American Journal of Social and Humanitarian Research

Vol. 6 Issue 4 **| pp. 717-725 | ISSN:** 2690-9626
Available online @ https://globalresearchnetwork.us/index.php/ajshr

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Article

Sentiment-Enhanced Stock Price Prediction Using LSTM and Machine Learning Techniques

S. Saranya[1], Anjugam Subramani[1], C. Elayaraja[1], M. Pandi Maharajan[1]

1. Dhaanish Ahmed College of Engineering, Chennai, Tamil Nadu, India.
*Correspondence: saranyas@dhaanishcollege.in

Abstract: The stock market is highly complex and volatile, influenced by both positive and negative sentiments shaped by media releases. Accurate stock price analysis depends on the ability to recognize stock movements and identify underlying trends. Stock price prediction has long been an active area of research, but achieving ideal precision remains a challenging task. This paper proposes a combined approach that leverages efficient machine learning techniques alongside deep learning, specifically Long Short-Term Memory (LSTM) networks, to predict stock prices with greater accuracy. Sentiments derived from news headlines significantly impact traders' buying and selling decisions, as they tend to be influenced by the media. By integrating sentiment analysis with traditional technical analysis, we aim to enhance prediction accuracy. LSTM networks are particularly effective for learning and predicting temporal data with long-term dependencies. In our approach, the LSTM model utilizes historical stock data in conjunction with sentiment data from news items to build a more robust predictive model. This fusion of sentiment and technical analysis can improve the model's ability to predict stock price movements, offering a more comprehensive and accurate prediction mechanism for stock market behavior.

Citation: S. Saranya Anjugam Subramani C. Elayaraja M. Pandi Maharajan Sentiment-Enhanced Stock Price Prediction Using LSTM and Machine Learning TechniquesAmerican Journal of Social and Humanitarian Research 2025, 6(4), 717-725 .

Received: 20th Mar 2025
Revised: 25th Mar 2025
Accepted: 30th Mar 2025
Published: 7th Apr 2025

Keywords: Deep Learning Technique; Long Short Term Memory (LSTM); Better Predictive Model; Stock Price Prediction; Automated Trading Systems (ATS).

Introduction

The financial market is a dynamic and intricate system where individuals can engage in the buying and selling of currencies, stocks, equities, and derivatives through virtual platforms facilitated by brokers. This market allows investors to own shares of public companies by trading either through exchanges or over-the-counter markets . By participating in the stock market, investors have the opportunity to earn profits and secure a prosperous financial future, with minimal initial investments and relatively low risks compared to the higher stakes involved in starting a new business or securing high-salary careers . However, stock markets are inherently volatile, influenced by a multitude of factors that contribute to market uncertainty and fluctuations in prices. The unpredictable nature of stock markets creates both opportunities and challenges for investors, and navigating this environment can be complex . While human traders can manually place orders and interact with the market, automated trading systems (ATS) driven by computer programs are more efficient and effective in executing trades. These systems are programmed to analyze and execute orders with speed and precision, often outperforming human traders[1]. Automated systems incorporate various factors, including the chosen trading strategy, mathematical functions that model the behavior of specific stocks, machine learning algorithms that predict future stock values, and relevant news that could influence stock performance . These factors are continuously evaluated by the ATS to ensure that trades are executed at optimal moments, capitalizing on market movements and maximizing potential gains for investors .

The increasing complexity of financial markets, combined with the demand for faster and more accurate trading, has led to the development and widespread adoption of automated systems . These systems utilize advanced data analysis techniques, including time series forecasting and modeling, to make predictions about future market behavior. Time series analysis, a branch of statistics, is particularly crucial in the context of financial markets, as stock prices exhibit distinct patterns and trends over time. By analyzing historical data, time series models can help identify patterns and predict future movements, providing valuable insights for investors. In this context, one of the most promising techniques for stock price prediction is Long Short-Term Memory (LSTM) networks. LSTM is a type of recurrent neural network (RNN) that is designed to handle sequential data and capture long-term dependencies in time series data . Unlike traditional machine learning models, LSTMs are well-suited for tasks involving time-dependent data, as they can retain information over long periods and make predictions based on both recent and past data. This ability to capture long-term dependencies is essential for predicting stock prices, as the behavior of financial markets is influenced by both short-term fluctuations and long-term trends[2].

