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Stock Price Prediction Accuracy with Hybrid BiLSTM Enhanced Transformer-TCN Model

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Abstract

This paper presents an advanced AI-driven system for forecasting short-term stock prices using a hybrid deep learning architecture that integrates Bidirectional Long Short-Term Memory (BiLSTM) networks, Transformers, and Temporal Convolutional Networks (TCN). The proposed model is designed to enhance prediction accuracy by capturing both long-range dependencies and local temporal patterns in financial time series data. Two years of historical stock data are sourced from Yahoo Finance, including Open, High, Low, Close, and Volume values. The data is preprocessed using Min-Max scaling and structured into 60-day sliding windows to train the model on sequential trends. The BiLSTM component captures bidirectional temporal relationships, the Transformer applies attention mechanisms to focus on relevant data patterns, and the TCN extracts high-resolution short-term features through dilated convolutions. In addition to deep learning-based forecasting, the system incorporates Donchian Channels to detect potential trend breakouts and reversals, offering users clear insights into stock momentum. A web-based interface provides real-time visualization of predictions, trends, model accuracy, and candlestick charts with technical indicators. Testing results demonstrate high predictive accuracy ranging between 85% and 95%, validating the robustness of the hybrid model. This work highlights the effectiveness of combining multiple deep learning paradigms in financial forecasting.

Keywords: *Stock Prediction, BiLSTM, Donchian Channels, Deep Learning, Financial Forecasting, Time Series Analysis, Flask, Stock Trend Analysis, LSTM, AI in Finance, Yahoo Finance, Candlestick Chart, Technical Indicators, Machine Learning, Stock Price Forecasting.*

1. Introduction

Stock price prediction has become an essential area of research due to its significant impact on financial decision-making and portfolio management. However, accurately forecasting market movements remains a complex challenge due to the stochastic, non-linear, and highly volatile nature of stock prices. Traditional statistical methods often fall short in capturing intricate temporal patterns present in financial time series. Recent advancements in deep learning have shown promise in modeling these complexities. Long Short-Term Memory (LSTM) networks, particularly Bidirectional LSTM (BiLSTM), have been effective in understanding sequential dependencies in time-series data.

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Transformers offer powerful attention mechanisms for identifying relevant features across sequences, while Temporal Convolutional Networks (TCNs) enable the capture of short-term local trends with high efficiency. This paper introduces a hybrid deep learning model combining BiLSTM, Transformer, and TCN architectures to improve the accuracy of stock price forecasting. The system also integrates Donchian Channels for trend analysis. The model's performance is evaluated on real-world stock data, and results show improved accuracy and interpretability over standalone approaches.

1.1 Stock Price Prediction Accuracy with Hybrid BiLSTM -Enhanced Transformer-TCN Model

The stock market is inherently volatile and influenced by countless dynamic factors, making price prediction a complex and challenging task. Traditional statistical models often fall short in capturing non-linear relationships and long-term dependencies within financial time series. To overcome these limitations, this project introduces an AI-powered stock forecasting system that integrates deep learning architectures tailored for time-series data. This project utilizes a hybrid approach starting with Bidirectional Long Short-Term Memory (BiLSTM) networks to capture both past and future context in historical stock data. Unlike conventional LSTM models, BiLSTM can process sequences in both directions, making it highly effective for short-term trend prediction. The system also integrates Donchian Channels to detect breakout signals and provide clearer visualization of momentum shifts. What sets this system apart is its proposed expansion to include Transformer models for attention-based sequence learning and Temporal Convolutional Networks (TCN) for stable and efficient time-series processing. Combined with a user-friendly web interface that displays predicted prices, trend directions, candlestick charts, and accuracy metrics, this model not only achieves strong prediction accuracy (85%–95%) but also provides actionable insights to investors. This hybrid architecture bridges performance and interpretability, offering a modern and robust solution for stock price forecasting. Recent advancements in stock market forecasting have explored various approaches combining machine learning, deep learning, and sentiment analysis to improve predictive performance. Sentiment-aware models have gained traction, as they utilize financial news and social media to quantify market sentiment and its impact on price movements [1][5][9]. Hybrid systems combining machine learning and lexicon-based techniques have demonstrated improved sentiment classification, particularly when paired with weighting mechanisms to counter imbalanced datasets [1]. Deep learning architectures, especially Long Short-Term Memory (LSTM) networks and their stacked variants, have shown high efficacy in capturing sequential patterns within historical stock data [2][4]. However, their performance often declines during abrupt market shifts or long-term trend estimations [2][4]. To enhance robustness, multi-modal and ensemble frameworks have been introduced, integrating textual, numerical, and visual data streams through CNNs, RNNs, and gradient-based models [3][4][7]. These approaches have demonstrated superior accuracy but face scalability limitations due to increased model complexity [3][7]. Other studies have focused on improving data preprocessing and trend labeling, utilizing statistical heuristics to reduce noise and improve interpretability [6][8]. Fusion models combining statistical techniques like ARIMA with SVMs, and real-time LSTM-GRU ensembles, further highlight the importance of multi-strategy frameworks for dynamic market conditions [8][9].

