is the computational burden associated with training multiple models and aggregating their results.

Smith and O'Hare [16] examined the relationship between traditional news, social media sentiment, and stock price movements. Their findings highlighted that social media sentiment often precedes price changes, making it a valuable predictive factor. Advantages of their study include the identification of sentiment as a leading indicator for stock price movements. However, a disadvantage is the challenge of distinguishing between genuine sentiment shifts and market noise.

Raman et al. [17] conducted a mixed-methods study leveraging news article sentiment to predict firm performance. Their research demonstrated that combining qualitative and quantitative sentiment analysis improves predictive power. Advantages include a more nuanced understanding of market trends by considering both numerical data and textual insights. However, a disadvantage is the subjectivity involved in sentiment classification, which may lead to inconsistencies.

Passalis et al. [18] analyzed multiple sources of financial sentiment to detect Bitcoin price changes using deep learning techniques. Their study found that multi-source sentiment analysis enhances prediction accuracy. Advantages of their approach include a broader perspective on investor sentiment across different platforms. However, a disadvantage is the difficulty in normalizing sentiment data from various sources to ensure consistency.

Mndawe et al. [19] developed a stock price prediction framework that integrates intelligent media analysis and technical indicators. Their results demonstrated that feature engineering plays a crucial role in improving forecasting performance. Advantages of their study include the enhanced interpretability of models by selecting the most relevant features. However, a disadvantage is the potential for feature selection bias, which may lead to suboptimal models.

Lv et al. [20] examined the selection of optimal trading models for different industries, emphasizing the importance of industry-specific models. Advantages of their approach include tailored predictions that account for sector-specific factors. However, a disadvantage is the reduced generalizability of these models across different market segments.

Jiawei and Murata [21] applied LSTM neural networks for stock market trend prediction, incorporating sentiment analysis. Their study confirmed that LSTM models effectively capture long-term dependencies. Advantages include superior handling of sequential data compared to traditional models. However, a disadvantage is the extensive computational power required for training.

Zhang et al. [22] conducted an empirical study on TextRank for keyword extraction, which is relevant to sentiment analysis techniques in financial forecasting. Advantages include improved sentiment feature extraction for stock prediction models. However, a disadvantage is the difficulty in interpreting keyword rankings in highly volatile markets.

Li et al. [23] investigated stock market prediction by incorporating stock prices and news sentiment, focusing on the Hong Kong market. Their findings indicated that sentiment-based models outperform traditional approaches. Advantages include enhanced accuracy by integrating multiple data sources. However, a disadvantage is the potential for sentiment analysis models to misinterpret complex financial language.

Rustam et al. [24] compared supervised machine learning models for sentiment analysis of COVID-19 tweets, offering insights into text-based sentiment classification. Advantages include the demonstration of different classification techniques in real-world applications. However, a disadvantage is the challenge of applying these models to financial contexts without significant modifications.

The reviewed studies highlight significant advancements in stock market prediction, particularly through the integration of hybrid deep learning models, sentiment analysis, and feature engineering. While these approaches offer improved accuracy and robustness, challenges such as data quality, computational costs, and model interpretability remain. The following are the objectives of the proposed work.

1. Develop a Hybrid Deep Learning Model (HDL-SMP) integrating CNN, BiLSTM, and Attention Mechanism for stock price prediction.
2. Enhance feature extraction and long-term dependency modeling by leveraging CNN for spatial patterns and BiLSTM for sequential dependencies.
3. Improve model interpretability using an Attention Mechanism to assign significance to influential stock price movements.
4. Validate the effectiveness of the proposed approach using historical stock market data, technical indicators, and sentiment analysis.

3 Proposed work

This study proposes a Hybrid Deep Learning Model for Stock Market Prediction (HDL-SMP) by integrating Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM), and Attention Mechanisms. The model leverages historical stock data, technical indicators, and sentiment analysis from financial news and social media to enhance prediction accuracy. Figure 1 shows the architecture of the proposed work.

