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Research Article

Supervised Learning Approaches for Sentiment Analysis in Stock Market Predictions

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ARTICLE INFO	ABSTRACT

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Introduction: The exponential development of loads for business organizations and governments, compel scholars to accomplish their exploration in sentiment analysis. One of the most widely used social networking sites is Twitter, where users freely express their thoughts, opinions, and feelings. These tweets are recorded and examined in order to extract people's feelings on an extremist incident.

Objectives: The goal of this work is to use Machine Learning (ML) algorithms to create a classifier that can predict the polarity of a comment. Data mining, processing, and modelling are the three main responsibilities that comprise our work.

Methods: The NLTK dataset is used to build our model, and text mining procedures are used to generate and process the variables. Since our model is based on a supervised probabilistic machine learning algorithm (SPMLA), In order to categorize our tweets into good and negative attitudes, we tended to develop a classifier. In order to evaluate the model's performance, we then decide to do two trials, and we outperform earlier published research in terms of meticulousness. A part from above work we did comprehensive review examining the advancements in AI techniques for stock market forecasting This comprehensive review highlights the growing importance of artificial intelligence (AI) in financial markets while examining the advancements in AI techniques for stock market forecasting.

Results: Technical analysis and time series analysis are two examples of traditional forecasting techniques that frequently struggle to keep up with the intricacy and volatility of inventory markets. Promising solutions are offered by AI approaches such as deep learning models, reinforcement learning for trading strategies, natural language processing for sentiment analysis, and device learning algorithms.

Conclusions: The summary emphasizes the advantages and disadvantages of certain AI methods while highlighting how well they may replace conventional tactics. The vital role of statistics, going over various information sources, and preprocessing techniques that are essential for the correctness of AI models are explored. Evaluation metrics and benchmarks are provided to gauge the model's overall performance and provide information about the effectiveness of different AI techniques. Applications in the real world and case studies illustrate the reasonable advantages and challenging circumstances of AI in stock market forecasting. The evaluation closes by addressing present boundaries, such as the interpretability of records and models, and by investigating future trends and opportunities for innovation and multidisciplinary collaboration. AI methods could greatly enhance inventory marketplace forecasts, providing investors with new resources and altering market dynamics.

Keywords: Trading strategies, Stock market forecasting, Twitter, Text mining, Sentiment Analysis, Polarity, Machine Learning (ML), NLTK.

INTRODUCTION

The character of social networking sites like Twitter is enhanced by an increase in social knowledge. Anyone can post a tweet about any situation on Twitter, which is one of the most important and well-liked social media platforms.

Individuals can freely express their thoughts and feelings on this open platform. People have Twitter accounts as a result of reduced internet costs, less valuable transportable bias, and increased social significance. The majority of them tweet about various occurrences. In the era of social networking, people use Twitter to share their editorials and hobbies. Thus, Twitter has a vast amount of data. People can compose tweets with the appropriate mood or thoughts for each word because we know that tweets are no longer than 140 characters. Simply analysing thoughts or emotions from textbook material is known as sentiment analysis or opinion mining. Sentiment analysis determines each person's sentiment or opinion regarding a particular occurrence. A document or textbook that can be analysed and provide a system or model that represents a condensed form of the document's opinions is required for sentiment analysis. Sentiment analysis on Twitter is a very new and difficult study topic. It is helpful to determine people's sentiments or opinions regarding a certain event because social media platforms like Twitter provide a vast volume of text sentiment data in the form of tweets. Opinion mining, also known as sentiment analysis, is helpful for reviews of films, goods, customer support, and events, among other things. This helps us to decide whether specific item or service is good/bad or preferred or not preferred. It is also useful to identify opinions of people about any event or persons and also finds polarity of text whether positive, negative or neutral. Sentiment analysis is a type of text classification which can classify text into different sentiments.

The endeavour to forecast a company's share price or the value of any other financial instrument traded on an exchange is known as stock market prediction. A substantial profit could be made if a stock's future price is accurately predicted (Nefaie and Aldhvani, 2022). The efficient market theory states that since stock prices fairly represent all available information, price changes that are not caused by recently revealed information are by definition unpredictable. On the other hand, some people do not agree with this. Those who disagree claim they have multiple methods and resources to determine future costs. These professionals can project inventory costs using technical evaluation, basic evaluation, or even artificial intelligence algorithms (Preil and Krapp, 2022). Technical analysis involves analysing market data, such as quantity and rate, to establish repeating trends that may indicate future price movements. In contrast, fundamental analysis typically involves comparing an employer's financial records to economic indicators and industry trends to uncover the company's underlying value and development potential. Many investors still use these methods to choose which ventures to fund, notwithstanding the controversies surrounding stock market prediction. While some contend that chance alone is all that is necessary for an accurate inventory market forecast, others acknowledge that having the right tools and information can provide an advantage over rivals. It takes an in-depth understanding of financial markets and an acceptance of the erratic and turbulent nature of the inventory market to make reliable predictions regarding the stock market. It could end up being a very risky and difficult situation. Recall that there is no ideal approach and that trading always carries some risk, even though some people may be skilled at predicting stock prices (Edwards et al., 2018).

The stock exchange can be advantageous to investors in several ways, including capital formation, investment opportunities, risk management, corporate governance, employment prospects, and economic indicators. It gives businesses a means of raising money for growth and development and gives shareholders a framework for holding businesses accountable. By investing in enterprises or businesses with promising futures, the markets are able to allocate resources efficiently, and many publicly traded corporations frequently create jobs in return. With the abundance of investment options that stocks provide, investors can diversify their portfolios and increase their chances of achieving profitable returns (Rahmani et al., 2023). It serves as an economic indicator, providing investors and decision-makers with crucial information. Since listed firms are required by law to disclose financial information, the market also plays a role in corporate governance by enforcing responsibility and openness. By spreading investments over a variety of sectors and asset classes to offset market volatility, a portfolio can lower potential risk.