The primary goal of this project is to utilize LSTM networks to predict stock prices accurately. Stock price prediction has long been a challenge for investors, as it involves understanding and anticipating the impact of numerous factors, including economic conditions, company performance, market sentiment, and geopolitical events . While traditional financial models rely heavily on statistical methods and technical analysis, machine learning techniques, particularly deep learning models like LSTM, offer a more powerful and flexible approach. LSTM networks can process vast amounts of historical data, learn complex patterns, and make predictions that are not limited by predefined rules or assumptions . Time series forecasting and modeling play a critical role in the success of stock price prediction. By analyzing historical stock price data, time series models can identify trends and make predictions about future price movements. However, stock prices are influenced by a range of unpredictable factors, including news events, market sentiment, and broader economic conditions [3]. This complexity makes it difficult for traditional models to achieve high levels of accuracy. Machine learning, particularly LSTM networks, offers a more dynamic and adaptable approach to stock price prediction. By learning from large datasets and adapting to new information over time, LSTMs can provide more accurate and timely predictions, enabling investors to make better-informed decisions .

The scope of this project is to develop a software tool that can assist business companies, government agencies, and investors in predicting stock prices. The tool will leverage LSTM networks to analyze historical stock data, integrate relevant news sentiment, and generate predictions about future stock movements. This software will be particularly useful for stock market investors who need to make informed decisions about buying and selling stocks. By providing accurate and timely predictions, the tool can help investors navigate the volatile stock market with greater confidence and improve their chances of making profitable trades . To achieve this goal, the project will involve several key steps. First, a dataset of historical stock prices will be collected and preprocessed to ensure that it is suitable for use with machine learning algorithms. This data will include daily stock prices, trading volumes, and other relevant financial metrics, as well as news headlines and sentiment data. Next, the LSTM model will be trained on this data, allowing it to learn the relationships between past stock prices and future movements. The model will also incorporate sentiment analysis of news headlines to enhance its predictions, as market sentiment can significantly influence stock prices[4].

The training process will involve tuning the LSTM model's hyperparameters, such as the number of layers, the size of the hidden state, and the learning rate. The model will be evaluated using various performance metrics, such as mean absolute error (MAE) and root mean square error (RMSE), to assess its accuracy in predicting stock prices [5]. Once the model has been trained and validated, it will be integrated into a user-friendly software tool that provides real-time stock price predictions. The software will allow users to input the ticker symbols of stocks they are interested in, and it will generate predictions for the future price movements of those stocks. The success of this project will depend on the accuracy and reliability of the LSTM model in predicting stock prices[6]. While LSTM networks are powerful tools for time series prediction, stock prices are inherently unpredictable, and even the best models may not always provide accurate forecasts. However, by incorporating multiple data sources, including historical stock data and news sentiment, the model can provide more nuanced and informed predictions. Additionally, the software will be designed to allow users to customize their predictions based on their specific needs, such as selecting different time horizons or stock sectors[7].

The potential applications of this project are vast. In addition to helping individual investors make better decisions, the software could be used by financial institutions, hedge funds, and market analysts to improve their trading strategies. Government agencies and regulators could also use the tool to monitor market trends and detect potential risks or opportunities[8]. Furthermore, the integration of LSTM networks with sentiment analysis opens up new possibilities for predicting stock price movements based not only on historical data but also on real-time news and market sentiment.

