RESEARCH PAPER

Stock Price Prediction By Integrating LSTM XGBoost, and FinBERT-Based Sentiment Analysis

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ABSTRACT
The financial markets are dynamic and nonlinear causing difficulties in predicting the stock prices. This paper suggests a compound predictive model that combines Long Short-Term Memory (LSTM) networks, XGBoost, and financial news sentiments evaluation with FinBERT. LSTM model learns the temporal dependencies of past price history, whereas XGBoost models nonlinear relationships of engineered technical input features. FinBERT uses contextual sentiment signals that are derived through the use of daily financial news to add market psychology and event-based influences. Probability based ensemble technologies are used to incorporate the outputs of these components to produce final directional predictions. The results of experimental findings reveal that the proposed hybrid model outperforms the performance of individual algorithms, which proves the efficiency of combining the time-series modeling, gradient boosting and financial sentiment analysis to obtain a higher level of accuracy in stock market predictions.
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I Introduction

Stock price prediction refers to the art of determining the future market movement based on past fi-nancial records, technical indicators as well as other outside sources of information. This makes stock market prediction complex and uncertain because of the extreme volatility, nonlinear and sentiment-driven qualities of fi-nancial markets. Conventional forecasting techniques may only use historical price data and tech-nical indicators, which makes them less effective in capturing markets changes that may occur suddenly due to external in-formation in the form of financial news and macroeconomic events [1], [5], [6]. Consequently, often quanti-tative models alone cannot deliver consistent and robust predictive accuracy, especially in the directional forecasting in the short term [3], [4].

Even though deep learning systems, like Long Short-Term Memory (LSTM) networks, are successful in capturing time-related dependencies of time-series data [4], they might fail to capture nonlinear interactions among features. In the same manner, ensemble learning models like XGBoost can work well with structured tabular data and have no sequential memory to learn long-term temporal behavior [9]. More so, neglecting textual sentiment information results in the failure to model investor behavior and market psychology fully. It has been shown in previous research that news sentiment and social media data have a positive influence on predictive performance and event-driven volatility [6], [7], [8], [10]. Thus, the hybrid framework that will incorporate time-series modeling, nonlin-ear feature learning, and contextual financial sentiment analysis into a single predictive system is required.

The suggested hybrid model of LSTM, XGBoost, and FinBERT will solve the problem statement in the following way:

• Temporal Modeling: LSTM incorporates sequential relationships and past trend patterns of stock price movements [4].
• Nonlinear Feature Learning: XGBoost takes into account the complex relationships between technical indicators and structured financial characteristics [9].
• Contextual Sentiment Integration: FinBERT derives financial sentiment on a domain-specific basis on news headlines to quantify investor psychology, generalizing the sentiment-based forecasting methods [6], [7], [8].
• Multi-Modal Fusion: Probability-based ensemble integration, Probability-based ensemble integration combines both quantitative and quali-tative signals in an attempt to give it greater robustness.
• Enhanced Forecasting Stability: The hybrid system eliminates forecasting errors and expands flexibility in unstable and event-driven market dynamics [5], [10].