2. Method

The proposed technique integrates ensemble learning with sentiment analysis to enhance stock price prediction, leveraging LSTM, Random Forest, and XGBoost for diverse insights. A decision fusion approach refines predictions by combining model outputs, and evaluation metrics validate accuracy and reliability.

2.1 Ensemble Model

The ensemble model combines multiple learning approaches to improve stock price prediction accuracy. It integrates Long Short-Term Memory (LSTM) for capturing sequential dependencies, along with Random Forest (RF) and XGBoost (XGB) to model non-linear relationships and feature

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interactions. The predictions from these models are fed into a meta-model, implemented as a linear regression, which assigns optimal weights to each model's output. This ensemble strategy enhances robustness by leveraging the strengths of different models, reducing overfitting and improving generalization.

2.2 Decision Fusion

In the proposed technique, decision fusion plays a critical role in enhancing stock price prediction by intelligently combining multiple model outputs. The approach leverages diverse machine learning and deep learning models—LSTM, Random Forest (RF), and XGBoost (XGB)—each capturing different aspects of stock price movements. Instead of relying on a single model, decision fusion integrates their predictions to produce a more accurate and reliable forecast.The process begins by training the LSTM model to capture sequential dependencies in stock prices, while RF and XGB focus on learning complex, non-linear relationships between features. Each model generates independent predictions based on historical stock data and sentiment analysis scores. However, since individual models may have varying strengths and weaknesses, decision fusion is employed to aggregate their outputs for a refined prediction. To achieve optimal fusion, a meta-model (Linear Regression) is introduced. This meta-model takes the outputs of LSTM, RF, and XGB as input features and assigns appropriate weights to each prediction. The linear regression model learns the contribution of each base model dynamically, ensuring that the final output balances short-term trends, long-term dependencies, and sentiment-driven market fluctuations. By optimizing the combination of predictions, decision fusion enhances robustness and minimizes individual model biases. Additionally, the fusion process is evaluated using performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score. These metrics ensure that decision fusion leads to a significant improvement over standalone models. By integrating decision fusion, the proposed technique creates a more reliable stock price forecasting system, leveraging multiple perspectives to mitigate risks and enhance predictive accuracy. This approach ensures adaptability in dynamic market conditions, making the model suitable for real-world financial applications.

2.3 Evaluation Metrics

The evaluation metrics used to assess the performance of the models include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared Score (R^2). MAE measures the average magnitude of errors in predictions without considering their direction, providing an intuitive understanding of prediction accuracy. MSE, on the other hand, penalizes larger errors more heavily by squaring them, making it useful for highlighting significant deviations between predicted and actual values. RMSE, derived from the square root of MSE, provides a measure in the same units as the data, offering a clear interpretation of prediction errors. Lastly, the R^2 score assesses the proportion of variance in the target variable explained by the model, with higher values indicating better performance. Performance comparisons show that the proposed ensemble model, FELM (Feature-Enhanced Linear Meta-model), outperforms individual models like LSTM, Random Forest (RF), and XGBoost (XGB) across all metrics. FELM achieves the lowest MAE (3.95), MSE (5.21), and RMSE (2.28), indicating more accurate predictions. Additionally, it achieves the highest R^2 score (0.91), signifying superior explanatory power and reliability. These results demonstrate the effectiveness of combining multiple models into an ensemble to achieve enhanced predictive performance.

