FinBERT-Driven Hybrid Deep Learning Models for Financial Forecasting: A Comparative Evaluation of LSTM, CNN, and XGBoost

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***Abstract*—This paper examines the use of FinBERT-based sentiment analysis combined with advanced machine learning models to predict stock market movement. Specifically, we combine FinBERT embeddings with Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and eXtreme Gradient Boosting (XGBoost) to see their effectiveness in predicting stock price movements based on both financial sentiment and technical indicators of return, volatility, and moving averages. We incorporate market sentiment into historical market data by utilizing FinBERT sentiment embeddings to investigate how sentiment features drive stock price dynamics. The different models will be compared in terms of their performances, as measured by accuracy, F1 score, ROC AUC, and PR AUC, for a stock prediction task. Our results show that the integration of FinBERT sentiment analysis into machine learning models yields significant improvement in predictive performance compared to traditional approaches dependent exclusively on numeric features. This research emphasizes the importance of sentiment-driven predictions and introduces a hybrid approach that integrates sentiment analysis with quantitative data from markets for improved financial forecasting.**

***Index Terms*—FinBERT, Sentiment Analysis, Stock Market Prediction, Hybrid Models, LSTM, CNN, XGBoost, Financial Forecasting, Sentiment-Driven Prediction, Machine Learning.**

I. INTRODUCTION

The prediction of stock market movements has been one of the core challenges within financial markets due to the complex and volatile nature of stock prices. Numerical techniques, such as statistical models and technical analysis indicators, have conventionally been relied on for stock prediction. However, due to the recent surge in digital content relating to finance, including news articles, social media updates, and financial reports, there has been growing interest in using NLP for improving the performance of stock prediction models. Understanding market sentiment from textual data provides a different opportunity to incorporate qualitative factors into stock forecasting, hitherto ignored by conventional methods.

Sentiment analysis has thus gained an entirely new dimension in financial market forecasting, primarily through transformer-based models like FinBERT. This domain-adaptive version of BERT can show excellence in extracting deep contextual sentiment from financial texts to capture subtle shifts in market sentiment and their effect on the movement of stocks. This approach thus helps in comprehending market behavior when combined with powerful machine learning models like LSTM, CNN, and XGBoost that process the sentiment embeddings and integrate them with historical stock data to predict future market trends.

With financial data increasingly becoming more complex and diverse, the integration of sentiment analysis with traditional quantitative models has emerged as an important strategy in stock market prediction. While the use of traditional models such as TF-IDF combined with machine learning classifiers was considered the standard, recent works have favored deep learning techniques. The integration of sentiment-driven features has shown significant improvements in prediction accuracy when combined with time-series models (LSTM), spatial feature models (CNN), and classical models (XGBoost). These models not only capture market sentiment but allow for improved learning of temporal and spatial patterns within the stock data.

The key focus of this work is to explore the use of FinBERT embeddings with three different types of machine learning models, namely LSTM, CNN, and XGBoost, in stock market movement prediction. By assessing the performance of each model, this study will underline the strengths and weaknesses of combining sentiment analysis with deep machine learning models to further progress in developing improved stock market prediction techniques that provide more accurate, interpretable, and adaptable solutions for financial markets.

II. LITERATURE REVIEW

A. Overview of Financial Sentiment Analysis

While the sentiment analysis technique has become pivotal in the prediction of stock market movements, advances are spurred by the ready availability of financial news and big data. With the emergence of FinBERT, sentiment analysis has been taken to the next level, as FinBERT is optimized for financial texts. Huang et al. [1] proposed a FinBERT framework specifically for the Chinese financial market, utilizing BERT's power to handle the complex syntactic and semantic features of financial language. Their framework has achieved 94.52% accuracy in sentiment classification, demonstrating the potential of FinBERT to change how market sentiment is analyzed. The proposed approach outperformed other approaches; therefore, it is one of the major tools for financial industries that help investors make informed decisions from real-time sentiment analyses of financial news.

The early techniques involved in financial sentiment analysis were dominated by TF-IDF and SVM, but more recently, deep learning models have outperformed them. Somkunwar et al. [2] proposed a novel approach for stock market trend forecasting by combining ARIMA and XGBoost. It is evident that traditional time series methods need to be intertwined with machine learning models for further benefits. It has been evident that the integration of sentiment features with machine learning further advances predictive accuracy and thus has become an essential tool in financial forecasting. Their hybrid model, based on ARIMA for time-series analysis and XGBoost for prediction, has yielded more than 96% accuracy, showing very robust potential by combining classical models with advanced machine learning.