In fact, stock markets serve a wide range of purposes in boosting global economic growth, including facilitating capital formation, offering investment opportunities, generating employment, and fostering sound corporate governance, risk management, and efficient markets in other words, they are tools for accumulating wealth and fostering better economic advancement (Sonkavde et al., 2023) Artificial intelligence (AI) in finance refers to the application of technology, such as machine learning (ML), to mimic human intellect and decision-making in financial firms' investment analysis, management, and money-protection processes. Artificial intelligence completely changed the banking sector because it allows for real-time data assessment, trends detection, and respectfully provides well-

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informed decisions. It enhanced operations, decreased costs, and increased customer happiness. Financial institutions can reduce losses and preserve their assets by utilizing AI algorithms that can anticipate risks and spot fraudulent activity. It might automate trading strategies, optimize investment portfolios, and offer personalized financial advice. These virtual assistants would aid with financial planning, give account holders access to all information, and respond to customer inquiries. AI has a great deal of promise for usage in the banking sector, and even more cutting-edge applications are anticipated soon (Harish et al., 2022). [Harish et al., 2022] shortly, one of the primary benefits of AI for stock market forecasting is its capacity to swiftly and effectively extract vast amounts of data. More accurate movement estimations will be created as a result of artificial intelligence systems' ability to spot patterns and trends that the human eye would easily overlook.

Because financial markets are so complicated, AI models are bound to overlook a significant number of factors that could affect stock prices. The market is influenced by a wide range of factors, including investor sentiment, economic data, and geopolitical developments, all of which are difficult for an AI system to precisely foresee or predict. Once more, it is prone to get overconfident with historical data, leading to over fitting and possibly erroneous forecasts. This could be a serious issue in extremely volatile markets where historical patterns may not necessarily portend future outcomes. Notwithstanding the obstacles in the way, institutions and investors keep funding AI research for stock market forecasting because the technology's potential advantages outweigh the likelihood of redemptions for decision-making and return maximization. The ability to predict stock market trends is growing along with AI (Fallah et al., 2018). The overall flow diagram of AI techniques for stock market forecasting is shown in Figure 1:

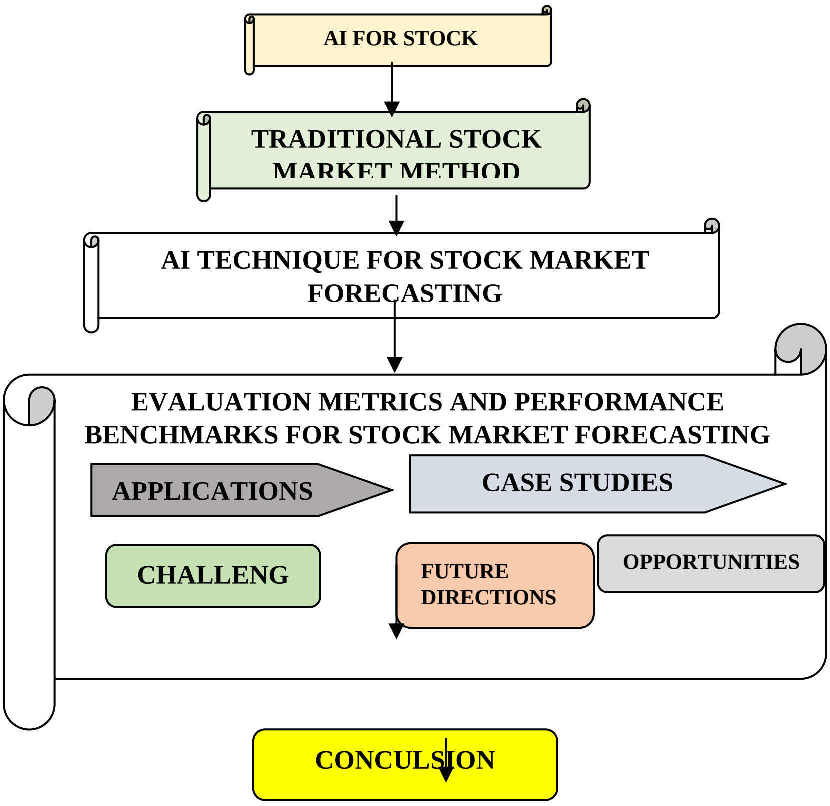

Fig 1: AI techniques for stock market forecasting

Artificial Intelligence in stock market

AI is transforming several industries, including risk management, fraud detection, trading algorithms, predictive analytics, and portfolio optimization. These devices allow businesses to forecast, streamline processes, and initiate decisions based on data. AI-powered trading algorithms automate trading decisions to ensure the best possible judgments on trading and selling. Massive data is analysed by AI-powered threat management systems so they can set in place and pinpoint any sort of possible threat, preparing them with proactive management, that will eventually mean lower losses. AI-based fraud detection systems can identify suspicious trends and anomalies, thus blocking fake activities on time and saving companies from massive monetary losses. It also allows portfolio optimization, which maximizes gains and minimizes risks while enabling investors to make qualified decisions based on large amounts of data, market trends, and risk variables through AI applications [9]. Some of the techniques used are:

Deep learning (DL)

Recurrent neural networks (RNNs) and long short-term memory (LSTM) in particular seem to be quite effective at modelling sequential data and identifying intricate patterns in lengthy data sequences. They are highly applicable in speech recognition and can process sequences of variable lengths they offer relevant information combined with precise forecasts, making them highly valuable in domains like clinical prognosis, stock market prediction, and sentiment analysis.

