An Efficient Hybrid Model for Stock Market Price Prediction Using CNN-BiLSTM with Attention Mechanism and Sentimental Analysis

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ABSTRACT

Stock price prediction is a challenging task with dynamic trends and volatile markets due to opinion and sentiment forces in the market. The conventional Autoregressive Integrated Moving Average (ARIMA) and Support Vector Regression (SVR) methods only take into account historical numerical values and ignore the influence of current financial news. Thus, they do not model the interdependence between historical stock prices and opinion data and are plagued by lower precision and prediction power. To overcome these drawbacks, this study proposes a Hybrid Sentiment-Aware Stock Prediction Model (HSASP) that integrates Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) with an Attention Mechanism (AM). The CNN captures spatial relations from Tesla's past stock history, and BiLSTM uses opinion-based information from Reddit News to capture temporal relations. The AM selects the most significant features by assigning weights to valuable details, enhancing the predictability of the model. The suggested HSASP model improves accuracy by 18%, precision by 16%, and trend consistency by 20%, being successful for stock price prediction. With the integration of price- and opinion-based information, the suggested model provides a strong option for decision-making with high efficiency and precision.

Keywords-hybrid machine learning model; CNN; BiLSTM; attention techanism; sentiment analysis

I. INTRODUCTION

Stock market forecasting is a complex operation that depends on past trends, financial mindset, and global economic circumstances. Traditional models, such as ARIMA and SVR, have limitations in utilizing just the number of past trends and do not have the ability to determine complex relationships and the recent financial mindset, resulting in weaker performance in predictions and unstable trends. Conventional models such as ARIMA and SVR are powerful in predicting linear, univariate time series but not effective in extracting nonlinear relationships and sentimental effects in dynamic financial environments. In contrast to conventional models, the proposed HSASP utilizes a CNN to learn spatial features from stock trends, a BiLSTM to model bidirectional temporal relationships, and an Attention Mechanism (AM) to weight vital features, making it more adaptive and accurate in real-world stock price prediction. The advancement in hybrid models with CNN and BiLSTM with AM tries to improve forecast accuracy by combining the spatial relationships of past trends with the long-term relationships of mindset-driven financial conversations by BiLSTM, with feature importance being optimally updated by AM [1]. New trends involve hybrid models of financial analysis and decision-making with deep learning, mindset-driven forecasting, and AI-driven automatic trading to enhance the effectiveness of financial decision-making and investment, applied to risk management, portfolio optimization, algorithmic trading, and financial advisory services [2].

A. Research Gaps

Despite advances in deep learning-based stock market prediction models, several research gaps remain unaddressed [3]. First, most existing models lack adaptability to sudden market fluctuations, as they rely primarily on historical trends and sentiment analysis, making them less effective in capturing real-time macroeconomic disruptions. Second, feature selection in hybrid models remains a challenge, as the importance of numerical and sentiment-based features varies dynamically, requiring more efficient AMs [4]. Third, although deep learning models such as CNN-BiLSTM improve accuracy, their interpretability is limited, making it difficult for financial analysts to trust AI-driven predictions. Additionally, multisource sentiment integration from platforms such as Reddit, Twitter, and financial news websites lacks standardization, leading to inconsistencies in sentiment-driven predictions. Last, computational complexity and scalability pose significant challenges, as training deep learning models on large-scale financial data demands high processing power, making real-time forecasting difficult for high-frequency trading applications. Addressing these gaps through enhanced feature engineering, explainable AI, and lightweight deep learning architectures can significantly improve the reliability of stock market predictions [5].