II RELATED WORK

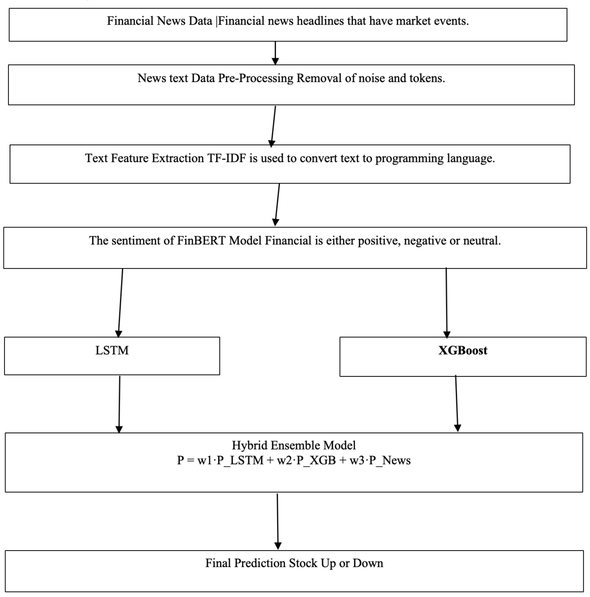
The Over the recent years, much attention has been given to the prediction of the trends in the stock market using computational models. Traditional mod-els and statistical methods were the early attempts at machine learning-based forecasting. Soni et al. gave a systematic review of the approach-es of machine learning to predict stock prices, and the weaknesses of models based solely on the past price characteristics are presented [1]. Udagawa investigated the elements of prediction of stock price based on candlestick blending method, which demonstrated how useful pattern recognition is in technical analysis [2]. Kan et al. and Bathla et al. explore the artificial neural network-based classifications, such as Long Short-Term Memory (LSTM) and Support Vector Regression (SVR), to model the price sequences and time-dependent sequences of financial data [3], [4].
Predictive performance has been demonstrated to be improved when external information (news and social media) is included. Wang and Wang also proved the usefulness of social media mining in stock price prediction, because of the ability to capture the sentiment of the population, and therefore the utility of the non-price information in the predicting-task [5]. Ranibaran et al. investigated the impact of news polarity regarding market prediction and found that sentiment-based models could be successfully used to provide meaningful improvement when used together with machine lear-ing methods [6]. On the same note, Bharti et al. applied the ensemble learning techniques of a conglomeration of sentiment analysis and price prediction, indicating improved results compared to the standalone models [7]. More recent works by Annalakshmi et al. went further and made use of sentiment analysis of news articles to better predict the accuracy of the forecast [8].
There has also been an exploration of hybrid and ensemble architectures to enable the balance of strengths of a number of models. In Khatri et al. a hybrid deep learning model was used to predict stock prices, which demonstrates that the integration of various model structures can enhance the accuracy [9]. To support the significance of a timely textual sentiment input to financial forecasting systems, Alostad and Davul-cu explored a stock direction prediction based on breaking news via Twitter Twitter [10]. Nevertheless, there are only limited studies that have been able to combine deep sequential models, gradient boosting and sophisticated sentiment analysis into a single framework in an effective manner.
Based on these results, the framework suggested combines the use of Long Short-Term Memory (LSTM) networks to model the temporal price changes, XGBoost to learn nonlinear features, and FinBERT to extract sentiment in fi-nancial news. This multi-modal strategy aims at solving the weaknesses that have been observed in previous research through the systematic integration of quantitative time-series trends with qualitative sentiment indicators, to get stronger and more precise predictions of the stock market.

III. Methodology

The proposed technique will use a hybrid predictive approach, which combines deep learning, ensemble learning, and textual analysis to enhance the prediction of the stock market. To produce technical indicators, which reflect market trends and risk characteristics, historically stock prices data serves to create the indicators of daily return, 5-day moving average (MA5), 10-day moving average (MA10) and volatility. Normalization of these numerical characteristics is done by use of MinMax scaling and a sliding window is used to generate sequential input data to the Long Short term memory (LSTM) network to allow the model to learn the temporal relationships and historical cycles in financial time-series data. Simultaneously, an XGBoost model that is trained on the same structured financial indicators captures nonlinear relationships between the technical characteristics in a complex way. To take into account the external market data, the daily financial news headline is processed with the help of TF-IDF vectorization, and the textual features are analyzed with the help of the financial language model to extract the sentiment-related signals of financial news. The emotion output of financial news is the probability score P News, which shows market perception (good or bad). Lastly, the results of the LSTM model P LSTM, the

XGBoost price model P XGB and the news-based sentiment model P Newsare are pooled together based on a weighted ensemble approach so that the hybrid probability P Hybrid is calculated. Such hybrid integration enables the system to exploit temporal pattern, nonlinear interaction between features and textual sentiment information at the same time, which lead to stronger and more accurate stock market direction prediction.