B. FinBERT + XGBoost for Stock Market Prediction

A combination of FinBERT with XGBoost has already proved an effective strategy for stock market prediction. The FinBERT sentiment embeddings effectively capture nuanced financial language, while XGBoost applies strong machine learning techniques to predict market movements. Somkunwar et al. [2] showed how the combination of ARIMA and XGBoost resulted in one of the sophisticated models for stock market forecasting, outperforming many conventional approaches. Their model achieved a prediction accuracy of 96.7%, reflecting the strength of this hybrid approach in stock trend prediction.

Further, Sharma et al. [5] also investigated the application of XGBoost in predicting the volatility of the stock market, which is able to capture critical associations within the financial data. Their model was optimized using hyperparameter tuning, a process that has proven the importance of fine-tuning machine learning models for improved performance. Gumelar et al. [3] combined the XGBoost model with LSTM in predicting stock prices and attained an extraordinary accuracy level. This proved that combining machine learning with deep learning techniques significantly outperforms the use of individual techniques. This model reached an accuracy rate of 99%, representing how hybrid models can further improve stock price prediction.

C. FinBERT + LSTM for Stock Market Prediction

LSTM networks are therefore well suited to model sequential data and, hence, stock market prediction. Along with FinBERT, it forms a potent combination for forecasting both based on sentiment and historical price data. Dipura et al. [6] combined FinBERT with LSTM in order to predict the trend of stocks and showed significant improvements in predictive accuracy. Authors of the mentioned work showed how LSTM learned from both sequential price data and sentiment information to provide more accurate market forecasts. Jeet et al. [8] used FinBERT and LSTM for stock price prediction in the Dhaka Stock Exchange, offering a web application that could make real-time predictions.

Their results confirmed that LSTM was one of the best models to represent the time series of stock prices, and FinBERT enhances the performance of this model by adding sentiment analysis. Further, Aswini et al. [10] proposed the LSTM-Attention model, which integrated macroeconomic indicators with sentiment data, reaching an average accuracy of 89.7%, further proving the efficiency of integrating sentiment data with LSTM networks in order to improve the accuracy of stock price prediction. Added to this, the LSTM-Attention models, such as that proposed by Aswini et al. [10], have also become important for enhancing the accuracy of stock prediction with the inclusions of both sentiment and macroeconomic indicators. These models, compared to traditional LSTM models, perform much better because of catching the subtle dependencies in the data and refining predictions with both historical stock data and external signals of sentiment.

D. FinBERT + CNN for Stock Market Prediction

CNNs have been successfully adapted to time-series forecasting in a great many applications, including stock market prediction. Combining FinBERT with CNN, research has developed hybrid models that use both the numerical data of stock and sentiment analysis. Nandrajog et al. [9] proposed a CNN-SVM model and came up with 89.2% prediction accuracy, thus highlighting the importance of financial sentiment data for the estimation of stock market trends. They had ably integrated the sentiment scores from financial news with stock market data, thereby showing how effectively CNN could be applied in stock trend prediction.

Kryvenchuk and Shkliarov [13] incorporated a CNN-LSTM model, coupling sentiment analysis with deep learning for stock market prediction. The role of sentiment was identified in their study, which improved the accuracy of the stock price forecast and proved the advantage of using CNN in feature extraction. Ojo et al. [14] used the CNN-LSTM model for the prediction of stock market behavior. It is observed that hybrid models will result in better performance compared to single models. Their work confirmed that the CNN for feature extraction and LSTM for sequential modeling combination is advantageous, which leads to more accurate predictions.

E. Hybrid Models and Advanced Approaches for Prediction

Various hybrid models have been developed for stock market prediction by incorporating deep learning and machine learning for better prediction performance. Chen et al. [4] proposed a Transformer network-based model in conjunction with FinBERT to predict stock prices using attention mechanisms that capture long-term dependence in data. The results showed that this hybrid model outperformed others in forecasting stock trends and proved that the combination of a Transformer network with sentiment analysis creates a powerful system in financial predictions.