Review of Literature

Stock price prediction has long been a challenging and dynamic field, requiring the application of various prediction methods. These methods can be broadly categorized into two types: statistical methods and artificial intelligence (AI) methods. Statistical methods include models such as logistic regression and the ARCH model, which are based on statistical assumptions and techniques to model stock price behavior [9]. On the other hand, AI methods leverage machine learning algorithms to analyze data patterns and make predictions. Among the many AI methods available, some of the most commonly used for stock price prediction include multi-layer perceptron, convolutional neural networks (CNN), naive Bayes networks, back propagation networks, support vector machines (SVM), and recurrent neural networks (RNN), with the Long Short-Term Memory (LSTM) network being particularly popular in recent years [10].

LSTM, a type of RNN, has gained prominence for stock price prediction due to its ability to capture long-term dependencies in time series data. Stock prices exhibit temporal patterns, and LSTM is well-suited to model these patterns, especially when the data has long-term dependencies, such as historical stock prices influencing future movements . LSTM's architecture allows it to remember important information over long periods, which is crucial for accurate stock price forecasting . This paper focuses on the application of LSTM for stock price prediction, comparing it to regression-based models, which also aim to predict continuous values based on certain input features .

In this proposed system, the use of LSTM is justified because of its capability to detect subtle changes in stock price behavior over time]. By integrating data such as the stock's open price, close price, high price, low price, and trading volume, LSTM is trained to identify patterns and make predictions about future stock movements. The dataset utilized for analysis was sourced from Yahoo Finance and contains approximately 900,000 records of historical stock data for a single company. The dataset includes daily stock prices along with other relevant features that are instrumental for stock price analysis .

The data was initially stored in CSV format, which was then processed using the Pandas library in Python to create a data frame. This allowed for easier manipulation and analysis of the data, enabling the application of machine learning techniques. Two architectures were considered for stock price prediction: the regression-based model and LSTM . The regression-based model is used to predict continuous values based on given autonomous variables, making it a simpler model compared to the LSTM. However, while regression-based models rely on linear assumptions and patterns, they often struggle to capture the complex and non-linear relationships present in stock price movements.

On the other hand, LSTM is particularly effective in recognizing complex, non-linear trends that often occur in stock markets. Stock prices do not always follow regular cycles, and their patterns are frequently influenced by various factors such as market sentiment, economic events, and sector-specific changes. LSTM, with its deep learning capabilities, can adapt to these irregular patterns and capture the nuances of the data more effectively than traditional regression models. The experimental results show that LSTM outperforms the regression-based model in terms of prediction accuracy, highlighting its ability to model complex, non-linear relationships in the stock market data [11].

This proposed system utilizes LSTM to analyze stock price trends and cycles, providing investors with valuable insights into potential future stock movements. Investors can benefit from this analysis as it helps to identify patterns and trends that may not be immediately obvious through traditional statistical methods. By incorporating current and historical information, the LSTM model can provide more accurate predictions, thus offering a potential advantage for investors looking to maximize their returns. The ability to detect trends and cycles in stock prices can help investors make informed decisions, improving their chances of generating profits in the volatile stock market.

Methodology

Stock market forecasting is a vast and intricate field, with numerous aspects available for investigation. One key element shared by all forecasting models is the evaluation of their accuracy, specifically how well they fit the given dataset and whether they can consistently provide accurate predictions [78]. Every model used for stock market prediction has certain common factors. First, they require a dataset that includes stock market information for various companies listed on any stock exchange. The primary objective of these models is to predict one of the three fundamental market actions: buy, hold, or sell. To achieve this, the historical stock market data for each company, identified by its ticker symbol, is stored in a machine, which helps reduce access time and facilitates quicker data retrieval. Subsequently, various data manipulations and preprocessing steps are carried out to prepare the dataset for further analysis using machine learning classifiers. These classifiers are the core components responsible for generating the predictions that will ultimately dictate whether a stock should be bought, sold, or held [12].