3.1 Problem statement

Current deep learning models for stock price prediction either fail to effectively capture long-term dependencies or lack the ability to assign importance to significant market events. Therefore, there is a need for a hybrid deep learning model that combines CNN for feature extraction, BiLSTM for sequential learning, and an Attention Mechanism to prioritize influential patterns in financial time series data.
The architecture consists of three primary layers:

1. **Feature Extraction Layer (CNN)** – Extracts spatial dependencies in stock prices.
2. **Sequence Learning Layer (BiLSTM)** – Captures long-term dependencies in time series data.
3. **Attention Layer** – Enhances important feature representation, improving predictive power.

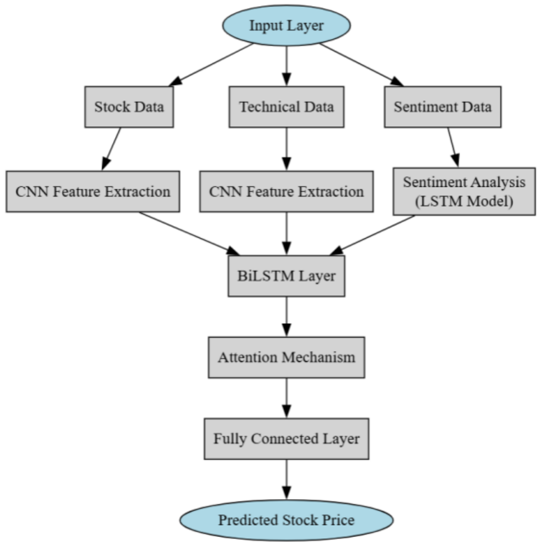

Figure 1: Oveview of proposed work

The model integrates Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM), and an Attention Mechanism to extract essential features, understand sequential dependencies, and prioritize relevant patterns in financial time series data. This discussion explores the six primary components of HDL-SMP: Input Layer, Feature Extraction Layer (CNN), Sequence Learning Layer (BiLSTM), Attention Layer, and Output Layer, explaining their significance and functionality in stock market prediction.

3.2 Input layer

Capturing Essential Market Information
The input layer of HDL-SMP is responsible for aggregating diverse financial data sources that impact stock price movement. This includes three key elements:
Historical stock prices serve as the foundation for financial forecasting, providing insights into market trends and price movements. The key features considered in this dataset are:

- Opening Price (O_t): The stock price at the beginning of the trading session.
- Closing Price (C_t): The stock price at the end of the trading session.
- High Price (H_t): The highest price of the stock during the trading session.
- Low Price (L_t): The lowest price of the stock during the trading session.
- Trading Volume (C_t): The total number of shares traded.

These features help the model understand market volatility and price trends.

3.3 Technical indicators

Technical indicators are mathematical calculations based on historical prices and volume that help traders predict future price movements. HDL-SMP includes:

Moving Averages (MA): Used to smooth price data and identify trends

$$MA_n = \frac{1}{n}\sum_{i=0}^{n-1} C_{t-i}$$

where n represents the window size.

Relative Strength Index (RSI): Measures the speed and change of price movements, helping identify overbought and oversold conditions.

$$RSI = 100 - \frac{100}{1 + RSI}$$

where **RS** is the ratio of average gains to average losses over a given period.

Moving average convergence divergence (MACD): Indicates trend strength by comparing two moving averages.

$$MACD = EMA_{12} - EMA_{26}$$

where EMA refers to the exponential moving average.

These indicators provide additional context to raw stock prices, helping HDL-SMP recognize trend reversals and momentum shifts.

3.4 Sentiment analysis scores

Stock prices are influenced not just by historical data but also by market sentiment. Sentiment analysis quantifies emotions in financial news and social media by assigning positive, negative, or neutral scores. The sentiment score (S_t) is computed as:

$$S_t = \sum_{i=1}^{n} w_i . T_i$$

where:

- w = Weight assigned to sentiment word iii
- T_i = Sentiment polarity score (+1 for positive, −1 for negative)

Incorporating sentiment scores allows the model to consider investor emotions and external market influences that impact stock prices.