The framework will lead to a greater generalization of models and reduce the flaws of each mod-el through the use of various modalities of data and prediction techniques. This is a combination approach, which enhances stability and reliability of stock market short term projections. The hybrid architecture also enables the enhanced sensitivity to the changing market dynamics, that is, utilization of not only the structured financial indicators but also unstructured textual data. The balance of strengths of numerous models can also be employed to reduce the variance of prediction as well as increase robustness via the ensemble approach. In addition, the news sentiment is incorporated so that it allows a phenomenon capture of the sudden market responses due to economic announcement or financial events by the model. The hy-brid structure is another method of alleviating the overfitting as the learning is distributed across the different pre-dictive components. Besides, blurring fusion mechanism is probabilistic in that each model is always making a proportional contribution towards a final prediction. This multi-modal way of learning will provide a deeper understanding of the market behavior. As a result, the proposed system is a more effective and scalable way of predicting the financial markets of dynamic environments.



Data Description

The information in this research incorporates financial time-series indicators and textual news to forecast the movement of the stock market. The financial part is generated using the information of the stock price in the past and consists of various indicators of the recent market (daily) like closing price, daily return, 5-day moving average (MA5), 10-day moving average (MA10), 5-day rolling volatility which reflect short-term market trends, stock momentum and stock risk. The indicators are normally applied in financial analysis to reflect the market behavior over a period of time. A binary target variable is a generated variable to denote the direction of subsequent day market, i.e. 1 when the next day closing price is greater than the current day one and 0 when not so that allows the problem to be formulated as a classification task. Besides numerical financial data, the dataset includes daily financial news head-lines, which give the information concerning economic events, political situation as well as other outside factors, which can affect the behavior of the stock market. Each of the headlines of the same day is clustered to capture the sentiment of the news of the day. Term Frequency -Inverse Document Frequency (TF-IDF) vectorization, which converts textual news data into numerical representations in both unigram and bigram representations, enables the application of machine learning models to process and learn the patterns of textual data. The numerical financial characteristics are then normalized with Min-Max scaling before training the model, this will guarantee that all the variables are within a similar range, hence enhancing stability and training efficiency of the model. Besides, a sliding window strategy is used to produce sequential input data so that the model can identify temporal dependencies and sequential patterns within financial time-series data. The mix of technical market indicators and sentiment-based textual characteristics offers a broad description of market conditions by utilizing the dataset, which enables predictive models to make use of quantitative financial indicators as well as qualitative news information to enhance predictive performance of stock markets.

1.Time-Series Modeling using LSTM

Financial time-series are subject to sequential dependence, volatility clustering and momentum effects. A sliding window method is used in order to obtain these temporal properties:

$$X_t = \{p_{t-n}, \dots, p_{t-1}, p_t\} -----(1)$$

where $n$represents the window size.

The LSTM network processes the sequence and updates hidden states:

$$h_t = LSTM(X_t) -----(2)$$

The output probability is computed as:

$$P_{LSTM} = \sigma(W_h h_t + b_h) - - - - - (3)$$

where σdenotes the sigmoid activation function. Theoretically, LSTM can be applied to financial prediction due to its ability to address the vanishing gradient issue and long-term memory due to gated processes, which enables it to capture the trend per-sistence and time-based dependencies.

2. Nonlinear Feature Modeling using XGBoost

Whereas LSTM is able to capture sequential behavior, structured financial indicators have nonlinear interactions that are necessary to capture. Let the feature vector be:

$$F_t = \{Return_t, MA_t, RSI_t, Volatility_t, \dots\} - - - - - (4)$$

XGBoost models the prediction using gradient boosting over decision trees:

$$\hat{Y}_t = \sum_{k=1}^{K} f_k\,(F_t) - - - - - (5)$$

where $f_k$represents individual regression trees.

The probability output is:

$$P_{XGB} = \sigma(\hat{Y}_t) - - - - - (6)$$

XGBoost maximizes a loss function which is a combination of prediction loss and regularization, enhancing the performance of generalization. In theory, boosting decreases bias and variance, through sequential correction of residual errors, so it can be used with structured financial data.

3. Financial News Sentiment using FinBERT and Hybrid Integration

Market behavior is strongly influenced by news events and investor sentiment. To quantify qualitative information, FinBERT is applied to daily financial headlines:

$$N_t = \{n_1, n_2, \dots, n_m\} - - - - - (7)$$

FinBERT produces sentiment probabilities:

$$S_t = \{P_{pos}, P_{neg}, P_{neu}\} - - - - - (8)$$

An aggregated sentiment score is computed as:

$$P_{News} = P_{pos} - P_{neg} - - - - - (9)$$

FinBERT is pre-trained on financial corpora, enabling contextual understanding of domain-specific terminology such as earnings reports, policy changes, and market downturns.

