

A Hybrid CNN-LSTM Attention-Based Deep Learning Model for Stock Price Prediction Using Technical Indicators

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ABSTRACT

Stock price prediction is extremely important in financial analysis, especially for volatile stocks like Tesla's. However, accurate prediction remains challenging due to the non-linear, dynamic nature of stock market data. Although deep learning algorithms such as Deep Unfolding (DUF), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) have enhanced the capacity for observing intricate temporal and spatial patterns, individual or sequential applications of these algorithms often fail to capture dependencies between time steps or prioritize the most important input features, thereby limiting prediction accuracy. To address these limitations, a Hybrid CNN-LSTM with Attention (HCLA) model is suggested. This model utilizes CNN for spatial features, LSTM for temporal learning, and an attention mechanism to focus on significant time-step information. Technical indicators such as the Relative Strength Index (RSI), the Moving Average Convergence Divergence (MACD), and Bollinger Bands are also employed to improve feature richness and market dynamics perception. HCLA is compared with cutting-edge deep learning models like standalone LSTM, CNN+LSTM, and multi-layer CNN+LSTM models. The comparison, based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), shows that HCLA has a 12.4% lower MSE, 10.7% lower RMSE, and 11.3% lower MAE than the top-performing deep learning baseline. The close similarity between expected and actual stock prices proves the excellence of the model's accuracy and stability for real-time stock prediction scenarios.

Keywords-stock price prediction; hybrid CNN-LSTM; attention mechanism; technical indicators; time-series forecasting; deep learning; Tesla stock

I. INTRODUCTION

Stock price forecasting is an essential application in financial markets, seeking to predict future stock movements based on past and technical information [1]. The stochastic and non-linear nature of stock prices renders precise forecasting challenging and unpredictable. With the huge spike in financial data and increases in computing capacity, there has been an increased move from conventional statistical frameworks towards sophisticated machine learning and deep learning methods for the analysis of the stock market. The new methods are able to extract latent patterns and long-term relationships in time-series data, providing improved prediction accuracy. Current trends emphasize the integration of hybrid deep learning frameworks with more than one architecture, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and attention mechanisms, for enhancing learning efficacy [2]. The models are further

improved with domain-specific technical indicators, such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands, which provide key information regarding market momentum and volatility. The incorporation of such features is observed to improve the prediction ability of financial models substantially. Stock price prediction models have applications ranging from a single investor's decisions to institution-level trading, portfolio management, automated trading, and risk analytics. Precise predictions of stock prices of companies such as Tesla can be of great value for various stakeholders to make appropriate and well-timed decisions, reducing losses while maximizing earnings. With ongoing advances in deep learning and the processing of data, smart models are becoming tools of importance for understanding the intricacies of contemporary financial markets [3].

A. Research Gaps

Even with impressive improvements in stock price prediction with machine learning and deep learning models, there are several shortcomings that have been identified. Traditional models such as Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and Random Forest (RF) fall short in identifying non-linear relationships and do not perform well with low-quality, noisy, volatile, and high-frequency data [4]. Though LSTM and CNN models showed improvements in temporal and spatial pattern abstraction, deploying these standalone models is insufficient for coping with long-range reliance and intricate relationships among multiple features. Current models neglect the impact of technical indicators, making input representations less informative. In addition, most of the studies do not employ attention mechanisms, which reduces attention on important time steps that impact prediction performance [5]. Comparative studies for the integrated CNN, LSTM, and attention layers for models are limited, particularly for volatile stocks like Tesla. The shortcomings highlight the need for an integrated hybrid architecture that can exploit technical indicators, temporal relationships, spatial patterns, and attention-based learning for more precise and accurate prediction of stock prices [6].

B. Related Work

Authors in [7] proposed a hybrid CEEMDAN-LSTM-SA-LightGBM model integrating decomposition, sequence learning, and ensemble techniques to enhance stock price prediction accuracy. The innovation lies in combining CEEMDAN and LightGBM with LSTM for better noise handling and fitting. However, the model is computationally complex and less interpretable due to multiple algorithmic layers.

