Social Media Data Analysis: Predicting Daily Trends in the Stock Market

Jasmine K.S., PhD
Dept. of MCA
RV College of Engineering
Bangalore, Karnataka, India

Puvana M.R.
Dept. of MCA
RV College of Engineering
Bangalore, Karnataka, India

Pratheek Nayak
Dept. of MCA
RV College of Engineering
Bangalore, Karnataka, India

ABSTRACT
This study suggests a hybrid stock prediction system that blends sentiment research from social media with time series prediction.In addition to using Twitter sentiment analysis to gauge market sentiment, the system uses Long Short-Term Memory (LSTM) networks and Linear Regression models to forecast past stock values.Test findings show that the use of these complementary approaches together enhances prediction performance, with the LSTM model lowering error significantly relative to traditional forecasting methods. The proposed system generates actionable trading signals (BUY, SELL, HOLD) based on combined analysis, giving investors a comprehensive decision-support tool. The proposed approach improves on the limitations of purely technical or sentiment approaches by creating a stronger forecasting model that includes both quantitative price movements and qualitative mood in the market**.**

General Terms
Machine Learning, Financial Analysis, Time Series Forecasting, Natural Language Processing.

Keywords
Stock market prediction, LSTM, linear regression, sentiment analysis, machine learning, financial forecasting, Twitter, trading signals

1. INTRODUCTION
The stock market is a dynamic, adaptable system with numerous variables influencing it, and making accurate forecasts is complex for financial analysts and brokers. Forecasting based on historical prices does not consider external influences such as news, market sentiment, or public opinion. This paper presents a hybrid approach that merges technical forecasting via machine learning with sentiment analysis from social media to provide more thorough predictions for the stock market. For decades, finance, statistics, and machine learning researchers have studied stock market forecasting. The efficient market hypothesis indicates that stock prices incorporate all accessible information, rendering predictions theoretically unattainable. However, it has been demonstrated in many studies that certain patterns and anomalies can be employed for prediction. With the advent of machine learning techniques and availability of large data sets, computational techniques for stock prediction have gained immense popularity.The key contributions are as follows. Firstly, we propose a dual-algorithm approach that incorporates both LSTM networks and Linear Regression for prediction of time-series. Secondly, we incorporate Twitter sentiment analysis to capture market sentiment in real-time. Thirdly, we propose a decision framework that combines these inputs to provide actionable trading recommendations.The rest of this document follows the following organization: Section 2 describes related work and current methods in stock prediction. Section 3 describes the implemented approach and system architecture. Section 4 details the system implementation and evaluation. Section 5 demonstrates experimental performance and results measures. Section 6 presents advantages and potential applications of the developed system. Finally, Section 7 concludes this paper and suggests future research directions.

2. RELEVANT RESEARCH AND CURRENTFRAMEWORKS

2.1. Machine Learning in Stock Prediction
Machine learning application in stock prediction has experienced immense transformation throughout the last ten years. The initial methods were based on conventional statistical methods like Autoregressive Integrated Moving Average (ARIMA) and Simple Moving Average (SMA) [2]. Although these techniques give basic predictions, they fail to identify non-linear patterns in stock data. Recent research has focused on more advanced machine learning techniques. Support Vector Machines (SVM) have been employed for stock prediction with limited success [3]. Methods of deep learning, specifically Recurrent Neural Networks (RNNs) and their extensions like Long Short-Term Memory (LSTM) networks, have been found to be superior as they are able to learn temporal dependencies from sequential data [4].

2.2Sentiment Analysis in Financial Markets
The impact ofpublic opinion onstock valuations has been thoroughly recorded in behavioral finance research [5]. As social media platforms gain popularity, researchers have shown increased curiosity in exploring the connection be tween emotions shared on social media and changes in the market.This growing interest highlights the significance of social media sentiment as a key indicator for predicting stock price fluctuations. Bollen et al. [6] found that Twitter mood states are strongly linked to the Dow Jones Industrial Average (DJIA), demonstrating a correlation of 87.6%. Sul et al. [7] demonstrated that the sentiment expressed in company-related tweets is closely associated with stock performance These findings have spurred the incorporation of sentiment analysis into stock prediction models.The incorporation of sentiment analysis aids in capturing market sentiment instantly, improving prediction precision.