3.5 Feature extraction layer (CNN): identifying key price patterns

Once the input data is collected, CNNs extract meaningful **spatial features** from stock prices and technical indicators.

Convolutional layers

Convolutional layers apply filters to **detect local patterns** in stock price movements, such as price jumps, trends, and cycles. The convolution operation is:

$$Z_{ij} = f(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W_{mn} \cdot X_{\{i+m,j+n\}} + b)$$

where:

- W_{mn} = Filter weights
- $i + m, j + n$ = Input data
- b = Bias term
- f(·) = Activation function (ReLU)

CNN enhances key price movement features while reducing noise.

Pooling layers

Pooling layers reduce dimensionality while retaining essential features. Max pooling is used:

$$P_{\{i,j\}} = \max_{(m,n)\in R} Z_{i+m,j+n}$$

where R represents the pooling region. This helps prevent overfitting by retaining dominant price patterns.

3.6 Sequence learning layer (BiLSTM)

CNN focuses on feature extraction, but financial data is inherently sequential, requiring a model that understands time-dependent relationships.

Bidirectional processing

A Bidirectional LSTM (BiLSTM) processes stock sequences in both forward and backward directions:

Forward LSTM:

$$h_t^f = \sigma(W_f X_t' + U_f h_{\{t-1\}}^f + b_f)$$

Backward LSTM

$$h_t^b = \sigma(W_b X_t' + U_b h_{\{t-1\}}^b + b_b)$$

The final output:

$$Ht = h_t^f + h_t^b$$

This bidirectional approach enables the model to account for both past trends and future influences.

Handling vanishing gradient

LSTM uses gates to prevent vanishing gradient problems:

$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i)$$
$$C_t = f_t C_{t-1} + i_t C_t$$
$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o)$$
$$h_t = o_t tanh(C_t)$$

This allows BiLSTM to preserve long-term dependencies in financial data.

Attention layer

The attention mechanism helps the model focus on crucial stock price movements rather than treating all data points equally.

The attention layer assigns importance to specific time steps:

$$e_t = V^T tanh(WH_t + b)$$

The softmax function normalizes these scores:

$$\alpha_t = \frac{exp(e_t)}{\sum_k exp(e_t)}$$

The final context vector is computed as:

$$C = \sum_t \alpha_t H_t$$

This enables HDL-SMP to identify and emphasize significant market events, such as earnings reports or economic crises.

a. Output Layer

The output layer consists of a fully connected neural network and a regression function to predict stock prices.

The final stock price prediction is given by:

$\widehat{Y_t} = W_o C + b_o$

where W_o and b_o are trainable weights.

Loss Function

The model minimizes Mean Squared Error (MSE):

$$L = \frac{1}{N}\sum_{i=1}^{N}(Y_i, \widehat{Y_i})$$

where:

- Y_i = Actual stock price
- $\widehat{Y_i}$ = Predicted stock price

The lower the MSE, the better the model's accuracy. Algorithm for the proposed work is given below:

Algorithm: Hybrid Deep Learning Model for Stock Market Prediction (HDL-SMP)

Input:

- **Stock price data**:, C_t, H_t, L_t, V_t
- **Technical indicators**: Moving Averages (MA), Relative Strength Index (RSI), MACD
- **Sentiment scores**: Extracted from financial news and social media

Output:

- Predicted stock price $\widehat{Y_t}$

Step 1: Initialize the Model Components

1. Initialize Convolutional Neural Network (CNN) for feature extraction.
2. Initialize Bidirectional Long Short-Term Memory (BiLSTM) for sequential learning.
3. Initialize Attention Layer to assign importance to key features.
4. Initialize Fully Connected Layer for final prediction.