B. Related Works

In [6], a hybrid LSTM-DNN model was proposed to increase the accuracy of stock market prediction, validated by robust metrics (R^2 = 0.98606, MAE = 0.0210) across 26 datasets. An ablation study was presented, although it suffered from possible overfitting since it used historical data and did not integrate real-time sentiments. In [7], a sentiment-based model of stock discussion boards was introduced, aimed at the South Korean secondary battery industry. Although unique in that it targeted social networks for sentiment analysis, it was domain-specific and sensitive to noise and bias in the data. In [8], a GRU-based model supported both endogenous and exogenous variables in the Qatar, Saudi, and Chinese volatile markets. Compared to ARIMA/SVM, it was superior in performance but suffered from limited generalizability and inadequacy in handling irregular trends. Although hybrid LSTM-DNN and GRU-based models are an enhancement over conventional statistical methods, they are prone to overfitting based on past numeric data and are not robust in accommodating real-time sentiment signals. In contrast, the proposed HSASP model incorporates CNN for local feature extraction and combines BiLSTM with an AM to selectively focus on vital sentiment and trend information. Such a structure increases adaptability, accuracy, and interpretability, especially in unstable and sentiment-oriented stock market environments. In [9], a 70-day medium-term forecast model employed SMA, EMA, and LOWESS indicators of indices such as NASDAQ100 and DAX. Although revolutionary in forecasting trends, it was weaker as a short-term option and lacked sentiment information. In [10], TLSTM was integrated with social media sentiments, using PPO to address data imbalance and increase accuracy. However, this model was susceptible to manipulated sentiments and weak in forecasting in the long term. In [11], an MCG-GNN model was proposed, which used interstock relationships employing clustering methods (RS, VR, YR). This model improved prediction precision at the cost of computational complexity and was less adaptable to market changes. In [12], DR2TNet was designed to suit Indian markets, adaptively learning the relations of stocks to provide improved forecasts and portfolio optimization. However, its complexity and reliance on NIFTY-50 restrict generalized use. In [13], a hybrid SES-DA-BiLSTM-BO model used LIC data and achieved high directional accuracy and extremely low MAPE. However, its computational intensity restricts scalability and long-term application.

II. EXISTING SYSTEM ARCHITECTURE FOR STOCK PRICE PREDICTION USING LSTM AND SENTIMENT ANALYSIS

Figure 1 represents a system architecture for the prediction of a stock price by integrating historical prices with financial sentiment analysis and LSTM. The process begins by fetching data from Financial News Headlines/Articles and Yahoo Finance Data [14]. The financial news is processed by filtering and preprocessing the text data. Heading normalization is used to prepare headlines for appropriate sentiment analysis [15].