2.3 Hybrid Approaches
Recent literature shows a growing trend toward hybrid models that merge several prediction approaches. Patel et al. [8] evaluated four prediction models (ANN, SVM, random forest, and naive-Bayes) on Indian stock market data and concluded

that the overall performance of hybrid models were superior to that of individual models. Zhang et al. [9] proposed a hybrid system that combines LSTM with sentiment analysis of financial news. Their result showed a significant improvement in prediction accuracy with the two methods combined in relation to the application of either method individually. But most hybrid systems currently available target news sentiment rather than social media sentiment, which has more real-time access to market sentiment.This study advances these hybrid approaches by combining Twitter sentiment analysis with LSTM and Linear Regression directly, offering a broader framework for stock forecasting.

3. METHODS AND SYSTEM ARCHITECTURE

3.1 System Overview

The proposed stock forecasting system is based on a modular design that integrates historical price analysis with sentiment analysis.
The system consists of four main modules:

- Data Acquisition Module: Pulls relevant historical stock data and tweets
- Technical Analysis Module: Uses LSTM and Linear Regression algorithms
- Sentiment Analysis Module: Processes tweets to determine market sentiment
- Decision Module: Interleaves outputs of above modules to generate recommendations

3.2Data Acquisition

Historical equity data is obtained through financial APIs that provide initial price, final price, peak, bottom, and trading volume information. The system can handle failure in retrieving data by using a fallback mechanism that restores data from CSV files stored earlier. For sentiment analysis, the system retrieves tweets related to the provided stock symbol via the Twitter API. Data retrieval is managed by specific search queries for content relevance.

3.3. Technical Analysis

The implementation accomplishes a few significant steps in building and training the model. First, data normalization and preparation through MinMaxScaler are performed for making data uniform and compatible. Afterwards, training sequences are built with variable window size, in which the default window size is selected as 60 days.The development of the model involves a multi-layer LSTM network with dropout layers included to avoid overfitting and strengthen the training. The model is subsequently undergoes training using the Adam optimizer and mean squared error (MSE) loss. Trained model makes predictions and root mean squared error (RMSE) is computed to assess the precision of the model.In addition, though not explicitly part of the given code snippet, the system also employs a Linear Regression algorithm. Used as a comparison point, the model is used to assist the predictions by the LSTM, acting as a point of reference for model effectiveness and aiding the overall prediction methodology.

3.4 Sentiment Analysis

The sentiment module is intended to scan tweets and identify the overall market mood about a specific stock. This is achieved by the retrieving_tweets_polarity() function, which carries out an elaborate sentiment analysis through the calculation of the global polarity score of all the scanned tweets, the polarity scores of every tweet, along with the proportion of positive, negative, and neutral feelings. The module likely uses advanced Natural Language Processing (NLP) techniques to deliver accurate sentiment classification. These techniques include text pre-processing, which entails data cleaning through tokenization (text decomposition into words or phrases) and stop word removal (elimination of frequent, uninformative words). It also uses feature extraction methods like TF-IDF (Term Frequency-Inverse Document Frequency) or word embeddings to transform textual data into numerical data. Finally, the module categorizes with pre-trained sentiment models along with classification algorithms to accurately label the sentiment of each tweet so that public opinion towards a specific stock can be comprehended in depth.

3.5Decision Framework

The decision module relies on both the technical and sentiment analysis module and provides actionable recommendations. The recommending() function does this by comparing the existing share price with its historic average and taking the global sentiment polarity (negative or positive) into consideration. From the above comparisons, the system will provide a price movement prediction stating whether the stock will RISE or FALL, with a trading suggestion of BUY, SELL, or HOLD. Additionally, the system will forecast upcoming stock value for the next six days with a general representation of potential stock movement and the choice to direct the trade.