Natural Language Processing

It is a very efficient tool in the analysis of social media, financial news, and economic indicators. It produces insightful data through powerful algorithms using linguistic techniques and allows for making effective decisions and predicting market trends. Moreover, NLP supports studying conversations from social media too; by determining influential people and after that, it makes it feasible to study economic indicators.

Sentiment Analysis

Natural language processing and machine learning are used in textual data analysis to glean valuable information from unstructured text, including news stories, social media posts, and earnings reviews. These bits of information are all related to market movements and company performance, which in turn affects stock prices. Traders could carry out a sentiment analysis when making investments. of social media posts in an attempt to stay ahead of the trend of the market.

Reinforcement learning

Informed decisions on when to buy or sell assets are driven by real-time analytics applied by AI-driven trade algorithms in reaction to information events and patterns in the market. This innovative strategy gives it an edge over in-person purchases by reducing risks and maximizing profit potential in a fast-moving market.

Traditional stock market forecasting methods

Mean reversion, momentum, and forecasting techniques all impact market trends. Stocks that perform well are likely to continue, but those that perform poorly might also continue, according to momentum. Mean reversion implies that the market might eventually level out. The following are some examples of forecasting methodologies: multiple linear regression, moving averages, straight lines, quantitative and qualitative methods, and basic linear regression. Prediction accuracy can be increased by combining AI with traditional techniques. In 2019, Picasso et al. used data science and ML approaches to integrate technical and fundamental analysis for stock market prediction that forecasts a portfolio of NASDAQ 100 firms using technical analysis indicators and the mood of news articles, generating an annualized return of over 80%. Shen and Shafiq investigated forecasting stock market movements and prices, DL is growing in popularity in 2020. Based on data from the Chinese stock market, a comprehensive method for predicting price changes in the stock market was created. Pre-processing, numerous feature engineering techniques, and a DL-based system make up the methodology. The system's significant feature engineering allows it to outperform commonly used ML models. The careful design and evaluation of prediction term lengths, feature engineering, and data pre-processing techniques assists the stock analysis research community both quantitatively and technically. In 2018, Ren et al. concentrated on a support vector machine, which is used in machine learning techniques to integrate sentiment analysis. It generates emotion indices that are more dependable by taking the day-of-week influence into consideration. When sentiment variables were included, the model's accuracy in forecasting the SSE 50 Index's movement direction increased to 89.93%, an increase of 18.6%.

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The model contends that mood gives investors meaningful information about the fundamental values of assets, making it a leading indicator of the stock market and helping them make better judgments. Atkins et al. analysed Information from news feeds, both quantitative and qualitative, that has an impact on financial market statistics in 2018. The use of information gleaned from news to forecast stock movement and future asset prices has been the subject of recent literature. This study shows that information from news sources is more accurate in predicting changes in asset volatility than price movement. The average prediction accuracy for volatility is 56%, and the asset closure price is 49%. This implies that volatility swings are more predictable than asset cost variations, which could enable the rating of derivatives contracts. In 2019, Zhong and Enke presented a thorough big data analytics procedure that makes use of both conventional artificial neural networks (ANN) and deep neural networks (DNN) to forecast the SPDR S&P 500 ETF's daily return direction. Principal component analysis will be used to transform two datasets to anticipate future returns on stock market indexes. Comparing the DNNs with PCA-represented datasets against other hybrid ML algorithms and the entire dataset without modifications, the results show a significant increase in classification accuracy. Trading strategies that apply the DNN classification method slightly beat traditional benchmarks. Basak et al. (2019) aimed to lower forecasting error and investment risk by employing stock market return forecasting as a direction-predicting activity. It uses random forests and gradient augmented decision trees to provide an experimental framework for predicting changes in stock values. The technique improves projections for a variety of companies and uses technical indicators to anticipate the direction of medium- to long-term stock prices. In their 2018 study, Chatzis et al. used the Levenberg-Marquardt, Scale Conjugate Gradient, and Bayesian Regularization learning algorithms to anticipate the stock market. The results show that these algorithms have an accuracy of 99.9% when using tick data, but their accuracy decreases while working with 15-minute datasets, highlighting the challenges in stock price prediction. In 2019, Cai et al. investigated DL-based day-ahead multi-step load forecasting techniques for commercial buildings. Using RNN and CNN, the gated 24-hour convolutional neural network (CNN) model outperforms seasonal ARIMAX in terms of accuracy, computational economy, generalizability, and durability. In 2020, Huang et al. modified sound spatial positions using headphones using signal processing methods. They may generate identical virtual sounds when restricted to static noises. However, sustaining localization performance becomes difficult when sound sources are replicated at random places and react to head movements. The viability of employing these displays for both short and lengthy virtual sounds was demonstrated by a study that employed a virtual synthesis approach to create head-tracked virtual sounds with equivalent localization performance to genuine sound sources.

Artificial Intelligence techniques for stock market

Strong models called ANNs forecast inventory prices by using historical data. They are effective for shooting nonlinear relationships, but they need to be tuned carefully and have enough educational material. SVM are flexible algorithms that work well for regression and type tasks, but they struggle with noisy statistics. The best neural networks for capturing temporal dependencies are RNNs with LSTM. They are frequently used for time collection prediction, which includes inventory charges. Any other AI technique that examines financial reviews, news articles, and social media to determine investor sentiment and influence stock prices is known as sentiment analysis. AI is sensitive to noise and context, but it can evaluate vast amounts of textual data to derive insights in real-time. Although quantitative analysis is limited by the need for data that is pleasant, it is still used to examine profit and balance sheets, economic statements, and profit and loss statements to identify performance trends. Predictive modelling predicts future stock prices by combining a variety of factors and historical data. It is adaptable and comprehensible, provided that historical styles persist. Although AI improves inventory assessment, the stock market is still dynamic, therefore it's important to maintain human control and verify projections (Pang et al., 2020).