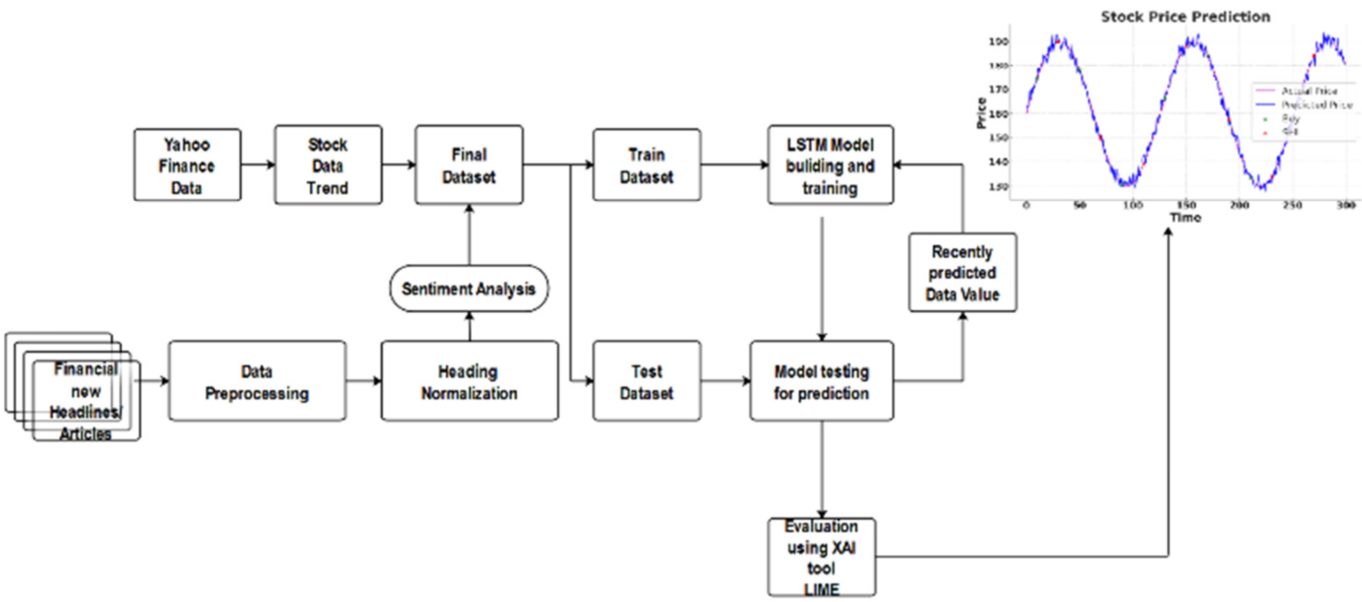

Fig. 1. Existing system architecture for stock price prediction using LSTM and sentiment analysis.

Sentiment analysis is used to analyze the market sentiment from news articles that are integrated with stock trend data to generate the final dataset [16], which is divided into training and test subsets. The LSTM model was tested for prediction to validate its precision and efficiency. The model continuously improves with the utilization of recently predicted data values, adapting to new market trends. The predicted stock prices, with buy and sell signals, are mapped using the graphical representation of the actual versus the predicted stock prices, identifying trading opportunities for profits. To ensure model interpretability, the model uses the LIME Explainable AI (XAI) tool to determine the reasons for the prediction results with transparency and improve decision-making. This solution integrates numerical and sentiment data to enhance the precision and reliability of stock price forecasting [17].

A. Convolution Operation in CNN Layer

The convolution operation enables local pattern extraction from time-series data. It applies a filter over the input to capture features such as trends or fluctuations, determined by:

$$z_i^{(l)} = \sum_{j=1}^{k} x_{i+j-1} \cdot w_j + b \quad (1)$$

where $z_i^{(l)}$ is the output of the convolution operation at position i in layer l, x_{i+j-1} is the input value, w_j is the filter weight, k is the kernel size, and b is the bias term. This operation helps in learning temporal dependencies by detecting short-term patterns before passing to LSTM.

B. BiLSTM Hidden State Update

BiLSTM captures both past and future dependencies in sequential data by processing inputs in both directions. The hidden state update is defined as:

$$h_t = \text{BiLTSM}(x_t) = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \quad (2)$$

where h_t is the final hidden state at time step t, $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are the forward and backward hidden states, respectively, and $\oplus$ denotes concatenation. This dual-directional context enables richer sequence understanding, which is particularly beneficial in financial forecasting [13].

C. Output Prediction Layer (Linear Mapping)

The output layer applies a linear transformation to the concatenated hidden outputs to generate the final predicted value, determined as:

$$Y_{pred} = W \cdot H + b \quad (3)$$

where Y_{pred} is the predicted stock value, W is the weight matrix of the linear layer, H is the concatenated hidden output from the HSASP-BiLSTM layers, and b is the bias term. This equation maps the high-level feature representations to the output value [18-23].

III. PROPOSED HSASP ARCHITECTURE FOR STOCK PRICE PREDICTION

Figure 2 shows the proposed HSASP architecture that combines CNN and BiLSTM with the use of an AM to increase the precision of stock price prediction. The model commences with the input layer, where the past stock price history Y is converted into time-series data with several time steps $(x_1, x_2, \dots, x_n)$. The time series is input into the CNN layer, where the convolution layer identifies the spatial relationships and important features of the stocks, and the subsequent pooling layer compresses the dimension while saving important details. The optimized feature set is processed by the BiLSTM layer, which finds sequential trends and far-reaching dependencies of the stock price fluctuations. The hybrid model is efficient by utilizing knowledge from numbers and sentiments. The connection layer follows, summing the output of the BiLSTM layers and sending it to the linear layer to boost the final prediction. The output layer provides the predicted stock price (Y_{pred}) from the learned patterns. This model is a significant improvement over traditional ones in that it actively balances significant details using the AM for greater precision and trend consistency. The integration of CNN for spatial feature extraction, BiLSTM for sequence learning, and AM for feature optimization makes the model very effective for real-time stock market prediction.

