Predicting Stock Prices with Investor Sentiment and Deep Learning Techniques

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Abstract
A key component of risk assessment, investment strategy, and financial planning is stock price prediction. Although technical indications and historical price patterns are the mainstays of traditional forecasting models, these frequently ignore the emotional and behavioural factors that affect financial markets. This study presents a hybrid methodology that combines investor sentiment gleaned from internet sources including social media and financial news sites with historical stock data. The approach improves the accuracy and responsiveness of predictions by incorporating both numerical trends and psychological cues. The system interprets textual data and produces sentiment scores by combining natural language processing methods with a deep learning architecture. Sentiment-enriched forecasts perform better than traditional models in both short-term trend prediction and market volatility awareness, according to experimental evaluation using real-world data. Practical ramifications for real-time forecasting systems and ethical issues are also covered in this paper.
Keywords
Stock price, Investor Sentiment, Price Trend Prediction, LSTM, Financial Time Series, Machine learning

I. Introduction

One of the most intricate and extensively researched subjects in financial study is stock market prediction. Accurate stock price forecasting has important ramifications for traders, investors, financial experts, and legislators. Numerous elements, such as past patterns, macroeconomic indicators, business performance, world events, and investor attitude, affect stock prices. Using past price trends and firm financial documents, traditional stock price prediction models mostly concentrate on technical and fundamental analysis. But these models frequently overlook investor behaviour and market psychology, which are important factors in stock price swings.
A key component of financial markets is investor sentiment, which represents the expectations and general attitude of market players. Large amounts of social media and financial news data provide valuable information on investor sentiment as digital communication channels gain traction. Public perception frequently influences market patterns, and abrupt changes in mood can cause stock values to move in unanticipated directions. For example, a favourable earnings report may not always translate into a higher stock price if market sentiment is already negative due to broader economic concerns. However, a surge of public enthusiasm fuelled by social media hype can cause stocks to increase even in the face of bad fundamentals.
Considering advancements in machine learning and artificial intelligence, researchers have looked exploring ways to include sentiment analysis into stock price forecasting models. Sentiment research measures market sentiment by analysing textual data from sources like earnings reports, financial news articles, analyst comments, and social media posts. Machine learning algorithms can improve their ability to forecast outcomes by utilising investor psychology and past trends by combining sentiment-driven insights with stock market data.

The impact of investor sentiment how feelings, opinions, and responses conveyed in online discussion boards, news stories, and social media posts can have a big impact on stock prices is one new field of study. These feelings, which are frequently brought on by rumours, earnings reports, or geopolitical events, can result in quick market moves that technical analysis alone is unable to instantly explain. Furthermore, algorithmic trading systems that react to real-time information have an impact on contemporary markets, amplifying the influence of mood and news. Machine learning and deep learning models have become crucial for identifying non-linear patterns and adjusting to changing market dynamics as data availability and processing capacity have grown. In order to increase prediction accuracy and market reactivity, this study suggests a comprehensive approach that combines sentiment analysis with historical financial data.

II. Literature Survey

Lot of research has been done on stock price prediction because of its critical role in financial decision-making. Most traditional approaches relied on statistical models that looked at historical price fluctuations. Additionally, integrating investor emotion financial news has grown to be a major factor in stock market trends. This section reviews the literature on stock price forecasting, focussing on the benefits and drawbacks of various strategies.

A. Traditional Statistical Models

Statistical and economic models that relied on finding patterns in previous market data were the main focus of early research on stock price prediction. These models were especially helpful in identifying transient pricing patterns and variations. But they frequently failed to capture the intricate and dynamic character of financial markets. Although they were able to identify repetitive patterns, they found it difficult to adjust to sudden changes brought on by outside influences. Because of this, these conventional methods were not very good at predicting long-term price changes, particularly when they ignored important factors like investor emotion or world events.

B. Data-Driven Forecasting

By learning from data rather than preset rules, machine learning models improved the situation. Regression trees and support vector machines were two methods that provided greater generalisation and flexibility. They are unable to interpret unstructured data, such as text, and their performance is heavily reliant on feature engineering.