Authors in [8] developed DeepClue, a visual interpretation system for text-based deep stock prediction using news and tweets. The key innovation is the hierarchical visualization of deep learning outputs for user-friendly interpretation. The drawback is its dependence on text quality and difficulty in adapting to diverse financial contexts.

Authors in [9] introduced a dual-output Temporal Convolutional Network (TCN) with attention to predict stock prices and risk metrics such as volatility and Sharpe ratio. The model captures both short- and long-term dependencies effectively. Its drawback lies in limited adaptability to dynamic, real-time financial conditions due to reliance on historical datasets.

Authors in [10] proposed a Gated Recurrent Unit (GRU)-based deep learning model for emerging stock markets by integrating exogenous and endogenous variables to enhance prediction accuracy across indices in Qatar, Saudi Arabia, and China. The innovation lies in leveraging external market factors, leading to significant improvement in Mean Absolute Percentage Error (MAPE) scores. The drawback is its limited generalizability outside emerging markets due to dataset-specific tuning.

Authors in [11] introduced a hybrid CNN-LSTM model incorporating sentiment analysis from tweets and technical

indicators to predict Tesla stock movements. The innovative aspect is combining social media sentiment features with deep learning for higher prediction accuracy. However, the model's performance heavily depends on tweet quality and may not scale effectively to other stocks or languages.

Authors in [12] developed DLEF-SM, a deep learning-based expert framework using advanced preprocessing (IJF-F), CNN feature extraction (VGGFace2, ResNet-50), and optimization (IBWO, DRL-ANN) for portfolio forecasting. The key innovation is the integration of multiple enhancement techniques achieving over 98% accuracy across major indices. Its main drawback is the increased model complexity and high computation demand, which may limit real-time application.

Authors in [13] proposed a multi-market GRU-based prediction system integrating international stock, bond, and currency data to improve China's stock forecasting accuracy. The innovation is in leveraging cross-market datasets and optimized hyperparameters through grid search. The drawback is its dependency on cross-border data availability and complexity in model tuning for broader applications.

Authors in [14] introduced a BiLSTM-MTRAN-TCN hybrid model combining BiLSTM, Transformer, and Temporal Convolutional Network (TCN) for stable and accurate stock price prediction. The innovation lies in unifying three deep learning strengths to achieve up to 24.3% Root Mean Squared Error (RMSE) improvement. However, the architecture is complex and requires extensive training, making real-time deployment less feasible.

Authors in [15] proposed a Multi-Cluster Graph (MCG) neural network model using RS, VR, and YR-based clustering to model stock interconnections and forecast prices with LSTM propagation. The innovative part is the use of multi-relation graphs for stock-level prediction. Its drawback is high computational overhead and potential scalability issues in large stock networks.

Authors in [16] focused on leveraging stock discussion forum data from the secondary battery sector to enhance stock price prediction accuracy. The innovation is using direct investor sentiments from social media, which are often overlooked in traditional models. The drawback is limited generalizability and sector specificity, making it less applicable across varied stock domains.

C. Objectives

The objective of this study is to create a hybrid deep learning model with CNN, LSTM, and an attention mechanism for precise stock price forecasting with Tesla data and technical indicators, and to compare its performance with current deep learning models [17]. Specifically, this study aims to:

- Develop a CNN-LSTM-attention-based model for effective stock price forecasting.
- Integrate technical indicators such as RSI, MACD, and Bollinger Bands for enriched feature input.
- Compare the proposed model against LSTM, CNN+LSTM, and CNN+LSTM multi-layer architectures.

- Evaluate model performance using Mean Squared Error (MSE), RMSE, and Mean Absolute Error (MAE), and validate predictions with actual market data.