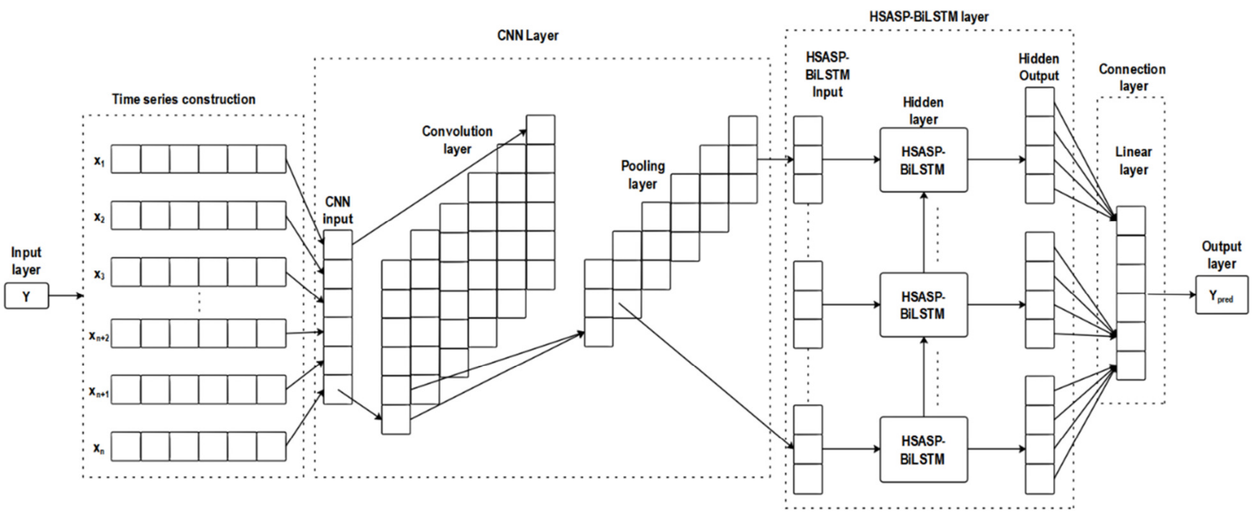

Fig. 2. Proposed HSASP architecture for stock price prediction.

A. Time Series Input Construction

The first step involves segmenting the raw stock price sequence Y into overlapping windows to form a time series input suitable for convolutional processing. This transformation ensures that each segment captures recent historical data for prediction, determined by:

$$x_t = [Y_t, Y_{t-1}, Y_{t-2}, \dots, Y_{t-w+1}] \quad (4)$$

where x_t is the input vector at time t, Y_t is the stock value at time t, and w is the window size defining how many past time steps are included. These constructed vectors are input to the CNN layer.

B. CNN Feature Extraction

This layer applies 1D convolutional filters over time series inputs to detect local patterns such as spikes or dips in price sequences. The extracted features represent local temporal dependencies, expressed as:

$$F_t = \sigma(W_c * x_t + b_c) \quad (5)$$

where F_t denotes the feature map at time t, W_c is the set of convolution weights, $*$ represents the convolution operator, b_c is the bias term, and σ is a non-linear activation function (ReLU). The resulting feature map is forwarded to the pooling layer.