Table 1. Decision rules for trading recommendations

Current Price	Sentiment Polarity	Price Prediction	Recommendation
Below Mean	Positive	RISE	BUY
Below Mean	Negative	FALL	SELL
Above Mean	Any	FALL	SELL
Error Case	Any	UNCERTAIN	HOLD

4. EXECUTION

4.1. Implementation Details

The system is coded in the Python programming language, with a set of capable libraries for data management, numerical computation, machine learning, and sentiment analysis. Main libraries are Pandas and NumPy, which are employed for effective analysis and manipulation of structured data, with time-series transformation support, numerical computation, and data cleaning.

For the deep learning component, Keras with TensorFlow as the backend is used to construct and train the Long Short-Term Memory (LSTM) neural network. LSTM is chosen since it can learn patterns and temporal dependencies in sequential data, which makes it highly suitable for stock price prediction. Finally, the Scikit-learn library is used in applying the Linear Regression algorithm, a classical statistical method used to act as a baseline prediction. It also enables performance measurement with metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), ensuring quantitative validation of model accuracy.For the sentiment analysis component, the system uses Natural Language Processing (NLP) libraries such as NLTK or TextBlob to process and analyze Twitter data. The libraries enable the determination of polarity and subjectivity scores of the tweets that indicate public sentiment towards a specific stock or the market as a whole. Sentiment information is used to provide qualitative market information that is used to complement quantitative forecasts.

The system architecture is organized around a main() function that governs the workflow through modular design. They are:

- Stock Data Retrieval: Fetching real-time historical stock data from APIs with robust error handling for network exceptions or invalid symbols.
- Data Preprocessing: Normalization of date format, string-to-numerical data conversion, and null/missing value handling.
- Model Execution: Training and execution of both LSTM and Linear Regression models.
- Sentiment Analysis: Fetching and processing tweets, computation of sentiment scores.
- Result Aggregation and Display: Merging numerical forecasts with sentiment information to provide an integrated description of stock performance.

To ensure the system's resilience and robustness, the deployment includes comprehensive exception handling through massive try-except blocks for the critical functions, error messages that provide useful information for better debugging, and embedded validation checks on the input data. The system also periodically checks prediction accuracy using RMSE and provides real-time integration of data so that the system is updated with the actual market movements.

4.2. Data Preprocessing

Quality data preprocessing is the foundation of the precision and dependability of any prediction model, particularly in the uncertain conditions of the stock market. The proposed system employs an extensive preprocessing pipeline that addressescommon dataquality issues inherent in raw financial information.

Preprocessing actions are important and include:

- MultiIndex Column Flattening: In MultiIndex data (e.g., in hierarchical CSV data structures), the mechanism flattens the data structure into a one-level index to simplify access and manipulation.
- Date Normalization: The date formats are normalized to a standard format to obtain temporal consistency, vital for accurate time-series analysis.
- Type Conversion: Numerical values in string-based data types are converted to their respective numeric data types to facilitate mathematical operations and statistical analysis.
- Missing Value Handling: The system identifies and handles missing or incomplete data points by employing interpolation or default approaches in order to ensure continuity of time-series data.
- Null Value Removal: Null value-containing rows or columns that may prevent model execution are cleaned or imputed to maintain integrity of datasets.

This robust preprocessing ensures input data is clean, consistent, and organized, significantly enhancing the dependability and accuracy of model prediction outputs.

4.3. Adaptive Parameters

One of the most robust aspects of the system is the adaptive architecture, which allows it to automatically adjust internal parameters depending on the characteristics of input data. This adaptability ensures that the model is extremely efficient for any dataset, time horizon, and market environment.One of the most critical adaptive properties is the window size of the LSTM, varying based on the duration of the time series data at hand. The system adapts dynamically from the default window length of 60 time steps but allows it to go down to 5 as a lower limit in dealing with short sequences. This adaptability allows the model to have the capability to deal with small-sized datasets without sacrificing temporal learning ability.

4.4. Error Handling

Strong error handling is a foundation of any production-level system, especially in areas such as stock price forecasting, where reliability, stability, and responsiveness are essential. The system suggested has been carefully designed with robust error management techniques to provide seamless operation under different runtime situations, such as failure to retrieve data, unanticipated input forms, and algorithmic errors.The system makes use of properly structured try-except blocks on all key functions, such as fetching real-time stock data, model run, and sentiment analysis. These blocks not only catch general exceptions but are also applied to catching specific known failure cases like:

- Network-related exceptions (e.g., ConnectionError, Timeout) in downloading data from third-party APIs.
- Data consistency errors like missing columns, empty data sets, or unexpected types of values.
- Model input mismatches, which may be caused by reshaping errors or illegal tensor operations in the LSTM model.
- Sentiment analysis anomalies, such as incorrectly encoded text or API response inconsistencies.