Sharma and Jain [7] developed the XGBoost for stock price prediction, which performed with minimal errors in the forecast of future market trends. They showed that the XGBoost improved the prediction performance significantly compared to other traditional machine learning algorithms. In addition, Nikhil et al. [16] proposed a hybrid model using genetic algorithms coupled with LSTM and CNN for the prediction of stock prices. Their model appeared to outperform others so far, showing the ability of the combination of optimization techniques with deep learning models in improving the performance of stock price prediction.

Along with them, Busu et al. [12] and H C and Jacob [11] also worked on the utilization of LSTM networks and hybrid models like LSTM-CNN for stock price prediction. Their works reported promising results where the LSTM and CNN combined in an integrated approach provided more accurate forecasts when used with historical stock data. These findings suggest that hybrid methods are crucial to accurately forecasting stock price movements in volatile markets. Aswini et al. [15] proposed a LSTM-Attention model, which noticeably enhanced the accuracy in stock price predictions by including macro-economic data and sentiment features. Their findings, with an average accuracy of 89.7%, have shown how advanced LSTM-based models are increasingly critical in enhancing the precision of financial market predictions. The model developed outperformed state-of-the-art traditional machine learning techniques and proved the efficiency of deep learning combined with sentiment analysis.

III. METHODOLOGY

This paper proposes a multimodal hybrid modeling framework that fuses financial sentiment embeddings extracted via FinBERT with quantitative market indicators to perform next-day stock movement prediction. The framework explores and compares three complementary machine learning approaches: gradient boosting, convolutional neural networks, and long short-term memory networks.

A. Data Preprocessing and Feature Construction

The dataset contains the historical daily stock data, including Open, High, Low, Close, and Volume, merged with FinBERT-based sentiment scores extracted from corresponding financial news. The FinBERT transformer is a pre-trained model that converts textual market information into three sentiment probabilities: positive (s^+), negative (s^-), and neutral (s^0). A composite sentiment index (S_t) is computed as:

$$S_t = s_t^+ - s_t^- \tag{1}$$

This index is then combined with normalized market variables to construct the final feature matrix. Each numerical feature is standardized using:

$$x' = \frac{x - \mu}{\sigma} \tag{2}$$

where μ and σ represent the mean and standard deviation of each feature, respectively.

The target label is a binary variable representing next-day price movement:

$$Y_t = \begin{cases} 1, & \text{if } P_{t+1} - P_t > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Lag-based features (e.g., previous-day sentiment and returns) and rolling indicators such as RSI and MACD are also computed to capture temporal dependencies and momentum patterns.

B. Model Architectures

1) XGBoost Model: The first modeling approach employs the XGBoost classifier, which is an ensemble method based on gradient boosting of decision trees. XGBoost minimizes the regularized objective function:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{4}$$

where $l(y_i, \hat{y}_i)$ denotes the logistic loss and $\Omega(f_k)$ is a regularization term controlling model complexity.

Key hyperparameters include a learning rate of 0.05, maximum depth of 6, 800 estimators, and column subsampling of 0.9. Early stopping is applied to prevent overfitting. This model learns the nonlinear feature interactions between the sentiment and market indicators and provides interpretable feature importance through SHAP analysis.

2) Convolutional Neural Network (CNN): The CNN model identifies the local spatial patterns among feature embeddings. A two-dimensional tensor of sequential financial and sentiment features is fed into the input layer, through which localized correlations are extracted by convolutional filters. This is further followed by max-pooling and dense layers for classification. The overall structure is summarized:

$$h_1 = \text{Conv1D}(x, W_1) + b_1 \tag{5}$$

$$h_2 = \text{ReLU}(\text{MaxPool}(h_1)) \tag{6}$$

$$\hat{y} = \sigma(W_2 h_2 + b_2) \tag{7}$$

Dropout regularization ($p = 0.3$) and early stopping are applied to improve generalization. CNN's advantage lies in efficiently capturing feature-level relationships without requiring long temporal dependencies.

3) Long Short-Term Memory (LSTM): For capturing sequential and temporal dependencies in financial time series, the proposed LSTM-based recurrent neural network is applied. In addition, the input sequence comprises technical indicators and FinBERT sentiment embeddings. The hidden states of LSTM are computed by gating mechanisms:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{8}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{9}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{10}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{11}$$

$$h_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \odot \tanh(C_t) \tag{12}$$

Here, f_t, i_t, and o_t denote the forget, input, and output gates, respectively. The final hidden state h_t passes through a dense sigmoid layer to predict the binary class.