Machine learning method

The importance of ML algorithms in stock market prediction comes in because they can process volumes of data, establish trends, and use the outcome to project into the future. In doing so, the algorithms help the analysts to pinpoint these trends and project changes in prices, hence enabling them to make informed investment decisions. They also learn and adapt constantly to new data, hence remaining relevant for use at any time in changing market conditions. ML algorithms will be very fast while processing bundles of data, enabling an all-out analysis of the market data to determine minor patterns and trends that can help an investor make a decision. Other advantages associated with using ML in stock market forecasting concern data-driven decision-making, flexibility, efficiency, and pattern recognition. The algorithm is then empowered to go through tremendous amounts of data at an extreme speed. This speed will help in the presentation of vital information necessary for trading and investment decisions in real-time. Predictions may be modified anytime based on the latest conditions and market trends, and intricate patterns and relationships within large volumes of data may be detected that a human analyst would not find. Incorporate ML methodologies for increased accuracy and reliability of stock market predictions in order to enable efficient investment decisions (Sidhu and Kaur, 2019; Khan et al., 2022).

Support vector mechanism

Strong supervised learning models, SVMs are useful for data regression and classification. Due to their ability to identify the greatest separating hyperplane between classes, these SVMs have exceptional prediction power. SVM is one of the typical uses in predicting the patterns of stock prices and classification as per the market sentiment of textual data. Most importantly, due to their efficiency in high-dimensional regions, SVMs are a well-liked option for challenging data analysis tasks. An SVM, on the other hand, is strong in resisting overfitting and boasts the most accurate predictions in almost all situations. SVMs have their shortcomings, though they perform well among an assortment of options in practical applications and necessitate the tiniest possible parameter tuning to bring them to their best performance. SVMs have drawbacks that should be considered when using them to ML tasks.

Regression

Through the process of determining the best-fitting linear equation, linear regression is one of the most widely used flexible techniques for determining associations between a dependent variable and one or more independent variables. Stock prices could be predicted often by using this method on past price data and financial indicators. One major advantage of linear regression is the fact that it is comparatively easy to use and interpret, thus remaining intelligible to those with less statistical background. It is very useful in datasets having linear relationships since this, in turn, allows for very accurate prediction under these conditions. The major weakness of a linear regression, however, lies in the fact that they do not capture with enough measure complex market dynamics and nonlinear interactions, hence returning forecasts in situations where relationships are nonlinear. Despite this flaw, the simplicity and potency of linear regression in modelling linear connections make it such a valuable instrument in many domains.

Decision Tree

Decision trees are used as media of choice when one has to model decisions and their possible consequences, for instance, changes in stock prices, with the goal of forecasting. Such hierarchical models operate by dividing data into different subsets according to the values of features. What a tree structure provides at each node is a feature-based decision, and at every leaf node, there is a resultDecision trees' interpretability and simplicity, which make them simple to comprehend and depict, are two of their main features. Their versatility for a wide range of applications stems from their ability to analyse both numerical and categorical input. However, because decision trees are prone to overfitting, they may not perform well on new, untested data. Furthermore, because they are sensitive to even a single change in the training data, they may produce various tree architectures and most likely inaccurate predictions as well.

Random Forest

In this sense, random forests are ensemble learning techniques that generate a more precise classification or forecast by combining the predictions of multiple decision trees. Consequently, random forests can be applied in this method to both predict stock values and classify stocks based on a collection of financial indicators. Reduction Overfitting has been one of the major advantages of random forests, which in turn gives better accuracy of prediction, especially when dealing with huge datasets. However, using random forests can be computationally time-consuming and will hence make the training process slow. Furthermore, the logic underlying the model's prediction is difficult to understand because a random forest is less accessible than a single decision tree because it is an ensemble of various decision trees. Notwithstanding these two drawbacks, random forests are favoured in many machine-learning applications because of their flexibility in efficiently processing complex data.

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Research Article

Deep learning method

Deep learning (DL), a type of ML that constructs advanced models, is changing the face of stock market forecasting by sending out intricate relationships and patterns in very large datasets. Some of the most popular techniques include LSTMs, RNNs, CNNs, and ANNs. While CNNs show an outstanding performance in time-series data analysis, RNNs are better at handling sequential data; LSTMs are fine at capturing long-term dependencies, and ANNs can be excellent at recognizing patterns. They require a huge amount of processing power and are prone to overfitting, though.

Artificial Neural Network (ANN)

A neural network is an ANN that has been computational, reflecting the architecture and working mechanism of the human brain. In an artificial neural network, neurons are disposed of in several different layers. These may be an input layer, a concealed, or an output layer. Accurate stock price predictions are one of the numerous practical uses for artificial neural networks. In addition, ANNs can be used to tackle categorization challenges, such as grouping equities according to their performance. The collection and subsequent normalization of historical stock price and financial indicator data will be part of the preparatory procedures for the implementation of an artificial neural network to forecast stock prices. Choosing the number of layers and neurons in each layer is the second step in the model design process. When an ANN is trained on historical data, weights are adjusted to minimize the prediction error. Stochastic gradient visitation and its derivative, backpropagation, are two methods for achieving this. In the future, we will have metrics such as accuracy or mean squared error, which will give an estimate of a model's Performance and maybe even tune the hyper parameters (Chhajer et al., 2022).