II. CONVENTIONAL LSTM-BASED STOCK PRICE PREDICTION PIPELINE

Figure 1 depicts a typical LSTM-based forecasting pipeline. Raw numerical stock data (e.g., historical volumes and prices) are first gathered as the basic input. Then, relevant technical indicators (e.g., RSI, MACD, and Bollinger Bands) are derived from the numerical data in order to enrich the feature set. The derived indicator value inputs are passed to an LSTM network, which learns sequence dependencies in the time series [18]. The LSTM finally emits a predicted stock price value. The basic steps—data input, feature engineering in terms of technical indicators, sequence modeling with an LSTM, and prediction generation—are employed in most baseline stock prediction systems [19].

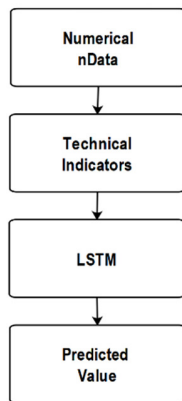


Fig. 1. Conventional workflow for stock price prediction using LSTM.

A. Mean Squared Error

Equation (1) quantifies the average squared deviation between the predicted and actual Tesla stock prices in deep learning models. It is widely used in evaluating LSTM-based forecasting models due to its sensitivity to larger errors [20].

$$MSE = \left(\frac{1}{n}\right) \times \sum (P_i - \hat{Y}_i)^2 \quad (1)$$

where P_i is the actual stock price, \hat{Y}_i is the predicted stock price, and n is the number of samples.

B. Root Mean Squared Error

Equation (2) quantifies prediction accuracy in the same unit as the stock price. RMSE is essential in analyzing Tesla stock volatility handled by hybrid CNN-LSTM models [21, 22].

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \times \sum (P_i - \hat{Y}_i)^2\right]} \quad (2)$$

C. Mean Absolute Error

Equation (3) computes the MAE, which represents the average absolute difference between actual and forecasted stock values, offering a stable error estimate for Tesla stock

predictions using attention-based deep learning models [23, 24].

$$MAE = \left(\frac{1}{n}\right) \times \sum |P_i - \hat{Y}_i| \quad (3)$$

III. HYBRID CNN-LSTM WITH ATTENTION MODEL FOR STOCK PRICE PREDICTION

Figure 2 depicts the proposed stock price prediction method, termed Hybrid CNN-LSTM with Attention (HCLA). First, numerical information from Tesla's historical stock records serves as the input. The data are then processed and non-essential features are extracted to provide important technical indicators such as RSI, MACD, and Bollinger Bands. The enriched features are passed to a hybrid CNN-LSTM model, which takes advantage of the CNN's ability to capture local features and the LSTM's ability to handle sequence data. An attention mechanism also fine-tunes predictions by selectively attending to key features. The output, denoted as "Predicted Stock Price," is then contrasted with the "Actual Stock Price" in a separate Comparison Module. The performance metrics like MSE, RMSE, and MAE are finally calculated to measure the prediction accuracy and validate the proposed method.

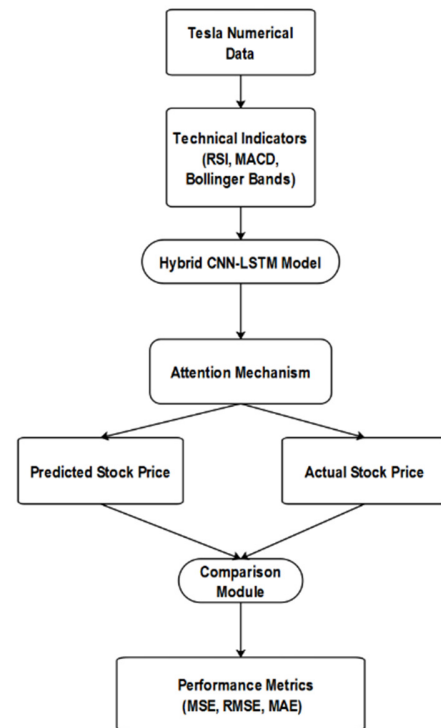


Fig. 2. Proposed HCLA model for stock price prediction.