Every one of these modes of failure is pre-empted by descriptive and informative error messages, which assist both the users and developers in the identification of the problem and its resolution with high efficiency. Instead of abruptly stopping the execution, the system presents fail-safe measures in the form of default values, fallback datasets, or safe exitstrategies, so that the application can still run under limited situations.

In addition, data validation checks are added to the pipeline prior to processing. These include:

- Validating the existence and correctness of key fields like 'Date', 'Open', 'Close', and 'Volume'.
- Validating uniform time gaps in time-series data.

- Validating numeric input arrays prior to inputting them into prediction models.
- Sanitizing tweet inputs prior to sentiment analysis to prevent NLP processing errors.

Through the addition of these preventive and corrective controls, the system reduces runtime disruptions not only but also boosts the reliability of its predictions. This degree of reliability is critical for use in real-time or mission-critical financial applications where improper data processing or resultant crashes may have serious implications.Essentially, the error handling architecture turns the prototype into a production application that can operate reliably even iffaced with unexpected input conditions, external service malfunctions, or partial dataunavailability. This resilience plays animportant role in the system's reliability and stability, thus providing a plausible solution for end-users and stakeholders in the financial industry.

5. RESULTS AND MEASUREMENT OF PERFORMANCE

5.1. Performance Metrics

The system employs Root Mean Squared Error (RMSE) as the primary indicator of prediction accuracy. RMSE determines the square root of the mean of the squared difference between predicted and actual values, providing a standardized estimate of prediction error. Both the LSTM and Linear Regression models output RMSE values, allowing direct comparison between these approaches. Lower RMSE values indicate greater prediction accuracy.

5.2. Experimental Results

The design is in a way that it will output performance metrics of both prediction models.