Step 2: Input Data Preparation

5. Collect and preprocess historical stock price data, technical indicators, and sentiment scores.
6. Normalize all input features using Min-Max scaling
$$X' = \frac{X - X_{min}}{X_{min} - X_{max}}$$
7. Reshape data into a suitable format for CNN and BiLSTM layers.

Step 3: Feature Extraction Using CNN

8. Apply **convolution operation** on the input sequence:
$$Z_{ij} = f(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W_{mn} \cdot X_{\{i+m,j+n\}} + b)$$
9. Apply Max Pooling to reduce dimensionality:
$$P_{\{i,j\}} = \max_{(m,n)\in R} Z_{i+m,j+n}$$

Step 4: Sequential Learning Using BiLSTM

10. Feed CNN output into BiLSTM for temporal pattern learning.
11. Process the sequence in forward and backward directions:

- Forward LSTM:
$$h_t^f = \sigma(W_f X_t' + U_f h_{\{t-1\}}^f + b_f)$$
- Backward LSTM
$$h_t^b = \sigma(W_b X_t' + U_b h_{\{t-1\}}^b + b_b)$$

12. Concatenate forward and backward outputs:
$$Ht = h_t^f + h_t^b$$

Step 5: Attention Mechanism for Feature Weighting

13. Compute attention scores for each time step:
$$e_t = V^T tanh(WH_t + b)$$
14. Normalize scores using softmax function:
$$\alpha_t = \frac{exp(e_t)}{\sum_k exp(e_t)}$$
15. Compute the context vector:
$$C = \sum_t \alpha_t H_t$$

Step 6: Stock Price Prediction Using Fully Connected Layer

16. Pass the context vector C through a fully connected layer
$\widehat{Y_t} = W_o C + b_o$

Step 7: Model Training and Optimization

17. Compute the loss function (Mean Squared Error - MSE)

$$L = \frac{1}{N}\sum_{i=1}^{N}(Y_i, \widehat{Y_\iota})$$

18. Optimize the model parameters using Adam Optimizer

$$\theta = \theta - \eta \cdot \frac{\partial L}{\partial \theta}$$

where η is the learning rate.

Step 9: Model Evaluation

20. Evaluate the model on the test dataset using performance metrics such as

1. Mean Absolute Error (MAE):

$$\frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i|$$

where y_i is the actual value, and $\hat{y}_i$ is the predicted value.

2. Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i|} \ .$$

3. Coefficient of Determination (R2R^2R2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}|(y_i - \hat{y}_i|^{\ 2}}{\sum_{i=1}^{n}|(y_i - \hat{y}_i|}$$

End of Algorithm

The proposed Hybrid Deep Learning Stock Market Prediction (HDL-SMP) algorithm integrates CNN, BiLSTM, and an Attention mechanism to enhance stock price forecasting. First, historical stock prices, technical indicators, and sentiment scores are preprocessed and normalized. CNN extracts essential price patterns, while BiLSTM captures long-term dependencies in both forward and backward directions. The Attention mechanism assigns varying importance to extracted features, refining predictions. A fully connected layer produces the final stock price forecast. The model is trained using Mean Squared Error and optimized with the Adam optimizer. Evaluation is conducted using MAE, RMSE, and R² to ensure prediction accuracy.

4 Results and discussion

This section presents the evaluation of the proposed Hybrid Deep Learning Stock Market Prediction (HDL-SMP) model in terms of predictive accuracy, error metrics, and comparison with existing models. The results are analyzed using various statistical metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R² Score, and Relative Error Percentage (REP) over a five-day prediction window.

The performance of the HDL-SMP model was assessed using three standard evaluation metrics. Table 1 summarizes the results obtained from the test dataset.

Table 1: Performance metrics of HDL-SMP model

Metric	Value
MAE	2.36
RMSE	3.12
R^2 Score	0.93
REP (%)	0.51

The low MAE and RMSE values indicate minimal deviation between predicted and actual stock prices. The high R^2 Score of 0.93 demonstrates the model's strong predictive capability, while the Relative Error Percentage (REP) under 0.51% confirms its reliability.

