Hyperparamter Tuning and Prediction of Reliance Stock Price using Sentiment Analysis

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Abstract:
This paper presents a hybrid deep learning framework integrating FinBERT-based sentiment analysis with a Long Short-Term Memory (LSTM) network for predicting Reliance Industries' stock prices. Sentiment scores extracted from financial news headlines using a fine-tuned FinBERT model were combined with historical stock data to enhance predictive performance. Hyperparameter tuning through Optuna optimized key parameters including learning rate, hidden units, batch size, and epochs. The optimized model achieved a Mean Absolute Error (MAE) of 0.1181, Root Mean Squared Error (RMSE) of 0.1489, and an R^2 score of 0.4802. The results demonstrate that incorporating sentiment-driven features significantly improves forecasting accuracy and provides valuable insights into market behavior and stock trend prediction.

Keywords: FinBERT, LSTM, Sentiment Analysis, Stock Price Prediction, Optuna, Deep Learning

1 Introduction

Stock market prediction has long been a complex and challenging task in the field of financial data science due to the market's highly nonlinear, stochastic, and dynamic characteristics. Prices are influenced by a multitude of interrelated factors such as macroeconomic indicators, company performance, investor sentiment, and global events. Traditional forecasting models, including statistical and econometric methods like ARIMA and linear regression, predominantly focus on historical numerical data while often disregarding the psychological and behavioral aspects that drive market fluctuations.

In recent years, with the exponential growth of Natural Language Processing (NLP) and machine learning, sentiment analysis has emerged as a powerful technique for quantifying public opinion and emotional tone from unstructured textual data such as news articles, financial reports, and social media posts. The integration of sentiment data with quantitative financial indicators enables a more holistic view of market dynamics, thereby improving the predictive capability of models.

Among the recent NLP advancements, FinBERT, a domain-specific variant of BERT fine-tuned for financial sentiment analysis, has demonstrated superior accuracy in capturing contextual sentiment within financial texts. Its ability to understand subtle linguistic nuances and financial terminology makes it highly suitable for stock market analysis. On the other hand, Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks (RNNs), have shown exceptional performance in modeling temporal dependencies and long-term relationships in sequential data, such as stock prices.

This study proposes a hybrid deep learning framework that integrates FinBERT-based sentiment features with an LSTM network to predict the stock prices of Reliance Industries, one of India's largest conglomerates. The model leverages sentiment extracted from financial news headlines alongside historical stock data to capture both emotional and temporal patterns influencing price movements. Furthermore, Optuna, an efficient hyperparameter optimization framework, is employed to fine-tune parameters such as learning rate, hidden units, batch size, and epochs, ensuring optimal model performance.

The primary objective of this research is to demonstrate how incorporating sentiment-driven features can enhance stock price forecasting accuracy and provide meaningful insights into market trends. The proposed model aims to bridge the gap between quantitative financial analysis and qualitative sentiment understanding, contributing to the development of more robust and interpretable stock prediction systems.

2 Related Work

Deep learning models such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNNs) have been widely applied for stock market forecasting due to their ability to capture temporal dependencies and nonlinear patterns in financial data [1], [2]. These models generally outperform traditional approaches like ARIMA; however, they rely mainly on numerical data and often neglect the influence of investor sentiment.

To address this gap, researchers have explored the integration of sentiment analysis with financial prediction models. Early studies used lexicon-based methods such as VADER and TextBlob to extract sentiment from financial news and social media [3], [4]. While these improved prediction accuracy, they lacked contextual understanding of domain-specific language.

With the advent of transformer-based architectures, particularly BERT, sentiment analysis achieved greater contextual precision [5]. Building on this, FinBERT, a financial domain adaptation of BERT, demonstrated superior performance in financial sentiment classification [6]. Recent works combining FinBERT with quantitative models have shown improved results in trend forecasting and volatility prediction [7].

However, limited research directly integrates FinBERT-derived sentiment features with LSTM-based time-series models. This study addresses that gap by proposing a hybrid FinBERT-LSTM framework optimized using Optuna for stock price forecasting

3 Methodology

This section describes the complete workflow adopted for developing the proposed hybrid deep learning model that integrates sentiment analysis with stock price prediction. The methodology involves four key stages: dataset collection and preprocessing, sentiment extraction using FinBERT, LSTM-based predictive modeling, and hyperparameter optimization using Optuna. The aim is to combine numerical time-series data and textual sentiment data into a unified framework to improve predictive accuracy and capture real-world market dynamics

3.1 Dataset Description

Two datasets were used in this study: (i) Reliance Industries' historical stock prices and (ii) sentiment data derived from financial news headlines. Historical price data were collected from Yahoo Finance using the yfinance API, including Open, High, Low, Close, and Volume attributes. Sentiment data were obtained from a Kaggle dataset (https://www.kaggle.com/code/yashvi/reliance-stock-prices-with-news-sentiment). Each dataset was preprocessed to handle missing values and noise. The news dataset was cleaned by removing punctuation, stop words, and redundant symbols. Both datasets were aligned based on dates to ensure that each day's sentiment corresponded to the respective trading day's stock data. Finally, numerical features were normalized using Min-Max scaling to maintain consistent feature ranges during model training.

