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E-Mail :
editor.ijasem@gmail.com
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Stock Sense AI: Real-Time Market Trend Prediction Using Python and Power BI

[1]Kotte Shivani, [2]Sujatha G,

[1]M.Tech Scholar,Dept. of CSE , Malla Reddy Technical Campus,Malla Reddy Vishwavidyapeeth, Maisammaguda,Hyderabad, Telangana 500100, India, shivani.kotte481@gmail.com

[2]Assistant Professor, Dept. of CSE, Malla Reddy Technical Campus, Malla Reddy Vishwavidyapeeth, Maisammaguda, Hyderabad, Telangana 500100, India, sujatha.godavarthi@mrvv.edu.in

Abstract:

Using sentiment analysis from social media and data processing, this article aims to examine several methods for predicting stock value change. To keep up with the ever-changing financial markets and make smart investing selections, real-time stock market trend analysis is a must. The purpose of this research is to examine how several machine learning algorithms, such as XGBoost, ADABOOST, Decision Trees (DT), and K-Nearest Neighbors (KNN), may be used to forecast stock market movements using both past data and current market signals. Our goal in using these machine learning models is to forecast stock price changes, spot patterns, and spot irregularities that may signal changes in the market. Integrating these algorithms with Power BI enables real-time analysis and dynamic dashboard reporting; Power BI is a powerful tool for data visualization and business analytics. Investors are able to make data-driven choices with the help of this technology, which analyzes massive information from many market sources and delivers practical insights via interactive Power BI dashboards. Precision, accuracy, and recall are some of the performance indicators used to assess the efficacy of the suggested method. Machine learning has the ability to revolutionize financial forecasts, enhancing decision-making and providing a strategic advantage in the stock market.

Keywords: Real-time, Stock Market, Machine Learning (ML)

Introduction

Predicting the future value of a stock using information found on social media platforms is called stock market prediction. On social media, people have a huge audience for their opinions. Social media analysis and sentiment analysis are closely related. This makes it easier to extract content based on opinions and emotions. In order to improve the overall accuracy of social network analysis, data mining techniques including neural networks, random forests, and natural language processing are used. Unrelated social media users do in fact exhibit striking patterns of discourse, according to recent studies. These tendencies could help in forecasting product sales and inventory costs. Business networks only connect workers of major corporations, as opposed to social networks that connect members of the public at large. In a business communication network, members are expected to mostly talk about things related to the firm, as opposed to social networks where people may talk about whatever interests them. Although patterns in human communication within social networks have been shown to forecast product sales or stock performance, the existence of patterns in corporate communication networks that enable continual execution may come as a surprise to some. In contrast to internal social networks inside a single company, email has long been the de facto standard for conveyance of information between and within organizations. A same logic applies to social media sites, which may log users' reactions to various events and topics. So, we argue that a corporate communication network, like an email system, also contains useful information, such structural stability and hardiness, two of the company's innovations. The explanation behind this aligns with what is said in corporate

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communications: that "employee communications will mean the success or failure of any major amendment program" after a management challenge, merger, acquisition, new venture, or new method improvement strategy. Paraphrased: "business operate that drives performance and contributes to a company's financial success" is the key that opens the door to efficient employee communication. Our assumption is that, grounded on these broad principles of corporate communication, each company has its own distinct protocol for internal communications. We maintain that the way a firm communicates with its stakeholders impacts its ability to weather major business storms like acquisitions, mergers, new ventures, technique improvement initiatives, going worries, and bankruptcy.

Literature Survey

Mining social media for sentiment research has been a current focus. Public sentiment as expressed by the speaker unit may have a correlation with the DJIA, according to research. Will, however, public opinion be used in order to foretell how a particular company's stock price will change? It follows the question of whether one company's stock value can be more reliably predicted than another's. Is there a specific company whose stock price has historically been quite sensitive to public opinion as shown in Twitter data? In this post, we will provide a method to get the answers to those questions by mining Twitter data. More specifically, we want to use an algorithmic program for information mining to the problem of predicting the prices of 30 companies listed in a data system and, by extension, the New York stocks market using a dataset consisting of fifteen million twitter records. We do this by first using information mining methods to glean patterns between public sentiment and actual stock value movements, and then by extracting knowledge about confusing matters from tweets using IP approaches to outline public mood. The projected method allows us to arrive at the conclusion that it is possible to predict the stock value of certain companies with a median accuracy of up to 76%.1 in 12. The info mining algorithmic software that we used is described in this article, and the main conclusions are discussed in respect to the shown questions.