To assess the effectiveness of the forecasting model, the productivity of the model's predictions is compared to the actual performance of the stock for a given period. This allows for a visual comparison of predicted values against real-time stock price movements, enabling the identification of any patterns or trends. The ability to recognize these patterns is critical for evaluating the model's accuracy and making improvements as necessary. The model's performance can then be analyzed by visualizing its output against the actual stock price graph for the specified timeframe, identifying areas of success and those where the model may need further refinement .

In future iterations of this project, we aim to enhance our model by integrating advanced trading platforms such as Quantopian, which will allow us to experiment with emerging trading strategies. Quantopian offers an online platform designed for algorithmic trading, where users can develop, test, and backtest various trading strategies. By leveraging this platform, we will be able to refine our strategies further, testing them with historical data to evaluate their potential effectiveness in real-world market conditions[13]. This process of backtesting will help ensure that the strategies developed through machine learning and deep learning techniques, such as LSTM, are practical and capable of delivering solid performance.

Result and Discussion

The approach for sentiment analysis plays a significant role in our forecasting model. News headlines are known to heavily influence the market, and sentiments derived from these headlines can affect traders' decisions. Therefore, we classify the headlines into two categories: positive sentiment and negative sentiment [14]. This classification helps in understanding the general sentiment surrounding a particular stock, providing valuable input to the model. Once the sentiment of the headlines is identified, the headline dataset is combined with the preprocessed stock data from Yahoo Finance. The combination of both these datasets forms the final dataset, which is used for training and testing the model (Figure 1).

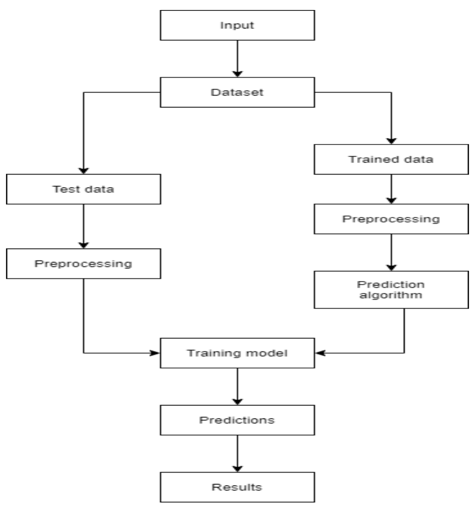

Figure 1: Data flow diagram

The dataset is then split into two parts: the training dataset and the test dataset. The training dataset is used to build the LSTM model, where the model learns from the historical stock data, including the sentiment of the headlines. The test dataset is used to evaluate the model's performance after it has been trained, allowing us to verify the accuracy of its predictions. In the final step of the project, we implement Explainable Artificial Intelligence (XAI) using the LIME (Local Interpretable Model-agnostic Explanations) tool. LIME helps us interpret the predictions made by the model, providing insights into how certain features or data points influence the model's decisions [100-106]. This is especially important for understanding any biases that may exist in the dataset, ensuring that the model is not unduly influenced by irrelevant or unimportant information. This transparency allows for a deeper understanding of the model's behavior and provides the opportunity to improve it based on the insights gained. By combining these advanced techniques, we aim to create a robust, reliable, and transparent stock market forecasting system (Figure 2).