Convolution Neural Network (CNN)

CNNs are mainly used in the processing of time series databased since they were essentially constructed to deal with grid structures rather effectively. Based on this, CNNs create spatial hierarchies of the features using convolutional layers so that the machines may learn new features on their own. It will help detect a pattern using CNN by separating any underlying trend or pattern in time series data, such as stock price movement analysis over time. The idea here when using CNNs for this purpose is to format data preparation by transforming historical stock prices into some CNN feed-friendly format. In this model, all components include an organization of convolutional layers in a way that aids feature extraction, a configuration of the pooling layers that helps in reducing the dimensionality, and then fully linked layers for the generation of final predictions. The historical data is focused on training a CNN to recognize core patterns that allow for a correlation with price movements. The next step is model performance evaluation regarding CNN's capacity to identify trends and make future value or movement predictions. Any adjustments to the network's architecture and parameters come next.

Recurrent Neural Network (RNN)

RNNs are designed specifically to solve such sequence prediction problems. Because they are capable of forming directed cycles, the network can then generate internal memory, which is very helpful in capturing time dependence in the data. For instance, one real application could be an RNN applied to predict stock price patterns. Evaluating the pattern of past price sequences, it becomes possible for an RNN to master effective learning from past historical trends and extract temporal dependencies in the data. This will become an implementation process whereby data preparation will involve the organization of past stock prices in sequences and normalizing them for consistency in their operation. After this, the model can be designed using a suitable RNN architecture, such as LSTM, very popular in learning long-term dependencies. In the training phase, sequences of historic data will be fed into the RNN, and it will change its inner state to catch the temporal trends. Finally, model predictions shall be tested against a test set for accuracy and refined for better performance in parameters and architecture.

Natural Language Processing for sentiment analysis

Sentiment lexicons consider the presence of these words to classify textual content as great, awful, or neutral. For enhancing the efficiency of stock movement predictions, advanced models like BERT enhance the efficiency of sentiment analysis. Therefore, it defines the context and meaning of words through phases, hence increasing the efficiency of the task. This would be assessed as unstructured data, like news articles and posts from social media, in pursuit of insight and knowledge about customer sentiment. In high-speed inventory purchases and sales, real-time sentiment analysis has a significant role to play because decisions executed on a quick basis tend to make a lot of difference in profit margins. However, text analysis depends heavily on large sets of data, which may not represent the discrete mood of the market where there is a lack of sufficient data. The presence of noise may arise from factors such as irrelevant or false information, thus affecting the accuracy of sentiment evaluation. Examples of language subtleties include dialects, unique languages, and cultural quirkiness—these represent some of the evaluation scenarios that may prove challenging. The models used in the course of this research also may fail to recognize and comprehend those subtleties hence leading to capacity errors while trying to discover the stock movement prediction.

Reinforcement learning for trading strategies

Trading strategy algorithms are computer programs that use a variety of techniques, such as Q-reading, Deep QNetworks, and Proximal Policy Optimisation, to make informed decisions in the financial markets. These algorithms have the capacity to generate profits since they can independently examine intricate procedures and adjust to changes in the market. The ability to use algorithms to discover new avenues for buying and selling is one of the main advantages of this technique. Because these algorithms can identify patterns and relationships that are not necessarily obvious to human users, they can examine vast volumes of historical data as well as changes in the market. They are able to take advantage of market inefficiencies in this way and generate consistent revenue. Positive obstacles do, however, exist for the purchase and sale of method algorithms. To begin with, they need a lot of computing power to process large amounts of data analysis quickly. Individual consumers or small enterprises with limited computer resources may also find this to be a project. However, a great amount of training is required for these algorithms to analyse large-scale purchasing and marketing plans. They must be exposed to a wide range of market conditions and scenarios in order to develop good decision-making abilities. However, training such algorithms would require a significant amount of historical data and would take time. Furthermore, the algorithms used in buy-sell strategies are highly susceptible to hyperparameters and sensitivities in the reward arrangement. A developer's help with certain parameters and settings can have a significant impact on the algorithms' average performance. A small adjustment to the hyperparameters or the way rewards are differentiated could have a significant impact on the algorithm's overall efficacy and profitability. Proximal Policy Optimization, Deep Q-Networks, and Qmastering are examples of state-of-the-art trading approaches that offer promising methods for buying and selling financial assets. These algorithms can identify novel buying and selling strategies, but they also come with drawbacks, including a high expertise threshold, a large processing power requirement, sensitivity to reward structures, and hyperparameters.

Role of Gen AI/Large Language Models

LLMs use sophisticated algorithms and large-scale datasets to identify patterns and predict future moves in the stock market. Modern algorithms are capable of processing and interpreting data at a much faster and larger scale than human beings, which enables more precise and timely insights into market movements. Natural language processing (NLP), big data integration, advanced predictive modelling, improved ML models, and algorithmic trading are all critical components. NLP uses textual content data from financial reports, news articles, and social media to estimate market mood and detect major events that affect inventory prices. With the development of flexible models that can adjust to changing market situations, LLMs now have the ability to handle a variety of data sources. Advanced ML Models make exact stock market predictions by leveraging preexisting models trained on massive datasets. Using advanced ML algorithms, GenAI generates models that predict market movements, optimize trading strategies, and improve investment decisions, consequently providing actionable insights for traders and financial analysts. Algorithmic buying and selling systems are able to execute trades by evaluating current data and applying preset criteria. To ensure the moral and equal application of AI in economic markets, ethical concerns and legal barriers have to be addressed (Aldhvani and Alzahrani, 2022).