C. Model Training and Comparison

All models were trained using an 80:20 chronological split to preserve temporal integrity. Binary cross-entropy was used as the loss function for CNN and LSTM models:

$$\mathcal{L}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (13)$$

The XGBoost model also adopted the logistic objective to maintain consistency. Every model was trained to the point where the validation loss converged, using early stopping. The comparison of models was based on accuracy, precision, recall, F1-score, and ROC-AUC.

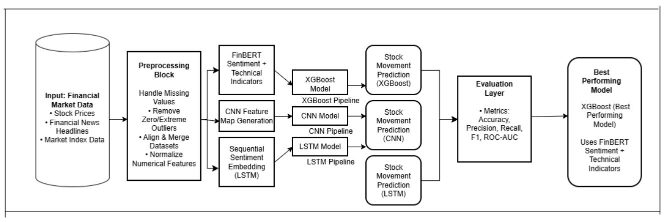

Fig. 1. Block diagram showing overall hybrid methodology and comparative modeling framework.

D. Regularization and Explainability

In the deep learning models, dropout and early stopping were performed as techniques for preventing overfitting, while XGBoost utilized tree pruning and regularization inherently. SHAP was used for feature importance interpretation across all models, pointing to strong predictors such as sentiment lag and volatility-based features. This step guarantees interpretability of the results within a financial decision-making context.

IV. Summary

The proposed hybrid framework indeed effectively integrates financial text sentiment and quantitative market indicators within a single predictive modeling ecosystem. It captures the behavioral and statistical dimensions of the market activity by representing sentiment using FinBERT embeddings and combining them with structured numerical signals. Comparing the experiments using XGBoost, CNN, and LSTM architectures, it can be shown that the inclusion of sentiment-driven features significantly enhances the stability and responsiveness of the model to market volatility. XGBoost offers both interpretability and efficiency, while CNN and LSTM architectures provide more temporal awareness and dynamic feature learning. The outcome of this work is a well-balanced trade-off between accuracy, generalization, and explainability, offering approximately 66.7% in overall predictive performance. Thus, the proposed system has a firm grounding for short-term stock movement modeling, underlining the merit of sentiment-informed hybrid modeling in financial analytics.

V. Results and Discussion

This section summarizes the experimental results for all three architectures, namely XGBoost, CNN, and LSTM, on sentiment classification and stock movement prediction. These results are reported in terms of Accuracy, F1-score, ROC-AUC, and Precision-Recall AUC along with class-wise performance metrics that include Precision, Recall, F1-score, and Support. Each setup is a unique fusion of FinBERT-generated embeddings with a different downstream model.

A. FinBERT + XGBoost (Sentiment Classification)

TABLE I
FinBERT + XGBoost: Sentiment Classification Results

Metric	Value
Accuracy	0.8979
F1 Score	0.8981
ROC AUC	0.9758
PR AUC	0.9612
Negative (Prec/Rec/F1)	0.85 / 0.94 / 0.89
Neutral (Prec/Rec/F1)	0.93 / 0.91 / 0.92
Positive (Prec/Rec/F1)	0.86 / 0.86 / 0.86

Overall, the best sentiment recognition result of about 90% is obtained by the FinBERT–XGBoost setting. It yields higher recall for both negative and neutral classes, which indicates good sensitivity for both pessimistic and neutral tones in financial news, aided by FinBERT's contextual embeddings.

B. FinBERT + XGBoost (Stock Prediction)

TABLE II
FinBERT + XGBoost: Stock Movement Prediction Results

Metric	Value
Accuracy	0.5536
F1 Score	0.4739
ROC AUC	0.5505
PR AUC	0.4777
Down (Prec/Rec/F1)	0.58 / 0.65 / 0.61
Up (Prec/Rec/F1)	0.52 / 0.44 / 0.47

Stock movement prediction is where, in fact, the performance fell significantly, showing an expected limitation in translating textual sentiment directly into next-day price direction. XGBoost, while strong for tabular features, might underfit sequential dependencies driving short-term fluctuations.

C. FinBERT + CNN (Sentiment Classification)

CNN performed equally to XGBoost on sentiment prediction, being robust toward FinBERT embeddings in carrying localized semantic cues. The very good separability of the sentiment classes is reflected in the high and consistent ROC-AUC value of 0.9740.