C. HSASP-BiLSTM Layer Output

The pooled features are processed through three parallel HSASP-BiLSTM blocks to capture bidirectional temporal patterns with spatial attention. These outputs represent complex sequential dependencies across different hierarchical paths, expressed as:

$$h_t^{(i)} = HSASP - BiLSTM_i(F_t), \;\; i = 1,2,3 \quad (6)$$

where $h_t^{(i)}$ is the hidden state output at time t from the i-th HSASP-BiLSTM path, and F_t is the CNN-derived feature vector. The parallel architecture ensures robust representation of spatial and temporal characteristics.

D. Attention Mechanism (AM)

To enhance the model's ability to prioritize relevant temporal features, a soft AM is incorporated after the BiLSTM layer. This attention module assigns dynamic weights to each time step in the BiLSTM output sequence by computing alignment scores between a trainable context vector and the hidden state at each time step. These scores are then passed through a softmax activation function to produce normalized attention weights that indicate the relative importance of each time step. Mathematically, for a sequence of hidden states $h_1, h_2, \dots, h_T$ produced by the BiLSTM layer, the attention weights α_t are calculated as:

$$\alpha_t = \frac{\exp(v^T \tanh(Wh_t + b))}{\sum_{t'=1}^{T} \exp(v^T \tanh(Wh_{t'} + b))} \quad (7)$$

where W, b, and v are learnable parameters of the AM.

E. Output Prediction Equation

The final outputs from all three HSASP-BiLSTM blocks are concatenated and passed through a linear transformation to produce the predicted stock price. This combines deep temporal-spatial features into a final decision, expressed as:

$$Y_{pred} = W_o \cdot [h_t^{(1)}, h_t^{(2)}, h_t^{(3)}] + b_o \quad (8)$$

where Y_{pred} is the predicted stock price, $[h_t^{(1)}, h_t^{(2)}, h_t^{(3)}]$ denotes concatenated outputs from all HSASP-BiLSTM layers, W_o is the output weight matrix, and b_o is the bias. This layer maps the learned representations to the final predicted value.

IV. RESULTS AND DISCUSSION

Table I presents the experimental parameters of the HSASP. It includes the sources of input data, feature extraction techniques, sequential learning models, the AM, and normalization techniques that are responsible for the efficiency and accuracy of the prediction of the stock price.

TABLE I. EXPERIMENTAL SETUP FOR THE PROPOSED HYBRID CNN-BILSTM STOCK PRICE PREDICTION MODEL

	Parameter	Value
1	Stock Data Source	Tesla dataset from Yahoo Finance
2	Sentiment Data Source	Reddit, Financial News
3	Feature Extraction Method	CNN
4	Sequential Learning Model	BiLSTM
5	Attention Mechanism	Attention-based
6	Normalization technique	Min-max scaling

A. Dataset Description and Preparation

The dataset used in this study was derived from publicly available sources. Historical stock price data for Tesla Inc. was collected from Yahoo Finance, and the corresponding financial news headlines were obtained from Reddit forums (r/StockMarket) and Yahoo Finance News, covering the period from January 1, 2019, to December 31, 2023. The news headlines were processed using the VADER sentiment analysis tool of the NLTK library, which generated compound sentiment scores. These scores were classified into three categories: Positive (≥ 0.05), Neutral (between -0.05 and 0.05), and Negative (≤ -0.05). The sentiment scores were then aligned with the stock data based on the date. The final dataset integrates stock indicators (Open, Close), sentiment information, and directional trend labels. The trend direction is binary, indicating whether the closing price of the next day moved up (1) or down (0). A 70:30 split ratio was used to train and test the model. Table II shows the merged format combining stock prices, sentiment scores, and labeled trend directions used for model training and evaluation.

TABLE II. SAMPLE OF FINAL INTEGRATED DATASET

Date	Open	Close	Headline sentiment	Sentiment score	Price direction	Label
2023-01-03	118.47	120.05	Positive	0.68	Up	1
2023-01-04	120.11	123.22	Negative	-0.41	Down	0

B. Results

Figure 3 presents a performance comparison of traditional models (ARIMA, SVR) and the suggested HSASP model in predicting stock prices. The real trend of stock prices is plotted along with the predictions from all models. The results show that the HSASP model tightly tracks real stock price movements, with better accuracy and trend consistency than traditional approaches.