The idea that email functions as a social network has received a lot of attention. Email networks have characteristics with more traditional types of social networks, such as those involving friendly relationships or intellectual cooperation. The characteristics of email networks, like those of other social networks, are determined by trends in human social behavior rather than the underlying technology.Therefore, the social context contributes to the characteristics of email social networks. Stability and robustness of structure are also factors in the general social behavior seen in a firm. Since the social network features of the network generated by the e-mail contact of its workers undoubtedly reflect changes in structure mood, they can also be used to detect the health and strength of the structure. The email activity of individuals inside the business reflects their anxieties, worries, gossips, and both good and bad things that happen. The issue, however, is to get this data from the network. This paper provides a first step toward proving that email social network analysis can tell us more about the company than we could ever imagine. By looking at the Enron corporation as a case study, we can see that the company's problems stemmed from the early stages of its email social network.The majority of India's farmers rely on harvesting crops throughout the autumn. Predicting when it will rain is so crucial for agricultural nations like those in Asia. The paper's focus is on comparing many neural network topologies, with a particular emphasis on BPNN, GR, and

Predicting collapse in the Thanjavur district of the southern Indian province of Madras using a Neural Network (GRNN) and a Radial Basis Neural Network (RBNN). The different models are trained using the training data set and then evaluated using publicly available test data to determine their correctness. The construction of models has made use of MATLAB. When evaluating and instructing all networks When it comes to making predictions, we discovered that RBNN works the best.

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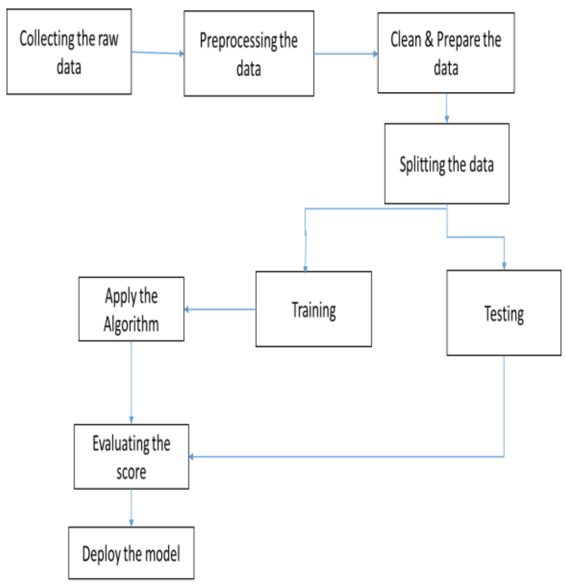
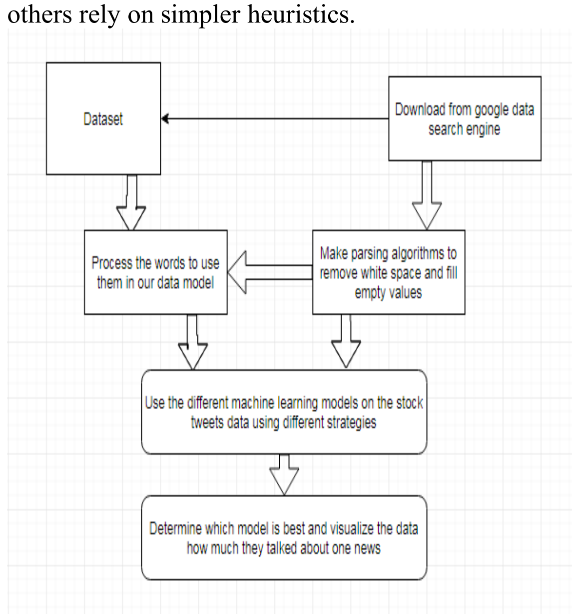
Methodology