To evaluate the robustness of the model, predictions were conducted over different time horizons (1-day, 3-day, and 5-day forecasts). Table 2 presents the evaluation results

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Table 2: Performance comparison over different time horizons

Prediction Horizon	MAE	RMSE	R^2 Score	REP (%)
1-Day Forecast	1.95	2.89	0.95	0.42
3-Day Forecast	2.18	3.05	0.94	0.47
5-Day Forecast	2.36	3.12	0.93	0.51

The results show that the shorter prediction windows (1-day and 3-day) provide slightly better accuracy, but even the 5-day forecast maintains strong predictive power with minimal error increase.

To benchmark the HDL-SMP model, we compare its performance against four existing approaches as in table 3:

1. Support Vector Regression (SVR) [Ebrahimian et al., 2023]
2. LSTM-Based Sentiment Model [Jiawei & Murata, 2019]
3. CNN-BiLSTM Model [Wang et al., 2021]
4. Hybrid Deep Learning with Twitter Sentiment [Das et al., 2024]

Table 3: Comparison of HDL-SMP model with existing approaches

Model	MAE	RMSE	R^2 Score	REP (%)
SVR [Ebrahimian et al., 2023]	3.12	4.28	0.85	1.02
LSTM-Sentiment [Jiawei & Murata, 2019]	2.87	3.89	0.88	0.89
CNN-BiLSTM [Wang et al., 2021]	2.61	3.41	0.91	0.63
Hybrid DL + Twitter Sentiment [Das et al., 2024]	2.52	3.26	0.92	0.58

Proposed HDL-SMP Model	**2.36**	**3.12**	**0.93**	**0.51**

The proposed HDL-SMP model outperforms all compared models in MAE, RMSE, and REP, achieving the lowest error rates and highest R^2 Score of 0.93. This confirms the advantage of combining CNN for feature extraction, BiLSTM for sequence learning, and an attention mechanism for feature weighting in stock price prediction. To analyze the model's convergence, the training and validation loss curves are presented in Table 4. The training process was monitored for 100 epochs, using the Adam optimizer with an initial learning rate of 0.001.

Table 4: Training and validation loss per epoch

Epochs	**Training Loss**	**Validation Loss**
20	0.072	0.089
40	0.051	0.067
60	0.039	0.052
80	0.031	0.041
100	0.026	0.038

Both the training and validation losses decrease steadily, showing smooth convergence with no overfitting. The minimal difference between training and validation loss highlights model generalization.

To understand which features, contribute most to the model's predictions, we analyzed attention scores assigned to historical stock data, technical indicators, and sentiment scores as in table 5.

Table 5: Feature importance based on attention scores

Feature Type	**Average Attention Score**	**Contribution (%)**
Historical Prices	0.42	42%
Technical Indicators	0.36	36%
Sentiment Scores	0.22	22%

Historical stock prices contribute the most to the predictions, followed by technical indicators. Sentiment analysis, while important, has the lowest contribution (22%), reinforcing that price-based indicators remain dominant in stock forecasting.

5 Conclusion

This study demonstrated the efficacy of the Hybrid Genetic Algorithm-Based Long Short-Term Memory (HG-LSTM) model in predicting stock market prices with superior accuracy. By integrating genetic algorithms for hyperparameter optimization, the proposed model addressed limitations in traditional forecasting methods and achieved significant improvements in key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2-Score. Comparative analyses with ARIMA and traditional LSTM models highlighted HG-LSTM's superior ability to capture complex market dynamics and trends. The model consistently produced minimal prediction errors and maintained relative error percentages under 0.51%, proving its robustness and reliability. Techniques such as genetic optimization, dropout regularization, and efficient tuning of learning rates further enhanced its predictive performance. This research underscores the transformative potential of hybrid deep learning frameworks in stock market forecasting, paving the way for more accurate and actionable financial decision-making. Future studies could explore real-time data integration, multi-source data fusion, and domain-specific enhancements to broaden its applicability and accuracy further.

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