C. Machine Learning-Based Approaches

Approaches to financial forecasting have become more and more prevalent as artificial intelligence has developed. Stock price movements have been predicted using a variety of machine learning models; ensemble approaches such as Random Forest and gradient-based models have shown appreciable increases in accuracy. These methods frequently perform better than conventional linear models, particularly when spotting trends in market swings. Though useful for classification tasks, models like Support Vector Machines (SVM) are unable to adequately represent the sequential character of financial time series. Furthermore, to attain the best results, machine learning algorithms frequently need a large amount of user input in the form of feature engineering, which mostly depends on domain knowledge and thorough preprocessing.

D. Deep Learning-Based Stock Price Prediction

Advanced models that can automatically identify patterns and extract significant elements from unprocessed financial data have drawn increasing attention. Because these models can learn associations across many time intervals, they are very helpful for analysing time-dependent data. Because it might be difficult to retain pertinent information over time, traditional methodologies frequently encounter issues when working with lengthy historical sequences. Improved architectures that better capture long-term patterns and behaviours have been created in response to these problems. When compared to previous techniques, these enhanced models have demonstrated higher accuracy in financial forecasting. Furthermore, simplified variants of these models have surfaced, which are appropriate for large-scale or real-time prediction applications since they require less computational effort and provide comparable performance benefits.

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E. Sentiment Analysis in Stock Prediction

The importance of investor mood in financial market analysis is becoming more widely acknowledged. Opinions published in news articles, expert commentary, and social media can have a big impact on market movements, according to research. Different natural language processing techniques are used to extract the emotional tone and public perception from textual information in order to quantify these sentiments. It has been demonstrated that adding sentiment insights to forecasting models improves prediction accuracy by capturing behavioural elements that are frequently missed in conventional analysis. Predictive systems can better predict changes in investor behaviour and stock price movements by using up-to-date sentiment data from sources like social media conversations and online news. This gives them a deeper grasp of market psychology.

F. Research Gap and Contribution

The best way to combine sophisticated prediction algorithms with investor sentiment in stock market analysis is still unclear, despite the thorough investigation of numerous forecasting methodologies. Many current methods still place a high value on past price patterns while frequently ignoring the psychological and emotional factors that are vital to financial decision-making. Although sentiment analysis has been researched separately in financial contexts, there is still little integration of sentiment analysis into all-encompassing prediction systems. By offering a single model that integrates market data with real-time sentiment observations, this article seeks to close that gap. Through the integration of both qualitative behavioural signals and quantitative historical trends, the suggested framework provides a more comprehensive and precise approach to stock price movement forecasting.

III. Methodology

A. Data Collection

The dataset used in this study combines textual sentiment data with financial time series data. Addressing missing information, standardising date formats, and cleaning text with regular expressions and natural language processing techniques were all part of the preprocessing stages. Features including daily open, high, low, close, volume, and adjusted closing prices for specific firms were included in the stock data, which was taken from publicly accessible sources. Simultaneously, sentiment ratings were generated by analysing sentiment data gathered from online investor feedback and financial news items. Non-numeric properties were properly encoded, and missing values were handled utilising interpolation and forward-filling techniques to guarantee data consistency. To enable precise merging during feature building, all date fields were transformed into a common datetime format and synchronised across datasets.