Earlier works using Artificial Intelligence Techniques

A crucial part of financial research and decision-making is stock market forecasting. Precise forecasts have a significant influence on risk management, funding tactics, and average market performance. For many years, traditional methods have been employed to anticipate market activities, together with technical analysis, essential

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Research Article

analysis, and time collection assessment. But those processes often struggle with the financial markets' intrinsic complexity, nonlinearity, and extreme volatility. The field of inventory market forecasting is facing revolutionary pressure from AI comprising a vast array of techniques and technologies that allow robots to mimic human intelligence processes. AI analyses large volumes of data, recognizes patterns, and makes predictions faster and more accurately than traditional methods in the financial markets. Sohrabpour et al., (2021) proposed a platform for applying genetic programming, an artificial intelligence method inspired by biological evolution, to model and forecast export sales. The model is used for six weeks to compare with actual sales data in an empirical case study of an export company. Additionally, a variable sensitivity analysis is shown. Carta et al. (2020) used ML to forecast future changes in stock prices for specific S&P 500 index businesses through feature engineering, creating lexicons from articles published worldwide, and feeding the resultant data to a Decision Tree classifier. The suggested method beats rivals and was understood by looking at the classifier's white box. Pallathadka et al. (2023) explained Artificial Intelligence is leveraging supply chain management, mate size reduction, customer experience, and operational efficiency in the finance and e-commerce industries. Businesses, government organizations, and private citizens all employ ML and DL for data learning and prediction. Applications include portfolio management, security, fraud detection, inventory management, sales growth, and profit maximization. Sharma et al. utilized the DOW30 and NASDAQ100 US stock market indexes and employed an intelligent forecasting approach combining Artificial Neural Network (ANN) and Genetic Algorithm (GA) in 2022. Traditional statistical and AI techniques are often insufficient due to nonlinearity in stock data. The GA and ANN hybrid model outperformed the single ANN technique in short- and long-term accuracy, offering a more accurate and efficient approach to stock market forecasting. This article provides a useful data mining technique for forecasting the daily direction of the S&P 500 Index ETF (SPY) return, based on an assessment of 60 financial and economic indicators conducted by Zhong et al. in 2017. The initial data structure Three dimensionality reduction techniques—fuzzy robust principal component analysis (FRPCA), principal component analysis (PCA), and kernel-based principal component analysis (KPCA)—simplify and restructure KPCA. The updated data sets are then classified using ANNs, which produce risk adjusted returns and classification accuracy that are marginally higher than those of others. In 2019, Pérez et al. presented a machine-learning algorithm that projects S&P 500 volatility. Compared to other models, the model predicts volatility levels more precisely, which improves the evaluation of market risk and addresses issues that firms face when handling uncertainty while funding operations or investments. The model makes use of ANNs, gradient descent boosting, support vector machines (SVMs), and random forests. In 2020, Chung and Shin, used DL methods, specifically multi-channel CNNs, to forecast fluctuations in stock indexes. The model's hyper-parameters are optimized using GA. The results highlight the effectiveness of the hybrid method since GA-CNN outperforms both CNN models and regular ANNs. The research also proposes a feature extraction-oriented approach to CNN parameter optimization Nabi pour et al. (2020) used DL and ML techniques to lower the trend forecast risk. Testing is done on four segments of the Tehran Stock Exchange's stock market: financials, non-metallic minerals, petroleum, and basic metals. Two DL techniques and nine ML models are contrasted. The results demonstrate that RNN and LSTM outperform other prediction models in continuous data and binary data, respectively, using ten technical indicators as input values. In 2018, Baek and Kim, used the ModAugNet framework, a unique data augmentation method for stock market index forecasting that combines an overfitting prevention LSTM module with a prediction LSTM module. The model's performance was evaluated using sample stock market data from the S&P 500 and the Korea Composite Stock Price Index 200. The results showed excellent prediction accuracy and lower test errors compared to SingleNet models. The model can be applied in several scenarios where data augmentation is challenging because its test performance is dependent on the prediction LSTM module. Carta et al. decreased over-fitting in stock market forecasting by introducing a group of reinforcement learning algorithms in response to noisy and unstable historical data in 2021. The method, which uses a Q-learning agent that has been repeatedly trained on the same set of data, performs better for intraday trading than the conventional Buy-and-Hold approach. The study also covers the qualitative and quantitative analyses of these results. In 2021, Tuarob proposed a comprehensive approach to real-time stock market prediction that makes use of contextual feature engineering and estimators based on ML. The technique surpasses conventional benchmarks and has the potential to be expanded into diverse financial uses, empowering investors to decipher narrative developments impacting company values and arrive at well-informed conclusions. In 2018, Mankar et al. provided that real-world issues like stock investing were resolved with the help of AI and ML approaches. Stock closing values and sentiment analysis on Twitter API can forecast stock price changes to assist novice investors and

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Research Article

allow for well-informed decision-making and possible gains. In 2020, Pang et al. introduced a cutting-edge neural network technique that uses real-time data and images from the Internet of Multimedia Things to improve stock market forecasts. Multi-stock high-dimensional historical data is used to introduce the idea of a "stock vector". Test findings indicate that the suggested deep LSTM neural network with embedded layer performs better in terms of accuracy for both individual stocks and the Shanghai A-shares composite index. In order to further neural network-based financial analysis, this study makes use of IMMT.

OBJECTIVES

The purpose of this work is to use Machine Learning (ML) algorithms to develop a classifier that can predict the polarity of a comment. The comments are collected and then process to find out the polarity i.e. positive or negative. Our work consists of three key responsibilities: data mining, processing, and modelling. The social media tweets are taken from different sources and then an effort has been made to determine the polarity to find the possible effect on the stock price movements.