The final hybrid probability is computed through weighted ensemble fusion:

$$P_{Hybrid} = w_1 P_{LSTM} + w_2 P_{XGB} + w_3 P_{News} - - - - - (10)$$

subject to:

$$w_1 + w_2 + w_3 = 1 - - - - - (11)$$

The final prediction is:

$$\hat{Y}_{final} = \begin{cases} 1, & \text{if } P_{Hybrid} > 0.5 \\ 0, & \text{otherwise} \end{cases} - - - - - (12)$$

IV.EXPERIMENT ANALYSIS

THE PROPOSED HYBRID MODEL (LSTM + XGBOOST + FINBERT) IS TESTED WITH THE HELP OF CLASSICAL MEASURES OF CLASSIFICATION TO EVALUATE THE PREDICTIVE PERFORMANCE. THE DATASET IS PARTITIONED INTO TRAINING AND TEST SETS ACCORDING TO A CHROMO-TEMPORAL SPLIT IN ORDER TO MAINTAIN INCIDENCES OF TEMPORAL CONSISTENCY. PERFORMANCE IN MODEL IS MEASURED IN TERMS OF ACCURACY, PRECISION, RECALL AND F1-SCORE. ACCURACY IS DEFINED AS:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} - - - - - (13)$$

PRECISION AND RECALL ARE COMPUTED AS:

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN} - - - - - (14)$$

THE F1-SCORE, REPRESENTING THE HARMONIC MEAN OF PRECISION AND RECALL, IS GIVEN BY:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} - - - - - (15)$$

THE HYBRID PROBABILITY IS CALCULATED AS:

$$P_{Hybrid} = w_1 P_{LSTM} + w_2 P_{XGB} + w_3 P_{News} - - - - - (16)$$

TABLE-1: ACCURACY COMPARISON OF PREDICTION MODELS ACROSS MAJOR MARKET INDICES

Market Index	LSTM	XGBOOST	FINBERT (NEWS)	HYBRID MODEL
DOWJONES INDUSTRIAL AVERAGE (DJIA)	0.58	0.60	0.57	0.64
S&P 500	0.59	0.61	0.58	0.65
NASDAQ COMPOSITE	0.60	0.62	0.58	0.66
NYSE COMPOSITE	0.57	0.59	0.56	0.63
FTSE 100 (UK)	0.56	0.59	0.55	0.63
NIKKEI225 (JAPAN)	0.55	0.58	0.54	0.62
DAX30 (GERMANY)	0.57	0.60	0.56	0.64

THE EFFECTIVENESS OF MULTI-MODAL ENSEMBLE INTEGRATION IS SUPPORTED BY EXPERIMENTAL FINDINGS THAT THE HYBRID MODEL IS MORE PREDICTIVELY STABLE AND HAS GREATER DIRECTIONAL ACCURACY THAN INDIVIDUAL MODELS.

LSTM

LMST (Long Short-Time Memory) is a recurring neural network that has been created to address sequential and time-series data. It employs gated mechanisms namely forget, input and output gates to regulate the movement of in-formation and preserve a memory cell state. It is a structure that allows LSTM to learn long-term dependencies and temporal patterns and removes the vanishing gradient problem, and hence is suitable to stock price prediction.

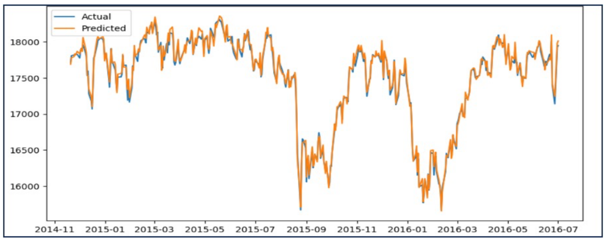


FIGURE ------(1)

XGBOOST

XGBoost (Extreme Gradient Boosting) is a progressive ensemble learner algorithm founded on gradient boost-over decision tree. It constructs a series of sequential trees with the new tree correcting the mistakes of the predecessor trees. XGBoost also includes regularization to stop overfitting and is a very efficient tool in predicting structured financial data by modeling any complex nonlinear relationship between features.