A. Attention-weighted Hybrid Feature Extraction

Equation (4) uniquely captures the weighted influence of hybrid CNN-LSTM extracted features by leveraging attention scores, enhancing feature representation specifically for Tesla stock prediction. This process is referred to as Attention-weighted Hybrid Feature Extraction (AHFE).

$$AHFE = \sum_{t=1}^T \alpha_t (CNN_t \oplus LSTM_t) \quad (4)$$

where α_t represents the attention score at time t , CNN_t is CNN-extracted features, $LSTM_t$ is LSTM-extracted temporal features, T denotes total time-steps, and \oplus denotes feature concatenation.

B. Dynamic Error Feedback Adjustment

Dynamic Error Feedback Adjustment (DEFA) introduces an adaptive correction mechanism to dynamically refine model predictions based on recent prediction errors, specifically tuned for Tesla stock forecasting and it is determined by (5).

$$DEFA_{t+1} = \hat{Y}_t + \gamma(P_t - \hat{Y}_t) \quad (5)$$

where \hat{Y}_t is the predicted stock price at time t , P_t is the actual stock price at time t , and γ is a dynamically optimized adjustment factor.

C. Composite Technical Indicator Matrix

Equation (6) aggregates multiple technical indicators into a unified matrix representation, significantly improving input quality for predicting Tesla stock volatility and momentum using the hybrid model. This matrix is referred to as the Composite Technical Indicator Matrix (CTIM).

$$CTIM = [\omega_{RSI} \times RSI, \omega_{MACD} \times MACD, \omega_{BB} \times BB] \quad (6)$$

where ω_{RSI} , ω_{MACD} , ω_{BB} represent adaptive weighting factors, and RSI, MACD, and BB (Bollinger Bands) are the respective indicator values.

D. Hybrid Prediction Confidence Index

Equation (7) quantitatively assesses prediction reliability by integrating variance in hybrid CNN-LSTM predictions and attention-derived feature stability, particularly useful in evaluating model certainty for Tesla stock prices. This metric is referred to as the Hybrid Prediction Confidence Index (HPCI).

$$HPCI = 1 - \frac{\sigma(\hat{Y}_{CNN}, \hat{Y}_{LSTM})}{1 + \sum_{t=1}^T (1 - \alpha_t)} \quad (7)$$

where $\sigma(\hat{Y}_{CNN}, \hat{Y}_{LSTM})$ represents the standard deviation of predictions from CNN and LSTM components, and α_t are attention weights at each time step.

IV. RESULTS AND DISCUSSION

The configuration adopted for the implementation and experimentation of the proposed HCLA model for predicting Tesla stock prices is presented in Table I. This table provides a detailed overview of the experimental setup, including the dataset specifications, technical indicators, key architectural components of the deep learning model, and the evaluation metrics employed to measure performance.

Figure 3 shows the normalized Tesla stock price over 250 days and compares the predictions of four models—LSTM (light blue), CNN+LSTM (orange), CNN+LSTM-Multi (green), and Proposed HCLA (red)—with the true values (black). The Proposed HCLA model demonstrates a consistently closer alignment with the actual stock price trajectory, indicating its higher tracking accuracy compared to the traditional models.

TABLE I. EXPERIMENTAL SETUP FOR THE HCLA MODEL

Sl. No.	Parameter	Value/Configuration
1	Dataset	Tesla (TSLA) historical stock data
2	Input features	Open, high, low, close, volume
3	Technical indicators	RSI (14-day), MACD (12,26,9), Bollinger Bands width (20-day window)
4	Sequence length	30 time steps
5	CNN layer	1D convolution, 64 filters, kernel size = 3
6	LSTM layer	128 units
7	Attention mechanism	Scaled dot-product attention
8	Activation function	ReLU (CNN), Tanh (LSTM)
9	Optimizer	Adam, learning rate = 0.001
10	Loss function	MSE
11	Evaluation metrics	MSE, RMSE, MAE