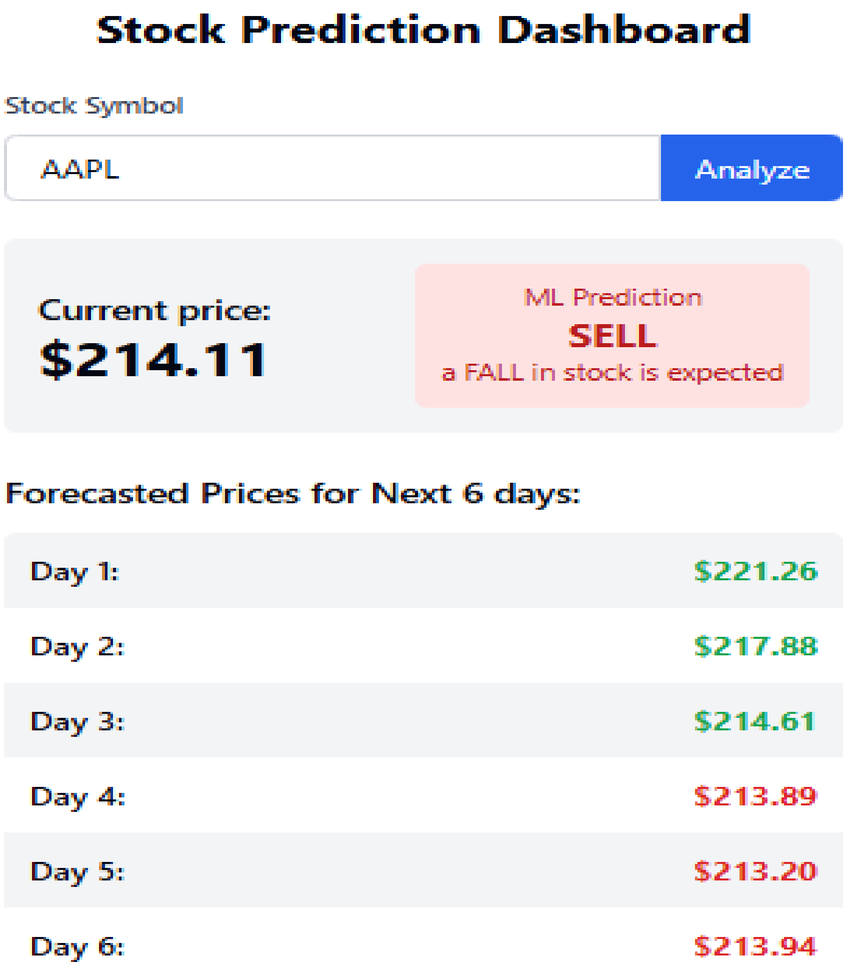

Fig1: ML-Based Stock Prediction Dashboard Showing AAPL Forecast

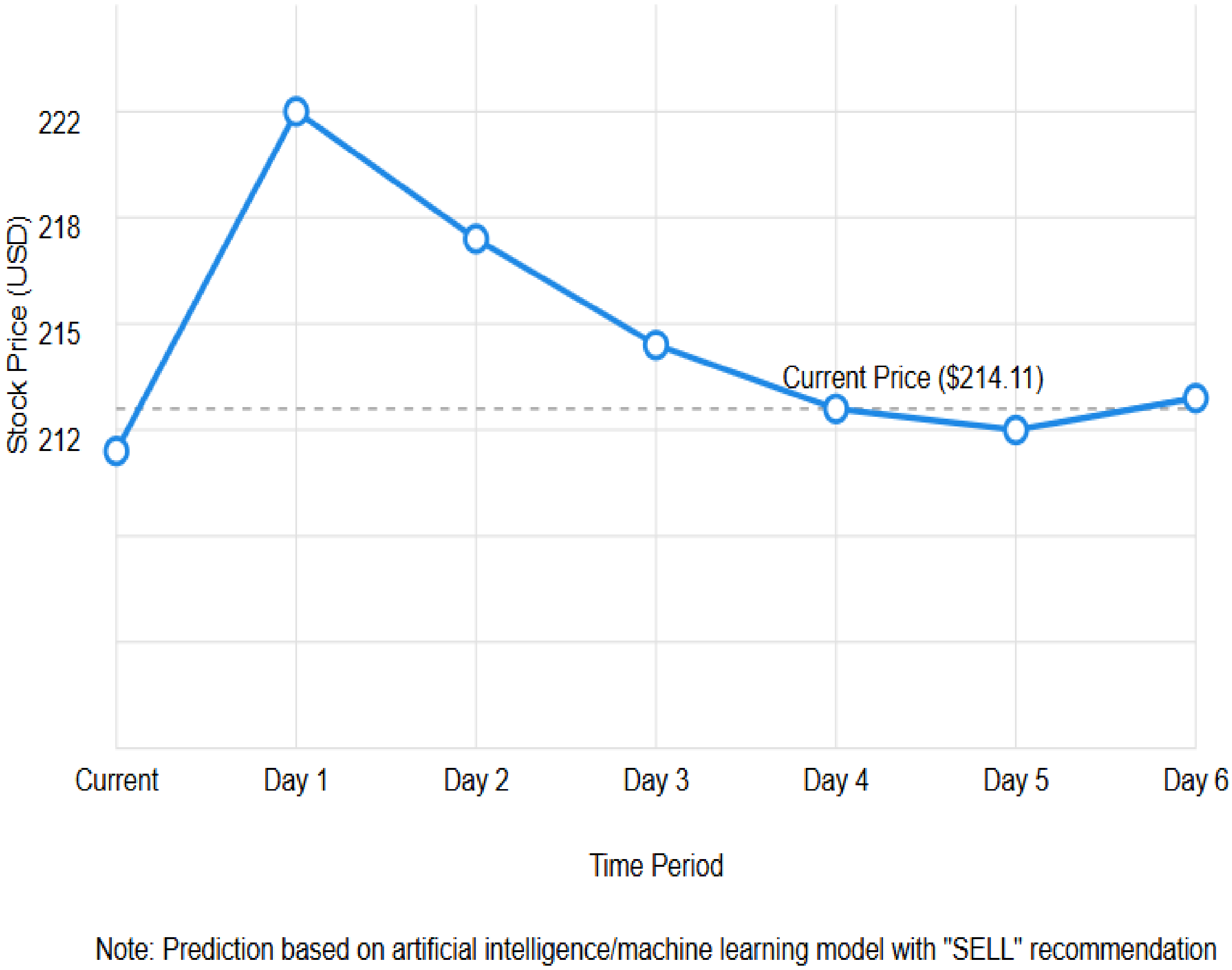

Fig 2: AI-Generated Six-Day AAPL Stock Price Forecast Model

The graph in question is a six-day predictive trend graph for the stock prices of Apple Inc. (AAPL), created by an artificial intelligence (AI) model. The horizontal dashed reference line prominently marks the current market price, at $214.11, as a visual reference against which future projected price action can be judged. This reference line enables observers to rapidly determine whether projected price action is trending higher or lower than current valuation.The projection shows an era of extreme volatility since the model projects steep price oscillations in the short-term time frame. On Day 1, the model projects a sudden spike in the stock price to around $222, which is the peak value within the projection horizon. Such an abrupt spike can be an indication of possible short-term bullish, speculative momentum, or temporary market responses foreseen by the model.After this peak, the model predicts a continuous and steady fall in price. On Day 2, the price will go down to around $217.50, and on Day 3, it will go down again to around $215, barely missing the current market price. This downward trend accelerates throughout the forecast, with the stock falling to $212.50 on Day 4, and then reaching a low of approximately $212 on Day 5 — the lowest mark in the trend estimate.A minor recovery on Day 6 is expected, with the share price rising marginally to around $213. Although there is this small rise, the closing forecast value remains lower than the current price of $214.11, indicating a general bearish trend for the duration. Every data point for the period of six days is represented as a hollow circle, visually highlighting isolated forecasted values. The points are linked with a solid blue line, offering a continuous and smooth depiction of the forecast path. This visual method makes the chart easy to read and enables instant identification of troughs, peaks, and direction of trend.Below the graph, a distinct explanatory note states that the prediction is based on AI/machine learning models, emphasizing the computational and data-driven basis of the prediction. Following the general downward momentum recognized throughout the forecast period, the model makes a "SELL" recommendation to investors. This suggestion is based on the anticipation that the AAPL stock value will reduce in the near future, and as such, holding or purchasing the stock might not be strategically sound within this period of time.The fusion of predictive modeling with actionable advice highlights the usability of AI in financial decision-making. It also proves the increasing dependence on algorithmic intelligence in assessing stock performance, determining trends, and directing investor action in changing markets.