Block diagram

This suggested system incorporates about every online platform you can think of these days, including blogs, social media sites like Facebook and email, news portals, e-commerce sites, and more. The goal of these opinions is to provide readers helpful information, yet there are so many that it may be overwhelming. Opinion summarization is a novel topic that has recently generated a lot of interest in the and Random Forest groups. Although "opinions" often denote biased written data like review articles or blog posts, they may also include numerical data like aspect ratings. Opinion summation includes any study that attempts to reduce a large number of opinions to a small, readily digestible text, regardless of whether different groups have different standards for what constitutes an opinion summary. Applying sentiment prediction to review data is one approach to approximate estimation of consumer sentiment. If the consumer is looking for more detailed information, they could be better off with topical or textual summaries. Opinion summarizing, in whatever form it takes, serves the same goal: to help customers make sense of the vast array of perspectives. To address this problem of summarization, a wide range of algorithms are used, such as sentiment prediction, text clustering, Random Forest, support vector machines, decision trees, logistic regression, and so on. Some of these techniques rely on robust statistical models, while others rely on simpler heuristics.



Proposed system

Data Collection

Daily stock market-related emails make up the bulk of our data. After we get the hang of analyzing the NYSE, we'll apply our model to data from Bangladesh with the utmost precision and launch a solution to aid Bangladeshi investors. Our first step was to locate labeled data, but we couldn't discover any free resources to do so. In order to extract conversation data from the email API, we developed our own web script. Every day, for eight hours, we capture a massive quantity of communication with this software. After that, we parse it and save it to our file storage using JavaScript Object Notation (JSON).

Pre-Processing

We cannot train our system to ignore these distracting words. The inclusion of these terms also tends to heighten the prejudice. When we include these terms, our learning system seems to search for quantifiers such as "a", "an", "this" and so on. We also don't appear to care about auxiliary verbs. Therefore, only terms connoting "good," "bad," or "neutrality" will do. Here is a rundown of all the steps we had to do to prepare the data for analysis: Remove any links from the tweet data that are hypertext. To illustrate, the "http://" or

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Vol 20, Issuse.2 April 2026

"https://t.co/3k7Bai5crQ" prefix is eliminated from the stream of tweets. Two, lowercase every word block in the email corpus. If there are any repeats, this helps us eliminate them and makes the text more consistent. Cleaning up the data from tweets by removing spaces. Because they provide context to the tweet, we decide to retain the emoticons. Fourth, we eliminate spaces and punctuation symbols such as periods and commas. Remove any tagging from the email records. Empty tags are eliminated. Hashtags like "#Stock #Crash" help us grasp the sentiment, therefore we maintain them. In our data email, please do take the corpus conversation. 6. Therefore, sort the tweets by "RT" and delete them.

Data Scoring

We came up with a straightforward and efficient method for tweet scoring. The first issue with the CSV files containing tweets is the abundance of irrelevant and sometimes loud words. In order for us to get relevant words, we need to get rid of them. We started by compiling a list of positive, negative, and neutral terms from the dictionary, keeping this purpose in mind. Then, our work was evaluated by counting how many times our list of terms appeared in tweets, along with how many times they appeared in negative or neutral sentiments. Assume that there are n words in the tweet. The following scoring formula is derived from the following considerations: the positive, negative, and neutral scores are Scorepos, Scoreneg, and Scoreneu, respectively; the list of all positive, negative, and neutral words is listneu; and the frequency of positive, negative, and neutral words is frequencypos, frequencies, and frequencyneu, respectively.

DATA GATHERING

A number of entries make up the data set used in this article. At this point, you should have settled on a subset of the publicly available data that you want to use for your project. It is good to begin ML problems with a large amount of data (perceptions or models) for which you know the optimal arrangement. Data for which you already know the desired outcome will be marked.