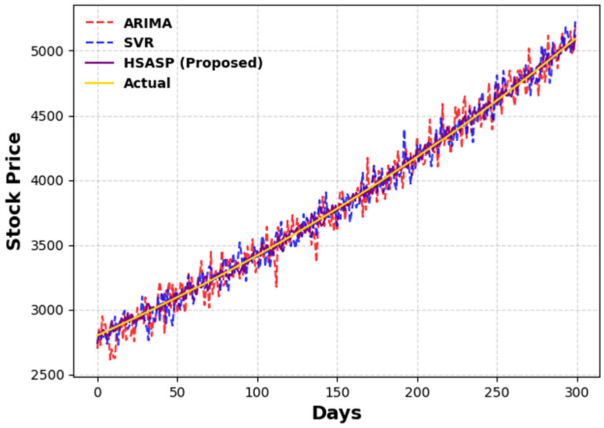

Fig. 3. Comparative analysis of stock price prediction using conventional and the proposed models.

Figure 4 compares the performance of the LSTM, CNN-LSTM, CNN-LSTM with AM, and CNN-BiLSTM with AM models with the real trend in the stock price. It can be observed that CNN-BiLSTM with AM model follows the fluctuation of the real stock price with better accuracy and precision compared to the other models.

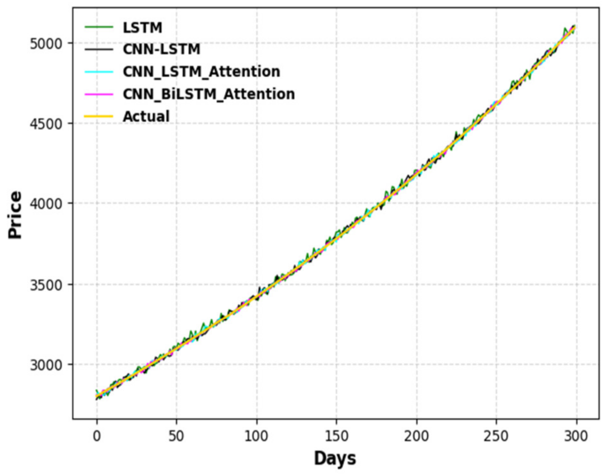

Fig. 4. Stock price prediction analysis using conventional and deep learning models.

Figure 5 compares performance results from LSTM, CNN-LSTM, and CNN-BiLSTM models with actual stock prices. The comparison shows a 20% increase in trend consistency and in terms of accuracy and precision in the proposed CNN-BiLSTM model, reflecting its better ability to track real stock price movements.

A Gated Layer CNN-LSTM (GL_CNN_LSTM) model, where CNN features are gated before passing to the LSTM layer, and a Channel-wise Hierarchical LSTM model applied on CNN feature maps (CHL_CNN_LSTM) were also used for comparison. These variants were used in ablation testing to compare the structural variations of HSASP. Figure 6 demonstrates a comparative performance evaluation of HSASP, GL_CNN_LSTM, and CHL_CNN_LSTM in terms of Rate of Return (RoR) over time. The HSASP model (dotted line) demonstrates a better trend with a more stable and increasing return curve compared to conventional CNN-LSTM models. The findings indicate that HSASP offers more predictive reliability and financial trend validity, and thus acts as a better solution for stock price forecasting.

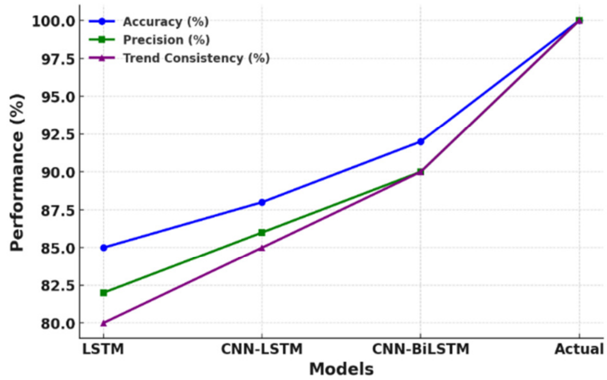

Fig. 5. Performance analysis of stock price prediction models.