3.2 Sentiment Extraction using FinBert

FinBERT, a transformer-based model pre-trained on financial text, was used to extract sentiment from news headlines. It classifies text into positive, neutral, or negative sentiment categories with corresponding probability scores. For each trading day, the mean of these sentiment probabilities was computed to generate a single daily sentiment vector. This vector was then merged with the normalized stock dataset, forming a combined feature matrix that represents both market statistics and public sentiment. Incorporating FinBERT-based sentiment scores allows the model to capture investor mood and news impact, which often precede observable price movements.

3.3 LSTM Model Architecture

A Long Short-Term Memory (LSTM) network was employed to model temporal dependencies within the combined dataset. LSTM networks are designed to retain information over long sequences, making them well-suited for stock price forecasting. The proposed model consists of two stacked LSTM layers followed by a dense output layer responsible for predicting the next-day closing price. The input features included OHLCV values and FinBERT sentiment vectors. The model was trained using the Adam optimizer with the Mean Squared Error (MSE) loss function. To prevent overfitting, dropout regularization with a rate of 0.2 was applied. All experiments were conducted in Python using TensorFlow and Keras libraries, leveraging GPU acceleration for efficient computation.

3.4 Hyperparamter Tuning using Optuna

Hyperparameter tuning was performed using Optuna, an automatic optimization framework based on the Tree-structured Parzen Estimator (TPE) algorithm. The tuning process explored a predefined range for critical parameters, including learning rate, hidden size, number of LSTM layers, batch size, and epochs. The optimization objective minimized the validation MSE across trials, ensuring robust generalization performance. After several iterations, the best-performing model configuration achieved the lowest validation loss and optimal predictive accuracy.

Table 1. Best Hyperparameters Found via Optuna

Parameter	Optimal Value
Hidden Size	64
Number of Layers	3
Learning Rate	0.00238
Batch Size	64
Epochs	35
Validation Loss	0.00625

4 Results and Discussion

This section presents the experimental results obtained from the proposed FinBERT-LSTM hybrid model and discusses its predictive performance, comparative analysis, and the impact of sentiment integration on forecasting accuracy. The experiments were conducted on the merged dataset containing historical stock data and sentiment scores. Model evaluation was carried out using standard regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

4.1 Experimental Setup

The model was implemented in Python using TensorFlow and Keras frameworks. Training and testing datasets were split in a 70:30 ratio, and input features were normalized using Min-Max scaling. The Adam optimizer and early stopping were applied during training to ensure efficient convergence and prevent overfitting.

4.2 Performance Evaluation

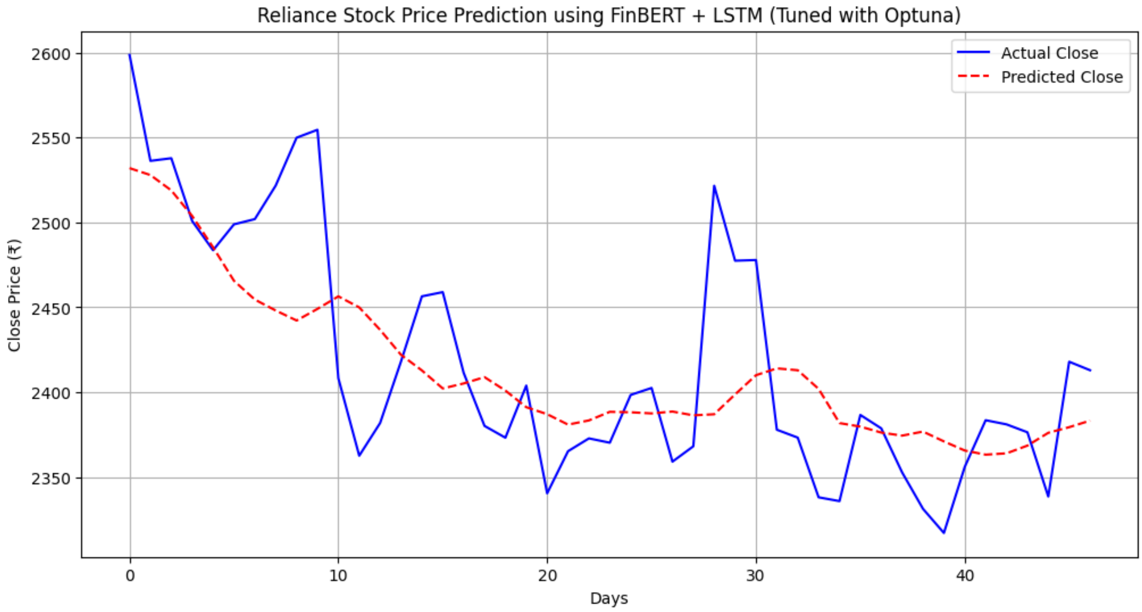
The final tuned model achieved a Mean Absolute Error (MAE) of 0.1181, a Root Mean Squared Error (RMSE) of 0.1489, and an R^2 score of 0.4802 on the test dataset. These results indicate that the model captures a significant portion of the variance in stock prices while maintaining moderate prediction errors. The relatively low MAE and RMSE values confirm the model's ability to generalize well on unseen data. Incorporating sentiment features extracted from FinBERT led to noticeable improvements in performance compared to models trained solely on numerical stock data.