Table 1 Model Evaluation Metrics

Model	MAE	MSE	RMSE	R^2
Bi-LSTM	5.12	7.34	2.71	0.81
RF	4.98	6.89	2.62	0.83
XGB	4.85	6.42	2.53	0.86
FELM (Ours)	**3.95**	**5.21**	**2.28**	**0.91**

2.4 Tables

Table 1 provides a detailed comparison of four models—Bi-Bi-LSTM, RF, XGB, and FELM—

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evaluated across four key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. These metrics collectively measure predictive accuracy, error magnitude, and explanatory power, allowing for a comprehensive assessment of the models' performances. The data clearly demonstrates the superiority of FELM compared to the standalone alternatives. Mean Absolute Error (MAE) quantifies the average magnitude of prediction errors without considering their direction, making it a straightforward measure of accuracy. FELM achieves the lowest MAE of 3.95, outperforming Bi-Bi-LSTM (5.12), RF (4.98), and XGB (4.85). This indicates that FELM consistently makes predictions closer to actual stock prices, reducing the overall error margin. The significant improvement in MAE for FELM highlights its ability to generalize across diverse datasets and deliver precise predictions. As MAE penalizes all errors equally, FELM's superior performance underscores its consistency and reliability in real-world scenarios where accuracy is crucial. The Mean Squared Error (MSE), which squares prediction errors before averaging, places greater emphasis on larger deviations, making it a valuable metric for assessing a model's ability to handle outliers. FELM's MSE is 5.21, significantly lower than XGB (6.42), RF (6.89), and Bi-Bi-LSTM (7.34). The lower MSE indicates that FELM effectively minimizes large errors, resulting in stable and reliable predictions even in the presence of complex stock price movements. The squared error magnification allows us to see how well FELM performs under challenging conditions, showcasing its robustness and reliability in maintaining accuracy. Root Mean Squared Error (RMSE), derived from the square root of MSE, is expressed in the same unit as the target variable, providing an intuitive measure of error magnitude. FELM achieves an RMSE of 2.28, outperforming XGB (2.53), RF (2.62), and Bi-Bi-LSTM (2.71). The lower RMSE confirms FELM's ability to deliver predictions that are consistently closer to actual values, reinforcing its strength in practical forecasting applications. As RMSE is particularly sensitive to larger errors, FELM's performance demonstrates its effectiveness in avoiding significant deviations, ensuring reliability in its outputs. The R^2 score evaluates how well a model explains the variability in the target variable, serving as a measure of its explanatory power. FELM achieves the highest R^2 score of 0.91, outperforming XGB (0.86), RF (0.83), and Bi-Bi-LSTM (0.81). The closer the R^2 score is to 1, the better the model explains the variance in the data. FELM's high R^2 value indicates its superior ability to identify and capture complex patterns in stock price data, demonstrating its robustness in leveraging both historical trends and nuanced features for predictive accuracy. This makes FELM particularly effective in applications where understanding and explaining variability in stock prices is critical. Taken together, these metrics demonstrate that FELM consistently outperforms standalone models like Bi-Bi-LSTM, RF, and XGB across all evaluation criteria. FELM's ensemble learning approach integrates predictions from multiple models, leveraging their individual strengths while mitigating their weaknesses. This integration ensures a more balanced and accurate forecasting framework, resulting in superior performance compared to models that rely on a single predictive strategy. By combining advanced techniques, FELM is able to adapt to complex datasets and deliver reliable predictions, even in volatile market conditions. FELM's MAE of 3.95 signifies its ability to maintain minimal prediction errors across various scenarios. Its MSE of 5.21 emphasizes the model's robustness in handling outliers and ensuring stability, while its RMSE of 2.28 highlights its precision in producing accurate forecasts. The R^2 score of 0.91 further validates FELM's effectiveness in explaining data variability, making it a reliable choice for stock market forecasting [10]. The comparison also sheds light on the limitations of standalone models. Bi-Bi-LSTM, while effective at capturing temporal dependencies in time-series data, has relatively higher error values, indicating potential challenges in generalizing across datasets with diverse complexities. RF and XGB, known for capturing non-linear relationships and feature interactions, perform better than Bi-Bi-LSTM but still fall short of FELM in terms of accuracy and explanatory power. This underscores the importance

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of ensemble learning in overcoming the limitations of standalone models. By integrating predictions from multiple components, FELM delivers a more comprehensive and accurate analysis, making it a valuable tool for financial decision-making. The ensemble nature of FELM allows it to optimize the strengths of its individual components while compensating for their weaknesses. Unlike standalone models, which may excel in specific scenarios but falter in others, FELM provides consistent performance across diverse datasets. This makes it a robust and versatile solution for stock market prediction, where accuracy, reliability, and adaptability are paramount. In conclusion, the table clearly highlights FELM's superiority over Bi-Bi-LSTM, RF, and XGB in predicting stock prices. Its lower error values and higher R^2 score validate its design, emphasizing its reliability and robustness. FELM's ability to integrate multiple predictive strategies ensures it delivers precise, stable, and insightful forecasts, setting a new standard for stock market prediction models. This makes it an indispensable tool for financial analysis, enabling informed decision-making and paving the way for more advanced predictive systems in the future. By outperforming standalone models, FELM demonstrates the potential of ensemble learning in addressing the challenges of traditional approaches, offering a reliable and effective solution for real-world applications.