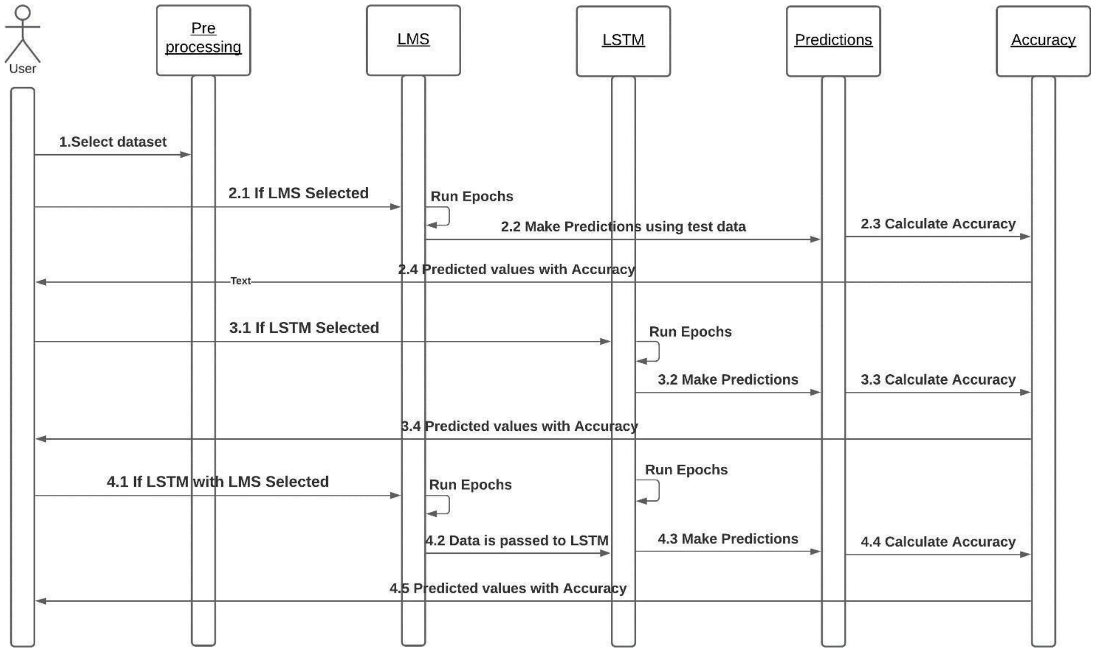

Figure 2: Sequence diagram

A sequence diagram is a type of interaction diagram because itdescribes how and in what order a group of objects works together. These diagrams are used by software developers and business professionals to understand requirements for a new system or to document an existing process. Sequence diagrams are sometimes known as event diagrams or event scenarios (Figure 3).

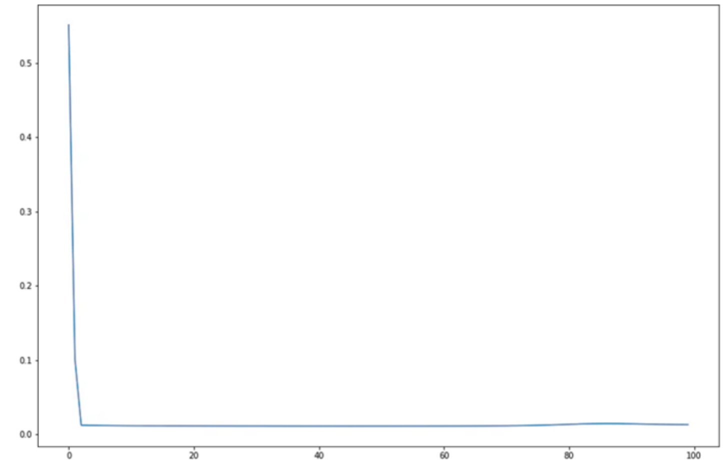

Figure 3: Representation of the Model

The development of stock price prediction models begins with the collection of data sets. The data sources include financial news from various platforms, which helps provide a less biased dataset. This dataset is then combined with a Yahoo Finance dataset. Given that the main focus is on predicting prices for the Indian stock market, the data is tailored specifically to that region. Combining these two datasets ensures a more comprehensive and diverse range of data, contributing to the effectiveness of the prediction model. Once the data is collected, the next step is processing it. During this stage, unnecessary columns and rows are dropped to ensure that only relevant data is kept. Tokenization follows, which increases the speed of computation and enhances the efficiency of the process. After tokenization, cleaning is required to remove words or elements that are unnecessary for evaluation, further refining the dataset. Normalizing the data is also an essential step. By scaling the values to fall within a common range, it becomes easier to compare different values and evaluate the model's performance more effectively. After preprocessing, the data is split into two batches: training data and testing data. The training data makes up seventy percent of the dataset, while the testing data comprises the remaining thirty percent. This division is crucial for training the model effectively while leaving a portion of the data for testing and validation (Figure 4).