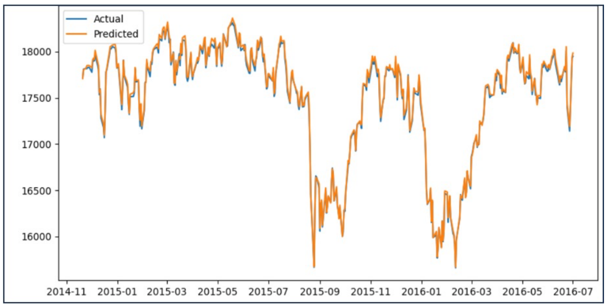


Figure ------(2)

FinBERT (News)

FinBERT (Financial Bidirectional Encoder Representations with Transformers) is a domain-specific language model that works on the analysis of financial texts. It is trained on financial corpora of a large scale with the aim of comprehending contextual and domain specific terms i.e. earnings report, market trend and eco-nomic event. FinBERT is a sentiment classifier that uses the probabilities to identify positive, negative and neutral sentiments so that it can extract investor sentiment of stock market prediction out of financial news.

FIGURE -----(3)

HYBRID MODEL

Hybrid Model is a hybrid predictive model based on LSTM, XGBoost, and FinBERT that has integrated these three models with their complementary capabilities. LSTM is an algorithm that learns temporal relationships in the past price movements, XGBoost forecasts nonlinear relationships among technical indicators, and FinBERT classifies sentiment sig-nals of financial news. These components are combined to come up with a final prediction using a weight-based ensemble technique to enhance robustness, stability and directional accuracy in stock price prediction.

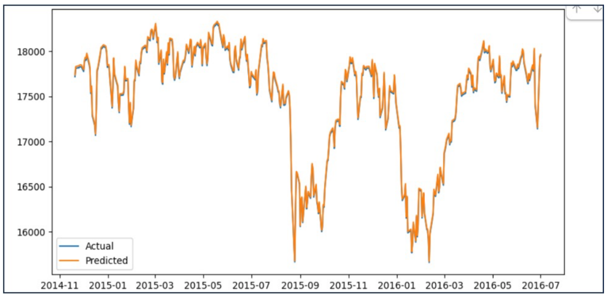


FIGURE -----(4)

V. CONCLUSION

Predicting the price of stocks is not an easy task since it is nonlinear, volatile, and sentimental in nature because of financial markets [1], [3], [5]. Existing machine learning and deep learning architectures are not always able to remain consistent in performance in cases where the market environment evolves rapidly [4], [9]. A hybrid pre-dictive model using LSTM, XGBoost, and financial news sentiment analysis were suggested in this paper to enhance the performance of directional stock forecasting.

The LSTM model was effective in capturing the temporal relations and sequential market trends as it is well established that the LSTM model is effective when it comes to the time-series prediction [4], [9]. XGBoost also fit nonlinear relationships between engineered technical indicators, which is consistent with the literature that indicates the suitability of en-semble learning on structured financial data [7], [12]. Also, the news sentiment in-formation helped to put the situation into perspective and to understand more about investor psychology and market externalities, which is consistent with studies on the relevance of sentiment-based forecasting processes [5], [6], [8], [10]. The experimental findings showed that the hybrid model performed better than single models in terms of quantitative price-based signals in tandem with the qualitative sentiment information. The weighted ensemble with optimized weights was better predictive robust and minimized classification errors than single methods, which are consistent with new hybrid deep learning frameworks reported in the literature [9], [11]. These observations underscore multi-modal learning role in the forecasting of financial outcomes and support the claim that using a combination of structured market data and unstructured textual sentiment in a financial forecasting model increases stability during volatile market periods [6], [7]. Overall, the proposed hybrid model has a more flexible and reactive approach to stock trend prediction in the short term and informative information about the activities of scientists and money traders. It was possible to do ex-tended work on more advanced transformer-based sentiment models, more macroeconomic variables, dimensionality reduction (PCA) [13], and cross-market validation to further enhance the predic-tive performance as well as the generalization behavior.

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