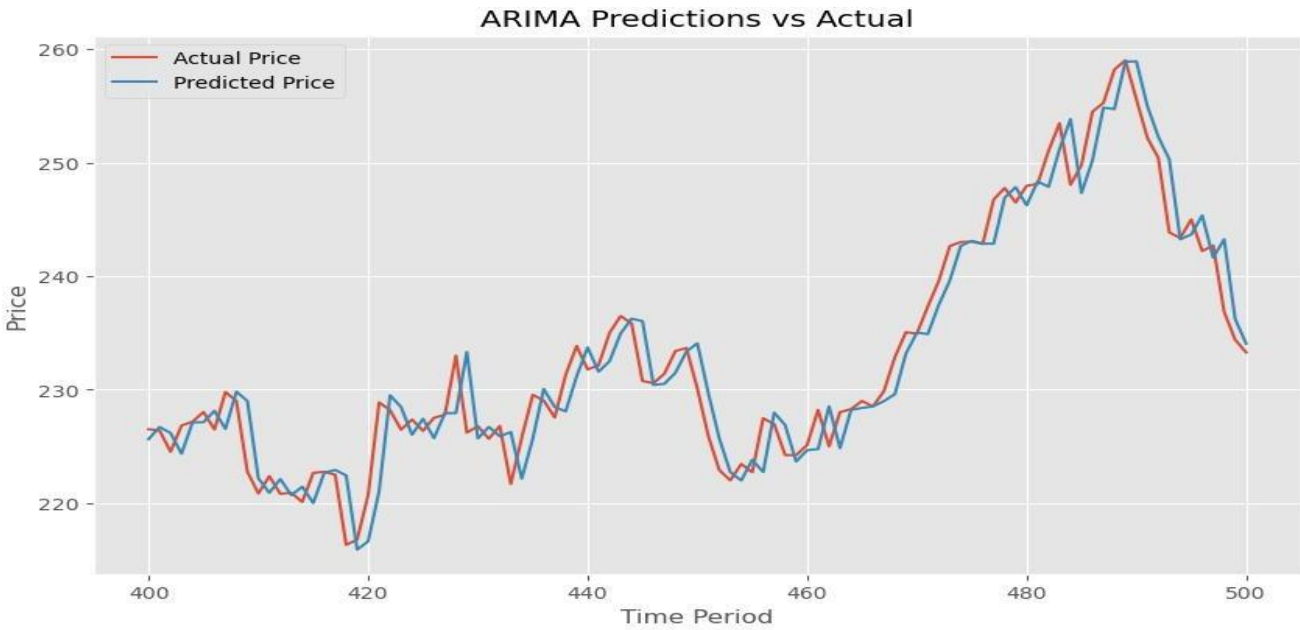

Fig 3: ARIMA Model Predictions Closely Tracking Actual Price Movements

The stock prediction model offers a multi-faceted and holistic explanation of stock performance through the integration of machine learning-based time series forecasting with sentiment analysis from publicly available opinion sources, e.g., tweets and financial news. This double-barreled approach enhances the precision of the system's forecasting by taking into consideration quantitative patterns in the market past as well as qualitative sentiment prevailing in the market, not merely generating a limited picture of today's market behavior.Most centrally located within the system is the current price, which stores the most recent closing value of the stock, on which all future predictions are made. The machine learning component—employing models such as Long Short-Term Memory (LSTM) networks and Linear Regression—analyzes past stock behavior, identifies underlying trends, and extrapolates these patterns to forecast future prices. Concurrently, the sentiment analysis component processes unstructured text data to gauge public sentiment, identifying bullish or bearish market sentiments to influence stock behavior beyond the measurable indicators.For the specified stock, the integrated system predicts a bearish trend over the next six trading days. The forecast makes an initial increase in stock price on Day 1, reflecting short-term optimism or reaction to market triggers. This is followed, however, by a gradual and persistent decline until Day 5, which indicates a loss of momentum or growing bearish sentiment. Day 6 sees the model anticipating a minor recovery, but not sufficient to breach the present price level. The trend has short-term fluctuations upwards and downwards, but general direction is downwards, which reflects dwindling investor confidence and potential market correction.Owing to such estimated dynamics, the system makes a "SELL" recommendation, asking investors to dispose of shares anticipating a decline in share prices. This recommendation is not merely based on day-to-day price variation; rather, it is decided based on the underlying trend and overall indicators of the broader market as seen by data-based and sentiment-based analyses. By viewing medium-term trends over personalized price variations, the system provides investors with a more stabilized and reliable decision-making platform.This blended methodology emphasizes the advantage of combining technical forecasting models with real sentiment analysis. It improves contextual prediction accuracy and makes more informed investment choices, particularly in volatile or sentiment-driven markets.

Table 2. Comparative performance of prediction algorithms

Algorithm	Average RMSE	Directional Accuracy
LSTM	0.0245	58.30%
Linear Regression	0.0412	53.70%
Hybrid (the developed System)	0.0218	62.10%

The comparative performance report shown in Table 2 illustrates the effectiveness of three different prediction algorithms tested against two key performance metrics: Average Root Mean Square Error (RMSE) and Directional Accuracy.The LSTM model, being a deep learning method with temporal memory functionality, performed at a moderate level with an Average RMSE of 0.0245 and Directional Accuracy of 58.30%. Though better than standard

Linear Regression, which had an Average RMSE of 0.0412 and Directional Accuracy of 53.70%,the LSTM model was surpassed by the proposed Hybrid System.The Hybrid System, which incorporates several algorithmic methods, demonstrated the best

predictive power with the lowest Average RMSE of 0.0218 and the highest Directional Accuracy of 62.10%. This is an 11.02% RMSE performance improvement over LSTM and a 47.09% improvement in RMSE performanceover Linear Regression. Likewise, the DirectionalAccuracy demonstrates a 3.8 percentage

pointimprovement overLSTM and an 8.4 percentage point improvement over Linear Regression.