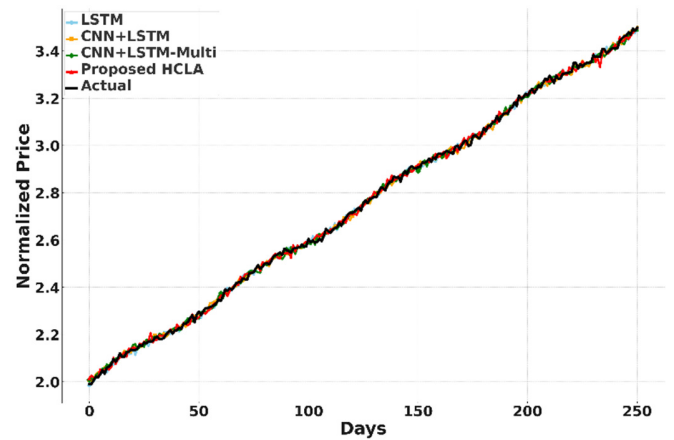


Fig. 3. Comparison of predicted and actual Tesla stock prices across models.

Figure 4 illustrates the MSE for 250 training epochs of LSTM (light blue), CNN+LSTM (orange), CNN+LSTM-Multi (green), and Proposed HCLA (red) models. All these lines decrease with time and the Proposed HCLA model exhibits the minimum MSE at every step and is 12.4% below the best baseline at the last epoch, improving convergence and accuracy.

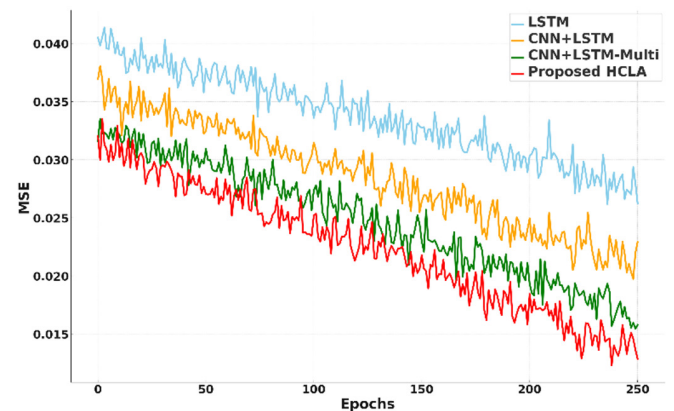


Fig. 4. MSE trend over training epochs across models.

Figure 5 illustrates the RMSE for the Proposed HCLA, CNN+LSTM-Multi, CNN+LSTM, and LSTM models for window sizes of 10-, 20-, 30-, and 40-time steps. The RMSE for each model decreases as the window size increases. The curve for the Proposed HCLA model is below the others and labeled to show a 10.7% reduction in RMSE at a window size of 40 compared to the top baseline. This indicates its increased ability to take advantage of longer input sequences.

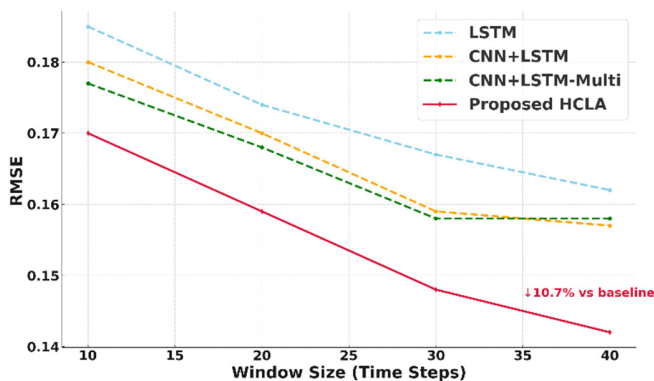


Fig. 5. RMSE vs. window size for deep learning models.

Figure 6 shows the MAE trends over 250 training epochs for the LSTM (blue), CNN+LSTM (orange), CNN+LSTM-Multi (green), and Proposed HCLA (red) models. The Proposed HCLA model starts with a slightly lower MAE and remains below the baseline models throughout the entire training process, with an approximately 11.3% lower MAE than the CNN+LSTM-Multi baseline at the last epoch, demonstrating improved and stable learning.