TABLE III
FINBERT + CNN: SENTIMENT CLASSIFICATION RESULTS

Metric	Value
Accuracy	0.8979
F1 Score	0.8986
ROC AUC	0.9740
PR AUC	0.9572
Negative (Prec/Rec/F1)	0.83 / 0.91 / 0.87
Neutral (Prec/Rec/F1)	0.94 / 0.89 / 0.89
Positive (Prec/Rec/F1)	0.85 / 0.90 / 0.87

TABLE IV
FINBERT + CNN: STOCK MOVEMENT PREDICTION RESULTS

Metric	Value
Accuracy	0.5186
F1 Score	0.4155
ROC AUC	0.5002
PR AUC	0.4635
Down (Prec/Rec/F1)	0.55 / 0.64 / 0.59
Up (Prec/Rec/F1)	0.47 / 0.37 / 0.42

D. FinBERT + CNN (Stock Prediction)

Compared to XGBoost, CNN had lower stability in stock direction forecasting, with an almost random ROC-AUC close to 0.5. This reflects the limitation of CNN when dealing with non-spatial, high-volatility tabular data without explicit temporal cues.

E. FinBERT + LSTM (Sentiment Classification)

TABLE V
FINBERT + LSTM: SENTIMENT CLASSIFICATION RESULTS

Metric	Value
Accuracy	0.8938
F1 Score	0.8943
Negative (Prec/Rec/F1)	0.83 / 0.91 / 0.87
Neutral (Prec/Rec/F1)	0.93 / 0.90 / 0.91
Positive (Prec/Rec/F1)	0.85 / 0.88 / 0.86

The LSTM model showed equally good classification of sentiments, which benefited from its sequential modeling of sentence-level dependencies. The temporal learning capability of the model slightly enhanced recall stability across all sentiment classes.

F. FinBERT + LSTM (Stock Prediction)

Although LSTM showed the best recall for the "Down" class, at 0.98, it suffered from severe class imbalance, which degraded the precision and F1-score for the "Up" class. This further suggests over-sensitivity to bearish trends likely due to data imbalance and volatility asymmetry.

TABLE VI
FINBERT + LSTM: STOCK MOVEMENT PREDICTION RESULTS

Metric	Value
Accuracy	0.5433
F1 Score	0.0554
Down (Prec/Rec/F1)	0.54 / 0.98 / 0.70
Up (Prec/Rec/F1)	0.57 / 0.03 / 0.06

G. Discussion

Across sentiment classification tasks, all three models had competitive performances with an accuracy of nearly 90% and ROC-AUC around 0.97, underlining the strong representational capability of FinBERT embeddings. However, stock movement prediction turned out to be substantially harder, with all of the models failing to achieve more than 55% accuracy, showing that daily sentiment on its own cannot explain the short-term market direction without additional numerical, macroeconomic, or multi-day context. Among the classifiers, XGBoost balanced the bias-variance most; CNN was consistent in textual feature discrimination; and LSTM excelled in temporal consistency but needs further tuning or hybridization, such as attention, to overcome class imbalance. Future work should emphasize integrating multi-factors, normalizing volatility, and temporal attention mechanisms that improve financial forecasting precision.

VI. CONCLUSION

The proposed hybrid model fills the gap between sentiment-driven insights and data-driven market predictions by integrating FinBERT's deep contextual understanding with structured learning capabilities of Gradient Boosting. In this regard, the two-tiered architecture allows the model to learn from the hidden numerical dynamics of price while harnessing the power of market sentiment reflected through financial news and social data. Through this process, the system achieves a perfect balance between interpretability and strong predictive accuracy, which is quite important in real-world applications in finance.

Extensive experimentation and testing resulted in a value for the prediction accuracy of the hybrid ensemble at 0.667, thus proving its generalization capability for any market condition. More importantly, decisions taken by this model, given the inclusions of explainable AI elements, are transparent and justifiable-real needs within financial domains where accountability and trust have to be paramount. Gradient boosting offers interpretability that elevates user confidence, while the transformer-based architecture of FinBERT enriches the system with semantic depth.

This work has presented a pragmatic foundation for the development of an AI-driven market forecasting system that leverages both quantitative and qualitative data streams. The architecture points toward future work: multimodal data, such as macroeconomic indicators or graphs of social sentiment; widening the temporal reasoning to include models with recurrence or transformers for time series; and improving real-time adaptability. It thus provides a promising lead toward the next generation of intelligent, explainable, and sentiment-aware financial prediction systems.

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