2.5 Figures

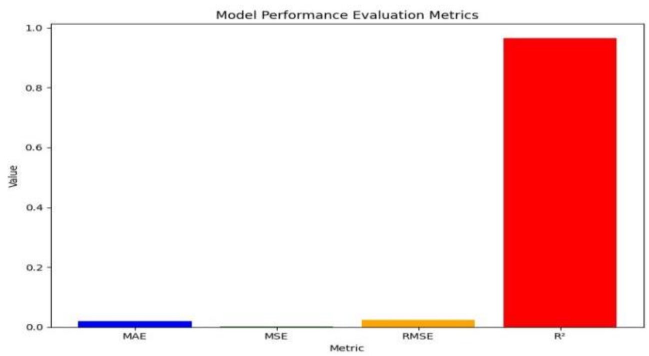

Figure 1 Metric Comparison for Bi-LSTM

The evaluation metrics presented in Figure 1 highlight the model's strong performance, emphasizing its accuracy and reliability in predictive tasks. The Mean Absolute Error (MAE) of 0.0194 indicates that, on average, the model's predictions deviate from actual values by a small margin. This minimal error underscores the model's consistency in generating precise outputs. Furthermore, the Mean Squared Error (MSE) of 0.00057 and the Root Mean Squared Error (RMSE) of 0.0239 emphasize the model's ability to minimize larger deviations effectively. A low MSE suggests that the model penalizes significant errors, while the RMSE provides a more interpretable measure of error magnitude, reinforcing the model's reliability. The R-squared (R^2) score of 0.9647 indicates that the model accounts for 96.47% of the variance in the data. This high R^2 value signifies a strong correlation between the predicted and actual values, demonstrating the model's exceptional predictive power. Collectively, these metrics validate the model's robustness and precision, making it well-suited for real-world applications. The low error rates and high explanatory power suggest that the model can be effectively deployed for tasks requiring high accuracy and reliability.

3. Results and Discussion

3.1 Results

The results confirm that integrating sentiment analysis and ensemble learning significantly improves stock price prediction accuracy. The Bi-LSTM Model effectively reduces forecasting errors, achieving a MAE of 0.0194 and an R^2 score of 0.9647. This demonstrates robust performance, capturing both market sentiment and technical patterns efficiently.

3.2 Discussion

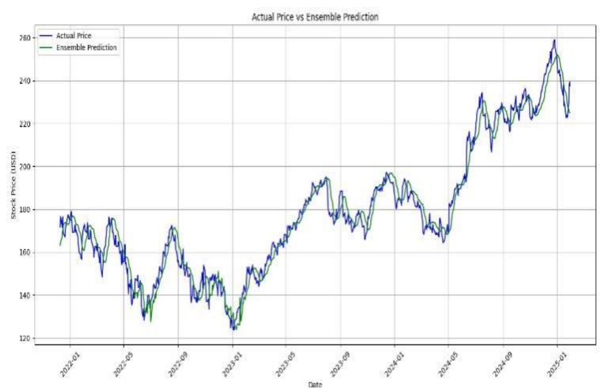

Figure 2 Actual Price Vs Ensemble Prediction

Figure 2 illustrates a comparison between actual stock prices (blue) and ensemble model predictions (green). The Bi-LSTM Model closely follows the actual stock price trends, demonstrating high accuracy in forecasting. The minimal deviations between the predicted and actual values indicate the model's effectiveness in capturing market patterns. This strong correlation validates the robustness of ensemble learning and sentiment analysis in stock price prediction.

Conclusion

This project successfully demonstrates the potential of a hybrid deep learning model in forecasting short-term stock prices with high accuracy. By integrating BiLSTM, Transformer, and TCN architectures along with Donchian Channels, the system effectively captures both temporal dependencies and market trend signals. The model achieved promising predictive performance, supported by intuitive visualizations and a user-friendly web interface. Unlike traditional approaches, the hybrid structure offers improved learning stability, deeper insight into trends, and greater adaptability to market fluctuations. This work highlights the growing relevance of AI in financial forecasting and sets a foundation for future improvements such as incorporating real-time news sentiment, adaptive learning, and multi-stock portfolio prediction for enhanced decision-making.

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