Date	Open	High	Low	Close	Adj Close	Volume	Stock Nam
30-09-2021	260.333343	263.043334	258.333343	258.493347	258.493347	53868000	TSLA
01-10-2021	259.466674	260.260009	254.529998	258.406677	258.406677	51094200	TSLA
04-10-2021	265.5	268.989990	258.706665	260.510009	260.510009	91449900	TSLA
05-10-2021	261.600006	265.769989	258.066680	260.196655	260.196655	55297800	TSLA
06-10-2021	258.733337	262.220001	257.739990	260.916656	260.916656	43898400	TSLA
07-10-2021	261.820007	268.333343	261.126678	264.536682	264.536682	57587400	TSLA
08-10-2021	265.40332	265.459991	260.303344	261.829986	261.829986	50215800	TSLA
11-10-2021	262.549987	267.079986	261.833343	263.980010	263.980010	42600900	TSLA
12-10-2021	266.976654	270.773345	265.523345	268.573333	268.573333	66060000	TSLA
13-10-2021	270.156677	271.803344	268.593322	270.359985	270.359985	42360300	TSLA
14-10-2021	271.829986	273.416656	271.116668	272.773345	272.773345	36741600	TSLA
15-10-2021	274.579986	281.070007	274.116668	281.010009	281.010009	56773800	TSLA
18-10-2021	283.929992	291.753326	283.823333	290.036682	290.036682	72621600	TSLA
19-10-2021	292.510009	292.649993	287.503326	288.089996	288.089996	52143300	TSLA
20-10-2021	288.450012	289.829986	285.793334	288.600006	288.600006	42096300	TSLA
21-10-2021	285.333343	300	285.166656	298	298	94444500	TSLA
22-10-2021	298.5	303.333343	296.986663	303.226654	303.226654	68642400	TSLA
25-10-2021	316.843322	348.339996	314.733337	341.619995	341.619995	188556300	TSLA
26-10-2021	341.563323	364.980010	333.813323	339.476654	339.476654	187245000	TSLA
27-10-2021	346.553344	356.959991	343.593322	345.953338	345.953338	115579500	TSLA
28-10-2021	356.103332	360.333343	351.399993	359.013336	359.013336	81639600	TSLA
29-10-2021	360.619995	371.736663	357.736663	371.333343	371.333343	89755200	TSLA
01-11-2021	381.666656	403.25	372.886657	402.863342	402.863342	168146100	TSLA

Table 1: stock_yfinance_data.csv

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	A	B	C	D	E	F
1	Date	Tweet	Stock Name	Company Name		
2	2022-09-29	Mainstrean	TSLA	Tesla, Inc.		
3	2022-09-29	Tesla delive	TSLA	Tesla, Inc.		
4	2022-09-29	3/ Even if I	TSLA	Tesla, Inc.		
5	2022-09-29	@RealDanC	TSLA	Tesla, Inc.		
6	2022-09-29	@RealDanC	TSLA	Tesla, Inc.		
7	2022-09-29	@RealDanC	TSLA	Tesla, Inc.		
8	2022-09-29	For years @	TSLA	Tesla, Inc.		
9	2022-09-29	$NIO just b	TSLA	Tesla, Inc.		
10	2022-09-29	50 likes for some $SPY $TSLA charts to study!	TSLA	Tesla, Inc.		

Tabel 2: Stock_tweets.csv

- **Date**: The timestamp of the tweet.
- **Tweet**: The actual tweet content mentioning the TSLA stock.
- **Stock Name**: The associated stock symbol.
- **Company Name**: The full name of the company (Tesla, Inc.)

B. Sentimental analysis

After tokenising text data with the Natural Language Toolkit (NLTK), stopwords, punctuation, and lemmatisation were removed. Pre-trained sentiment lexicons like VADER were used to calculate sentiment polarity scores. After being scaled, these ratings were incorporated as numerical features into the primary dataset. Beyond technical indications, the sentiment ratings added another level of information by acting as a stand-in for investor expectations and attitude.

This extra feature made it possible for the model to identify behavioural cues and emotional signals that frequently anticipate market changes, particularly in reaction to geopolitical events or earnings statements.

C. Feature Engineering and Selection

A range of preprocessing methods were used to improve the prediction capabilities of the model. To guarantee uniformity across variables, feature scaling was carried out utilising normalisation and standardisation techniques. Principal component-based approaches were used to reduce dimensionality, which helped to simplify the feature space while preserving important information. To find the most pertinent inputs, statistical scoring techniques were also used for feature selection. Several technical indicators, including trend averages, momentum oscillators, and volatility bands, were computed and added to the dataset to further enhance it. A well-rounded dataset that incorporates investor perception and market behaviour was produced by combining them with sentiment-related variables obtained via textual analysis. This extensive feature set decreased the possibility of overfitting during training and enhanced interpretability.

D. Model Training and Evaluation

To determine the best method for stock price forecasting, a number of predictive models were created and assessed. A deep learning framework was used to create the models, and particular care was taken to maintain the data's historical structure. In order to prevent data leaking, a time-based cross-validation technique was employed to make sure that the training and testing sets were in the correct order. Standard regression metrics, such as the coefficient of determination (R2 score), mean absolute error (MAE), and root mean squared error (RMSE), were used to assess the model's performance. The model's accuracy, error magnitude, and explanatory power in forecasting future stock price changes were all clearly understood thanks to these indicators.