METHODS

Machine learning techniques are used for sentiment analysis in order to rank sentences. To get to the evaluation phase, we must first go through the tweet collection phase, followed by the pre-processing, data preparation, and categorization phases. Because Python provides high-level tools and an easy-to-use syntax, and because Anaconda is the best way to install machine learning packages, we decided to utilize it as our development environment. For all NLP activities in this paper, we will use the Natural Language Toolkit (NLTK) guidance package, and for machine learning, we will use the open source Scikit-learn library.

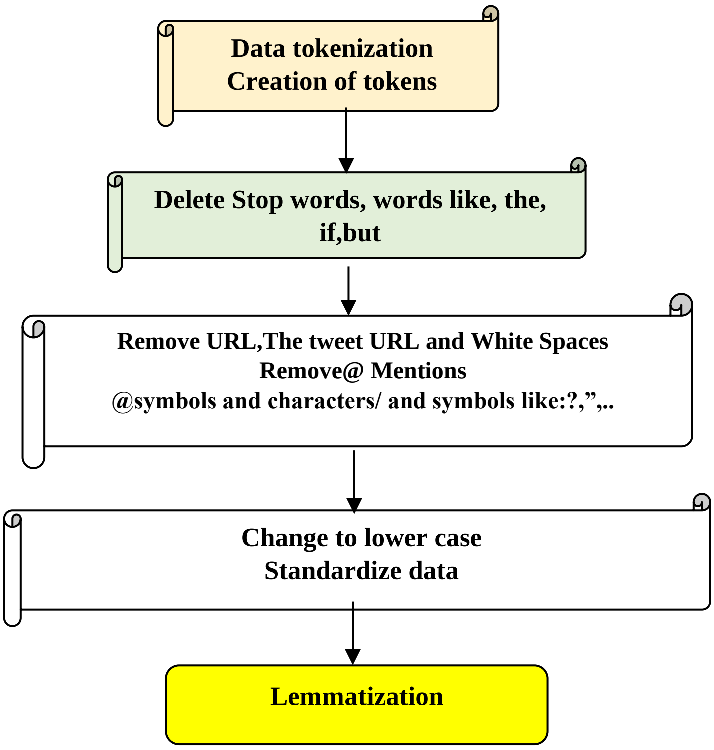

Fig2: Pre-treatment process.

Data collection phase:

A dataset of sample English tweets from the NLTK package served as the basis for this study. As of right now, NLTK's Twitter corpus includes a sample of 20,000 non-sentimental tweets (referred to as "twitter samples") that were obtained from the Twitter Streaming API in addition to an additional 10,000 tweets that have been divided into positive and negative sentiment categories (5,000 tweets with positive sentiments and 5,000 tweets with negative sentiments).

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2025, 10(42s)
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Phase of Preprocessing:

There are several slang terms and punctuation marks in tweets. Since a machine cannot accurately process the language in its original form, we must clean up our tweets so that a supervised machine learning algorithm can use them more easily.

(a) Data tokenization:

It is also known as the process of creating tokens, is a more widely used technique that divides a text body into many phrases and each sentence into a list of constituent terms.

(b) Eliminate stop words:

Remove words such as "is," "the," and "a" in English, which are the most frequently used words in a language.

(c)Remove UR:

Remove any URL from the tweet. It includes removing URLs starting HTTP, https and also pic:\\ then replace with an empty string.

(d) Eliminate @ mentions: The @ symbol that appears before these Twitter usernames gives no indication of the text's emotion.

(e) Change to lowercase: We change the data to lowercase to make things easier, which includes changing a body of text to all lowercase letters.

(f) Lemmatization: It is the process of normalizing a word by analyzing its structure and context. It does this by comparing the word's morphological analysis in the text with the vocabulary's context. However, before executing a lemmatizer, we must ascertain the context of every word in our text. This is accomplished by the use of a tagging algorithm, which assesses a word's relative location inside a phrase in order to identify it as a noun, verb, adjective, adverb, etc. The preprocessing procedure is depicted in Figure 1.

Data preparation:

We will convert the tokens to Python dictionary format with words as keywords and True as values, mixed at random, in order to prepare the data for sentiment analysis. Next, we split the mixed data into two sections. The first section's goal is to construct the model, and the second section evaluates the model's performance in a 70:30 ratio for training and testing. Since the number of tweets is 10000, we can use the first 7000 tweets from the mixed dataset to train the model and the last 3000 to test the model.

Classification Phase:

The training data can be used to train the machine learning algorithm once the data has been separated into training and test sets. The algorithms listed below were applied:

The supervised, probabilistic Naive Bayes (NB) classification method

Simple and effective supervised machine learning techniques are Nañve Bayes classifiers. In honour of Thomas Bayes, who developed the Bayes theorem to calculate probability, this classification is called Naive Bayes. Probabilistic classifications, which assign the likelihood of belonging to a class, are made possible by it. It makes the assumption that, given the class variable, the value of one feature is independent of the value of any other characteristic. Three variations of the NB approach, which is frequently employed for categorization, were used in this instance. Bernoulli Nañve Bayes and Multinomial Naıve Bayes.

Multinomial NB

For classifying texts, this form of NB is frequently used. It requires discrete features as input data and is referred to as the Unigram language model and the Binary Independence Model, respectively. In general, multinomials perform best when vocabulary sizes are greater. The multinomial distribution of each feature in this case creates a feature vector that shows how frequently that feature occurs in a certain instance.