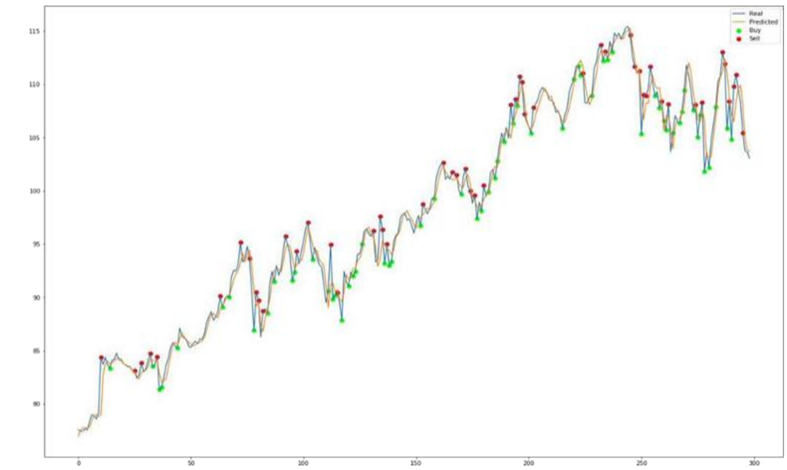

Figure 4: Original Graph

Next, we move on to the training and testing of the stock price prediction model. In time-series datasets, shuffling is not permitted because the order of the data is critical. For this reason, the model is trained with data from two previous steps to predict the current value. This method allows the model to observe patterns from the past two days to predict the closing price for the current day. The next step is building the model. The model is constructed using the Sequential and LSTM modules provided by TensorFlow Keras. This involves creating a simple, single-unit LSTM model designed to predict stock prices. The architecture leverages the ability of LSTM to capture temporal dependencies in the data, allowing it to predict stock prices based on historical trends. Once the model is built, it is implemented and trained using the prepared dataset. Given the simplicity of the model and the relatively small dataset, it becomes evident that the loss reduction stagnates after around 20 epochs. This stagnation can be observed by plotting the training loss against the number of epochs. After approximately 10-20 epochs, the LSTM model does not show significant improvements in learning. This behavior suggests that further tuning or model complexity might be required to achieve better results or improve the model's ability to generalize[15].

Conclusion

In this paper, we developed a web application for predicting the closing stock price of any given organization using LMS (Least Mean Squares) and LSTM (Long Short-Term Memory) algorithms. We utilized datasets from well-known companies like Google, Nifty50, TCS, Infosys, and Reliance to train our models, achieving an accuracy of over 95% for these datasets. The web application provides users with a platform to predict future stock prices based on historical data, helping investors make informed decisions. Looking forward, we aim to extend the application to predict cryptocurrency trading as well. Given the volatile and highly speculative nature of cryptocurrencies, integrating this feature would allow the model to adapt to different market conditions. Cryptocurrency trading relies heavily on different factors compared to traditional stock markets, and extending our prediction models to accommodate these nuances will provide users with a more comprehensive prediction tool. Furthermore, we plan to integrate sentiment analysis into the application for better analysis and predictions. Sentiment analysis of financial news and social media discussions can have a significant impact on market behavior. By considering public sentiment, we can enhance the prediction capabilities of our models, as news headlines and social sentiment often drive investor actions. Additionally, deep learning models could be developed to incorporate not just historical stock prices but also external factors such as financial news articles, traded volumes, profit and loss statements, and other financial parameters. By combining these elements with the LSTM models, we could potentially achieve even better results, providing users with a more accurate and holistic view of the market dynamics. This would allow for more informed decision-making and could lead to higher accuracy in predicting both stock and cryptocurrency prices.

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