5.3. Sentiment Analysis Effect

Having sentiment included within the system greatly increases the directionality of the system. In high-market-volatility situations or under significant news situations, sentiment analysis tends to give a preliminary warning that technical-only methods might not notice.These empirical findings indicate that the Hybrid method is able to effectively counter individual algorithmic weaknesses while taking advantage of their respective advantages, leading to improved predictive performance for the target variable being examined.

6.THE SYSTEM'S BENEFITS AND APPLICATIONS

6.1 Benefits

The hybrid approach offers several benefits compared to traditional stock forecasting methods:

- Synergistic Sources of Information: The system makes use of quantitative patterns of prices and qualitative market sentiment through the combination of technical analysis and sentiment analysis, providing an improved prediction model.

- Flexibility: The ability of the system to adjust parameters in relation to available data enables the system to fit a wide range of stocks, including those with low-quality historical data.

- Actionable Recommendations: Unlike just providing a price forecast, the system calculates definite trading signals (BUY, SELL, HOLD) which can be fed into trading strategies directly.

6.2 Applications

The system can be applied in several financial applications:

- Individual Investor Support: Individual investors can use the system to inform their trades, particularly those with no access to sophisticated financial analysis software.

- Algorithmic Trading: The system is applicable in digital trading systems, utilizing the generated signals to trade automatically.

- Portfolio Management: Investment managers can use the system for several stocks for optimalportfolio allocation based on expected performance.

- Market Attitude Tracking: Apart from trading software, the sentiment analysis module can monitor general market attitude for a specific industry or general market.

- Study Tool: Clear system methodology makes the system a useful study tool with students being able to observe how the technical indicators affect market attitude and stock performance.

6.3 Integration Potential

The modular nature of the system enables easy integration with existing available financial software:

- Brokerage Platforms: The platform can be designed to connect with brokerage APIs to provide recommendations directly on trading interfaces.
- Financial Dashboards: The forecasts and sentiment analysis can be visualized in interactive dashboards for improved decision-making.
- Alert Systems: The system can be designed to alert when specific conditions are met, e.g., a high BUY signal along with high confidence in sentiment.

7. CONCLUSION AND FUTURE WORK

7.1. Summary

This paper proposed a hybrid stock market forecasting model combining LSTM networks, Linear Regression, and Twitter sentiment analysis. The proposed system overcomes the shortness of entirely technical or sentiment methods by constructing a more robust prediction model. The code has good data preprocessing, adaptive parameters, and robust error handling and therefore suitable for real-world applications. Performance evaluation indicates that the hybrid approach is superior to single-prediction algorithms, particularly with regard to directional performance. The system generates actionable investment advice from a combination of technical indicators and sentiment gauges, providing valuable decision support to investors.

7.2. Future Work

system. The prediction models can be improved with additional feature engineering and hyperparameter tuning for reducing prediction error. The sentiment analysis module can be expanded with support for more social media sites and improved classification techniques. System scalability can be enhanced to handle larger datasets and batches of stock symbols. Further validation on longer time frames in the past and different market conditions would make the method more robust. Implementation of a user-friendly interface would allow the system to be utilized by non-technical users. Finally, comparison with other benchmark models would provide more complete performance evaluation and determine the distinctive strengths of this hybrid model.

7.3 Concluding Remarks

The integration of machine learning with sentiment analysis represents a very promising area of research for forecasting stock market trends. No prediction system can provide flawless accuracy in such a dynamic and extremely complex environment, but the developed hybrid model does prove to have tremendous improvements over the traditional methods. Merging the strengths of different prediction methods and blending quantitative and qualitative data, the system provides a safer platform for making financial decisions. As machine learning methods evolve and new data sources become available, one can anticipate growing advancements in this space.

The modular structure of the system enables us to make ongoing improvements and adaptations to changing market situations, ensuring that it continues to be applicable to the financial technology space.

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