PRE-PROCESSING OF DATA

Sort the data you've selected by formatting, cleaning, and sampling. Third, keep an eye on the design process: the data you've selected could not be in a usable format. You may choose a social data set or text document format for the data, or you may prefer an exclusive record configuration for the data, or you may prefer a level document format for the data. The most typical method for removing or replacing missing data is data cleansing. Inadequate instances of information could leave you without the facts you need to fix the problem. We should do away with these occurrences.In addition, certain qualities may include sensitive information, thus it may be necessary to antonymize or remove these attributes from the data. Analyzing: You may encounter much more meticulously selected data than you want. When dealing with larger datasets, calculations may need more time to complete and more computing power and memory to store the results. If you want to investigate and generate ideas more quickly on a smaller subset of the datasets before diving into the full thing, you may do a delegate test.

FEATURE EXTRACTION

Extracting is the next step in a process that gradually lowers quality. The continuing attributions are positioned according to their predictive pertinence since highlight extraction really alters the features rather than element choice. The altered characteristics or components are formed by directly joining the initial ascribes. Lastly, our models are prepared by using the Classifier computation. We make use of the categorize module from the Python Normal Language Tool stash. The acquired marked dataset is put to use by us. With the extra marked data at our disposal, we will survey the models. Using a handful of AI methods, pre-handled data was organized. Forest classifiers that are not regular were selected. Positions such as text grouping often make use of these computations.

ASSESSMENT MODEL

One strategy that incorporates assessment is the promotion of a model. The best model to use is the one that both fits our data well and gives us good predictions about how the model will act in the future. In the field of information science, assessing model performance only based on preparation data is inadequate as it rapidly results in overfitted and overly optimistic models. The two main tools at the disposal of information scientists for assessing models are cross-approval and waiting. A hidden test set is used by both methods to keep an eye on the model's performance and prevent overfitting. We compare the output of each classification model to its

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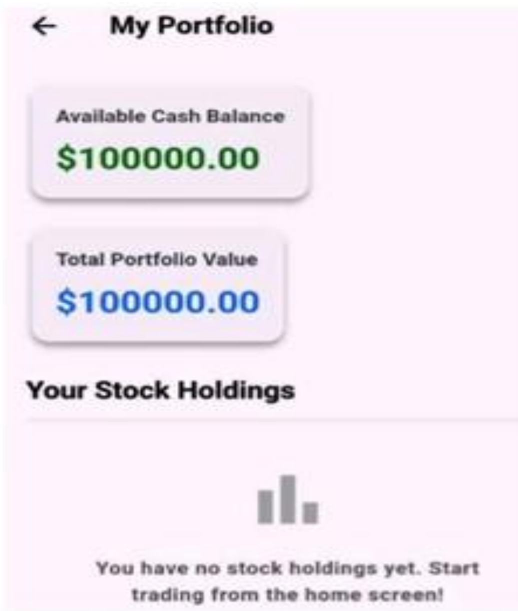
normal. In the end, the required shape will be achieved. visual depiction of the structured data. If you want your test results to be as accurate as possible, you need to aim for precision. Even after dividing the total number of forecasts by the number of accurate predictions, the outcome may remain uncertain.

Results



Trading interface with quantity selection and price chart

Portfolio dashboard showing initial cash balance and empty holdings

Conclusion

There are two perspectives on the theoretical implications and outcomes of this work. We started by listening in on Enron employees' chats on the main network to get a feel for their communication style. According to this research, a company's internal email system contains information on employees' communication patterns. While we mostly look at how often things are discussed, it's interesting to see that certain companies, like Enron, have noticeable trends when it comes to email correspondence. You may learn a lot about the company's core competencies and stability by observing these trends in the securities market performance of the targeted corporation. Accordingly, the patterns of interaction between the combined forces will be an accurate predictor of the performance of a stock. Here we detail the contributions of the planned algorithmic program, with the results of our experiments lending credence to the idea that the e-mail communication network is dependent on the value of Enron stock. Using the "adjusted residual" technique, we first search for a relationship between the amount of time spent communicating via email and the value of the company's shares. The "adjusted residual" live will

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Vol 20, Issuse.2 April 2026

keep working properly even if the stock knowledge covered periods are unequal and include missing or wrong data since it is a probabilistic live. Second, connecting the communication network to the financial market might be possible with the help of some basic applied mathematics. We demonstrated in our study that correlation analyses did not find any association between communication frequency and stock price fluctuations. On the other hand, our prediction approach may provide not only the condition half but also the conclusion half, together with the weighted half for the principles.

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