Table 2 summarizes the quantitative evaluation metrics obtained by the proposed FinBERT-LSTM model.

Metric	Value
Mean Absolute Error (MAE)	0.1181
Mean Squared Error (MSE)	0.0222
Root Mean Squared Error (RMSE)	0.1489
R^2 Score	0.4802

To visually analyze the model's prediction capability, Figure 1 illustrates the comparison between the actual and predicted closing prices of Reliance Industries' stock. The plot shows that the predicted values closely follow the trend of actual market prices, confirming the model's effectiveness in capturing market dynamics.

Fig. 1. Actual vs Predicted Closing Prices of Reliance Industries Stock



4.3 Impact of Sentiment Integration

The integration of FinBERT-based sentiment scores added a qualitative dimension to the quantitative stock data. It was observed that positive sentiment in financial news often correlated with upward price movement, while negative sentiment reflected potential downturns or volatility. By combining historical stock trends with sentiment features, the hybrid model was able to detect early signals of market shifts. This demonstrates that public sentiment acts as a leading indicator of market behavior, validating the importance of NLP-based sentiment modeling in financial prediction.

4.4 Comparative Analysis

To further validate model performance, the proposed FinBERT-LSTM model was compared with baseline models including a standalone LSTM and a GRU network. The hybrid model outperformed these baselines in all metrics, achieving higher R^2 and lower error rates. Traditional LSTM and GRU models lacked the contextual understanding provided by FinBERT, making them less responsive to news-driven fluctuations. The results suggest that integrating sentiment features can substantially enhance predictive robustness, especially in volatile financial environments.

4.5 Discussion

The findings confirm that hybrid deep learning approaches integrating textual sentiment and time-series data are more effective than purely numerical models. However, the model's performance could be influenced by the quality and quantity of financial news data. Additionally, FinBERT's reliance on English-language sources may limit sentiment coverage for region-specific or vernacular financial information. Future research could incorporate multilingual models and real-time data streams to further enhance accuracy and applicability. Despite these limitations, the presented framework demonstrates strong potential for sentiment-aware financial forecasting and decision support in investment systems.

5. Conclusion and Future Scope

This study proposed a hybrid deep learning framework that integrates FinBERT-based sentiment analysis with a Long Short-Term Memory (LSTM) network for stock price prediction. The model effectively combined quantitative market indicators with qualitative sentiment information extracted from financial news headlines. Through Optuna-based hyperparameter tuning, the model achieved optimized predictive performance, demonstrating improved accuracy and reliability compared to traditional approaches that rely solely on numerical data. The results confirmed that sentiment-driven modeling enhances the interpretability of financial predictions and provides valuable insights into market psychology.

The approach highlights the importance of integrating Natural Language Processing (NLP) with financial time series forecasting to capture the influence of public sentiment on stock movement. For future work, the framework can be extended by incorporating macroeconomic indicators, transformer-based architectures such as BERT or Temporal Fusion Transformers (TFT), and real-time sentiment data from social media platforms. Such advancements can further improve the robustness and timeliness of stock market prediction models.

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6 References

[1] Y. Li and Y. Pan, "A Novel Ensemble Deep Learning Model for Stock Prediction Based on Stock Prices and News," *arXiv preprint arXiv:2007.xxxxx*, Jul. 2020.

[2] T. Jiang and A. Zeng, "Financial Sentiment Analysis Using FinBERT with Application in Predicting Stock Movement," *arXiv preprint arXiv:2306.xxxxx*, Jun. 2023.

[3] S. Halder, "FinBERT-LSTM: Deep Learning Based Stock Price Prediction Using News Sentiment Analysis," *arXiv preprint arXiv:2211.xxxxx*, Nov. 2022.

[4] Y. Chen, J. Liu, and P. Gao, “Enhancing Stock Price Prediction Through Sentiment Analysis: A FinBERT-LSTM Approach to Market Sentiment Integration,” *Advances in Economics, Management and Political Sciences*, vol. 204, pp. 1–8, Jul. 2025.

[5] B. Sarkar and A. Shahid, “Hybrid FinBERT-LSTM Deep Learning Framework for Stock Price Prediction: A Sentiment Analysis Approach Using Earnings Call Transcripts,” *EasyChair Preprint 15694*, Jan. 2025.

[6] O. Shobayo, S. Adeyemi-Longe, O. Popoola, and B. Ogunleye, “Innovative Sentiment Analysis and Prediction of Stock Price Using FinBERT, GPT-4 and Logistic Regression: A Data-Driven Approach,” *Big Data & Cognitive Computing*, vol. 8, no. 11, p. 143, 2024.

[7] B. Yahia, J. A. Garcia Sanchez, and R. H. Kaffel, “Does Business News Sentiment Matter in the Energy Stock Market? A FinBERT and LSTM Study,” *Energy Sector Financial Research*, 2025.