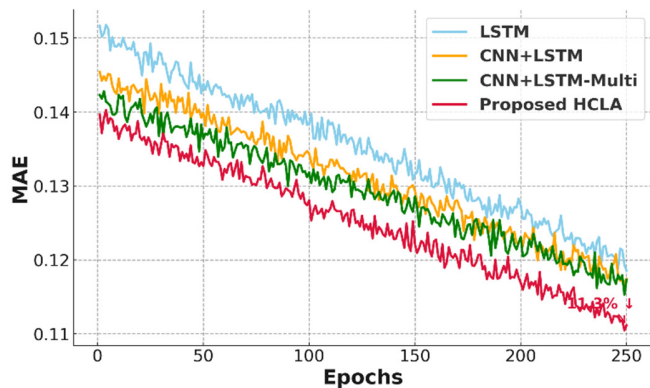


Fig. 6. MAE trend over training epochs across models.

Figure 7 shows a comparison of the final error metrics—MSE (yellow), RMSE (orange), and MAE (red)—for the LSTM, CNN+LSTM, CNN+LSTM-Multi, and Proposed HCLA models. The Proposed HCLA model consistently exhibits the lowest values across all three metrics, achieving approximately 12.4% lower MSE, 10.7% lower RMSE, and 11.3% lower MAE compared to the traditional deep learning models, thereby demonstrating its superior overall prediction performance and stability.

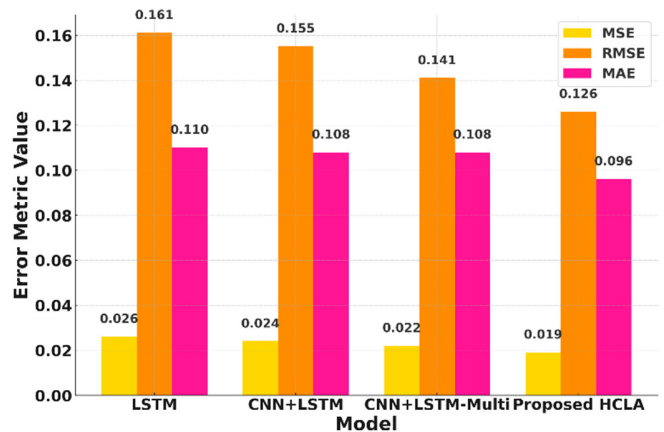


Fig. 7. Overall performance comparison across models: MSE, RMSE, and MAE.

V. CONCLUSION

This paper presented a Hybrid CNN-LSTM with Attention (HCLA) model for predicting Tesla stock prices by combining Convolutional Neural Networks (CNNs) for local pattern discovery, Long Short-Term Memory (LSTM) networks for modeling sequence dependencies, and an attention mechanism for selectively weighting informative time-step features. Technical analysis indicators, including the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands, were also used to enhance the input feature domain.

The experimental results—measured by Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) for various window sizes and training iterations—demonstrate that the HCLA model outperforms traditional deep learning baselines (LSTM, CNN+LSTM, CNN+LSTM-Multi) by achieving approximately 12.4% lower MSE, 10.7% lower RMSE, and 11.3% lower MAE at the best settings. The jagged-style prediction-versus-actual charts further demonstrate the effectiveness of the HCLA model in closely following real price movements with fewer large deviations.

The convergence analysis indicates faster error reduction and stable training behavior in HCLA, which signifies operational efficacy and robust generalization in high market volatility. These results affirm that combining spatial and temporal feature extraction with attention-driven weighting substantially enhances prediction accuracy for high-variance stocks such as Tesla.

Future work can evaluate the HCLA model on other financial assets and incorporate additional inputs, such as sentiment analysis or macroeconomic indicators, to improve robustness. Exploring more sophisticated attention mechanisms and performing ablation studies can help simplify the architecture. Finally, implementing online learning for rapid adaptation and developing attention-based explanations for interpretability would facilitate practical deployment in real-world trading scenarios.

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