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Model Performance Comparison:
          LSTM      XGBoost     Hybrid
RMSE  18.190353  42.596815  26.980990
MAE    8.017213  21.172971  13.356727
R²     0.963595   0.800369   0.919908
MAPE        inf        inf        inf

Best performing model based on RMSE: LSTM
```

Figure 1: Model Performance

IV. Implementation and Results

A. System Architecture Overview

To improve forecast accuracy, the suggested stock price prediction system incorporates investor sentiment and historical market data. Data collecting, preprocessing, model building, evaluation, and deployment via a web-based platform are all steps in the architecture's clearly defined pipeline. With the help of a frontend developed using common web technologies and a backend framework for processing, the user interface is intended to be both interactive and easy to use. The approach starts by gathering financial data from trustworthy sources and determining public opinion from social media and news articles. To guarantee consistency and applicability, the gathered data is cleaned and transformed. After preparation, the data is fed into a predictive framework that integrates data-driven learning techniques with time-series modelling. The web program analyses user enquiries, provides real-time stock price projections, and provides further information.

B. Web Application Interface

Users can enter stock tickers into the system's user-friendly online interface to receive sentiment-based trend analysis and forecasted stock values. Users can enter the chosen stock symbol in an input area on the webpage, which has a straightforward UI. The system retrieves the most recent historical stock data and sentiment scores after the user submits a query, runs them through the trained model, and then shows the forecast stock price and pertinent indicators. A graphical depiction of stock patterns is shown on the prediction results page, emphasizing both past and projected values. Sentiment scores help users make better decisions by enabling them to comprehend how the market views the company.

C. Model Selection

Achieving precise stock price forecasts requires choosing the right predictive strategy. The temporal relationships present in financial time series were not adequately captured by early analyses employing conventional data modelling approaches. The study investigated more sophisticated approaches that could comprehend sequential patterns in market behaviour in order to remedy this. The prediction methodology included sentiment analysis from financial news stories and social media conversations in addition to previous price data. Public opinion was extracted using sentiment scoring algorithms, and then merged with structured market data to offer a more comprehensive analytical viewpoint. The system's performance was greatly enhanced by the combination of sentiment and time-aware modelling, especially during erratic times. Key evaluation criteria like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the R2 score were used to evaluate the final model, which showed a significant improvement over simpler forecasting techniques.