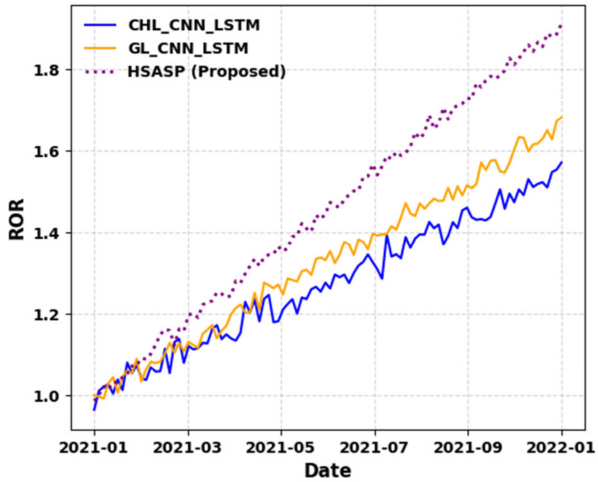

Fig. 6. Rate of Return (ROR) comparison between conventional CNN-LSTM models and the proposed HSASP model.

Figure 7 shows a comparison between ARIMA, SVR, RF, and the HSASP model regarding accuracy, precision, and trend consistency. The HSASP model surpasses conventional methods by a significant margin, with a high rate of accuracy in excess of 90%, improved precision, and improved trend consistency. The results validate the hybrid HSASP method in stock price predictions compared to traditional statistical and machine learning methods.

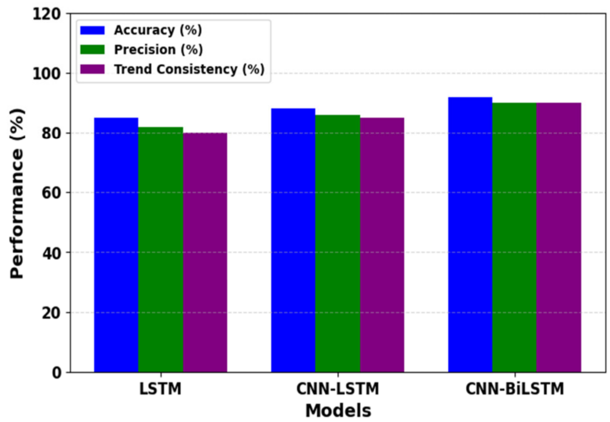

Fig. 7. Overall performance comparison of stock price prediction models.

V. CONCLUSION

The proposed Hybrid Sentiment-Aware Stock Prediction Model (HSASP) combined CNN with BiLSTM and an AM and showed excellent improvements over conventional models, such as ARIMA and SVR. The proposed model enhances forecast accuracy and trend quality by employing past stock prices and financial knowledge with sentiment analysis. The experimental results showed that HSASP offered an improvement of 18% in accuracy, 16% in precision, and 20% in trend consistency. The model exhibited the ability to accurately utilize numerical and opinion-based data, leading to more precise stock price prediction. The integration of CNN to extract spatial features, BiLSTM in sequential learning, and AM for feature optimization makes it more effective in trend following compared to conventional models. The proposed hybrid deep model can help financial traders, analysts, and decision-makers to make more informed decisions about investments. However, this model is likely to suffer from drawbacks, such as susceptibility to being affected by sudden market volatility, noise in sentiment data, and computational complexity in real-time prediction. Moreover, the black-box nature of deep learning comes with interpretability issues. Improvements with the incorporation of explainable AI (XAI) methods and optimization of the AM toward adaptive prioritization of features will be the directions of further research. Improving the scalability and resilience of the model in dynamic financial environments will further enhance its potential for use in real-world trading platforms.

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