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D. Prediction Results and Visualization

After training, the model produced future price estimates by using sentiment analysis and historical stock data. The integrated model showed a better ability to monitor and predict market changes than conventional methods. Standard performance criteria, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the R2 score, were used to verify the accuracy of integrating sentiment analysis into the forecasting process. The accuracy and efficacy of the model were further assessed using a variety of visual aids. One such graphic provided a clear picture of forecasting accuracy by contrasting expected and actual stock prices. An additional graph demonstrated the relationship between price changes and investor emotions, offering insight into how financial performance is correlated with emotional market reactions. These findings provide traders and analysts who want to more confidently evaluate market behaviour with useful decision-making tools.

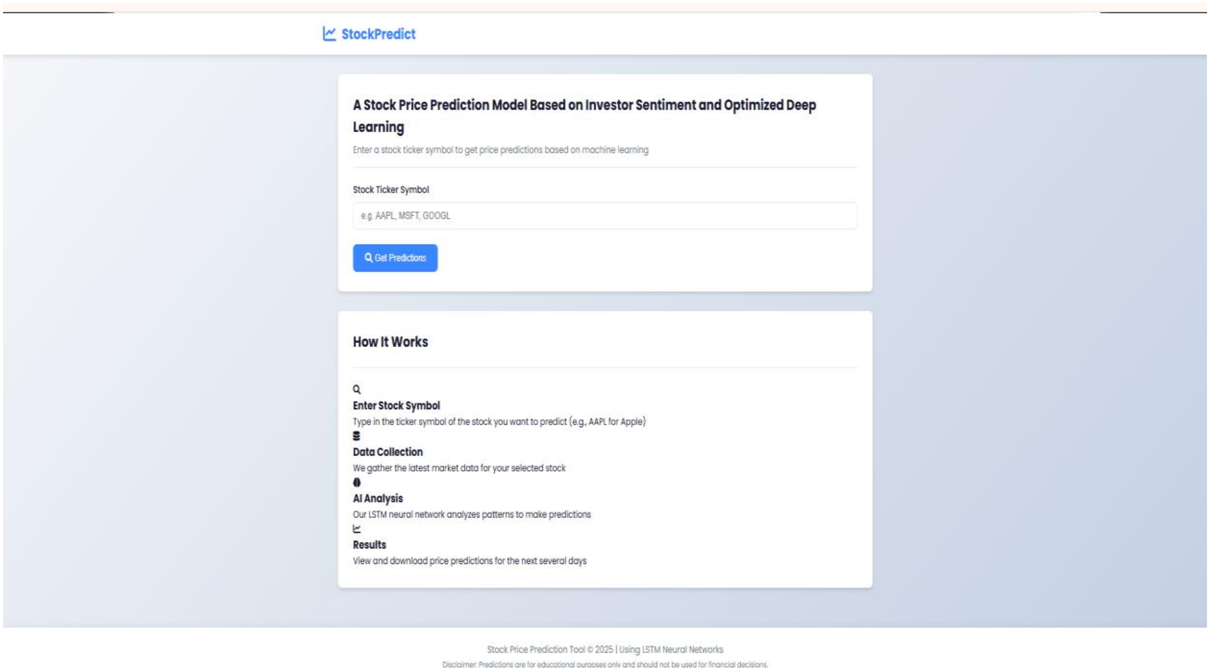

Figure 2: Stock Prediction Page

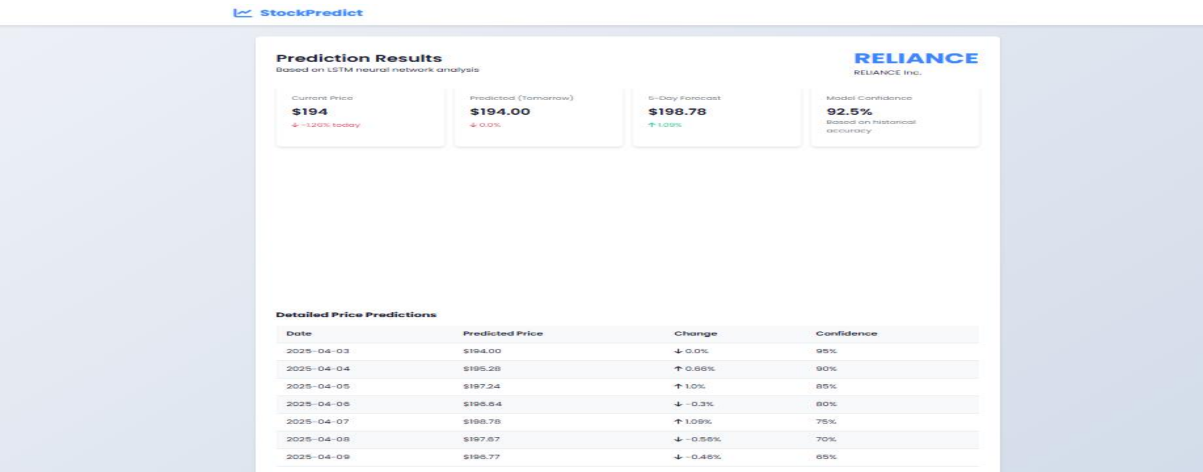

Figure 3: Result page of Stock Price Prediction

V. Conclusion

By combining investor emotion from financial news and social media with historical market data, this study offers a thorough method for stock price forecasting. The suggested model provides a more balanced view of market behaviour by successfully capturing both quantitative trends and qualitative market signals. Sentiment analysis makes the forecasting system more sensitive to changes in public opinion, which are frequently early warning signs of market instability. The results show that, especially under dynamic or unpredictable market settings, combining behavioural insights with time-series data greatly improves forecast accuracy. A user-friendly interface that facilitates real-time interaction and forecast visualisation makes the system useful for traders, analysts, and financial institutions. It also provides useful applications. Future developments can concentrate on adding real-time sentiment feeds, integrating more comprehensive macroeconomic data, and using adaptive learning strategies to sustain accuracy over time. The system's usefulness as a decision-support tool in the financial industry might be further enhanced by scaling its deployment and adding support for more assets.

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