Journal of Information Systems Engineering and Management
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Bernoulli NB

According to Bernoulli NB, instead of using probabilities like in Multinomial Naive Bayes, the features in this case are independent binary variables that indicate presence or absence [6]. In the literature, it is also known as the binary independence model, which is a Bayesian network devoid of word dependencies, binary word features, and unigram language models. Small vocabulary sizes are well-suited for the Bernoulli NB. This form of NB is used in situations when there may be more than one entity and each is thought to be a variable with a binary value. The word occurrence vector is utilized for both training and classification in text classification.

Benchmark datasets

For practitioners and instructors tackling the challenge of stock market forecasting, benchmark datasets, and competitions are invaluable resources since they enable one to assess the efficacy of several rival models. These datasets, which are included below, typically include some historical data on the stock market and, as such, provide a standard framework on which various approaches can be used to enable flexible assessments of accuracy and efficiency. This makes it possible to apply the method of choosing suitable styles in a variety of situations. Additionally, the benchmark datasets can save time by freeing up researcher time to focus on developing their models rather than gathering and preparing statistics. A spirit of competition is ingrained in competitions, which encourages creativity and unique problem-solving. As a result, the competitive environment will foster the development of novel ideas and concepts. Therefore, benchmark datasets and contests offer the chance for cooperation within the research community by offering a forum that will encourage discussion and evaluation of fresh viewpoints on opportunities. Ultimately, these tools are extremely useful tools for assessing the overall effectiveness of stock market forecasting models, experimenting with sales tactics, and expanding the company (Nabipur et al., 2020).

Kaggle dataset

Kaggle is an online community that shares a fascination with gadgets and record technologies. It holds abundant stock market datasets, including databases of financial data, historical fees, and purchase/sell volumes. This great database may be useful for lamp posts and examination contests about the models with respect to sources of financing, trading algorithms, and trend forecasts. For a variety of businesses and indexes, it offers historical rate information for daily, weekly, or monthly inventory charges. Moreover, Kaggle offers data on buy and sell order volumes that can be utilized for inferring market liquidity and trading dynamics. Other sources of financial information on the equity market whose use may help in finetuning models in their prediction task are news releases and information memories.

Yahoo finance dataset

Yahoo finance dataset Benchmark datasets and competitions are especially useful to all stripes of educators and practitioners involved in the stock market forecasting discipline, in that they can be used to benchmark and evaluate a wide variety of models. In this vein, this kind of historical record resource can turn out to be very useful by offering a single criterion with which one might resolve disputes over the overall efficacy of fashions versus their accuracy. This makes it easy to determine what types of styles would be suitable to be worn in a given situation. The use of benchmark datasets saves researchers time since they can focus on enhancing designs rather than collecting and organizing data. Besides, it enhances the development of new techniques. Competitions encourage creativity because of the competitive environment around it. These resources have provided scholarly collaboration and also fostered a good amount of idea exchange and exploration of different perspectives.

Quandl

It can also be used to take a close look at market trends and financial prospects. This platform provides access to current and historical data that helps make very well-informed financial decisions. More so, the depth of the financial environment may be understood due to the richness of information involved in the introduction of reliable financial styles and modes. The platform does two things: aids in the optimization of holdings for investors and helps financial analysts looking to understand how markets work.

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Kaggle Competition

A group of statisticians and IT enthusiasts who can be hired to oversee financial prediction contests are members of this online community. In this instance, they request that the employees create models that, using historical data from the inventory market, might forecast future inventory values. An examination of the tone of economic news using techniques like regression analysis, time accumulation, and DL are a few examples. Another feature of Kaggle competitions is the use of algorithms to identify patterns and anomalies in historical market data to carry out buying and selling strategies. This kind of competition will encourage innovation in modern purchasing and sales tactics that can outperform traditional investment methods. Participants in this challenge can explore and create modern financial prediction models by using complete data sets and Kaggle's version assessment platform.

Numerai

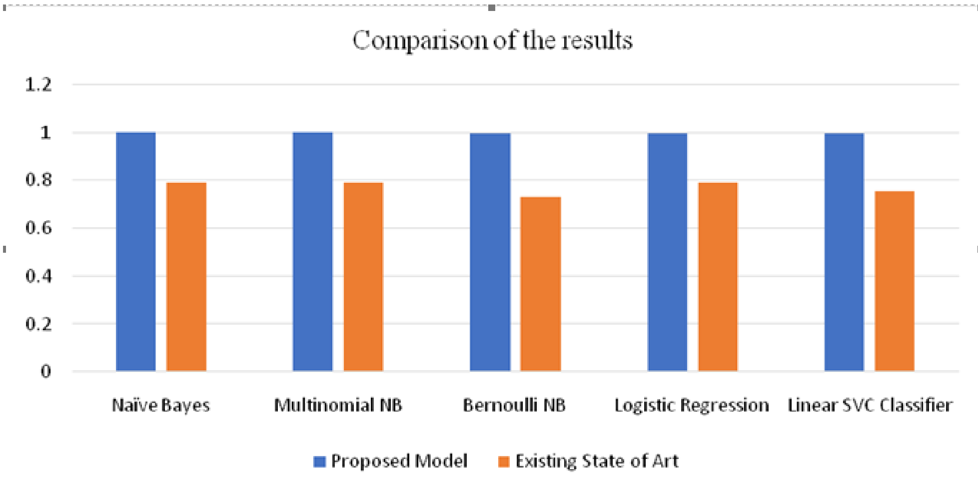
This record-keeping platform not only offers technical talent competitions but also, in a unique way, allows ML and statistics scientists to compete with one other. Participants add historical and current market data to their inventory expense prediction models. Subsequently, the styles are tested in real international market situations like remain purchasing or selling which proves them right. In addition to engagement with key financial institutions and recognition among the scientific community, it offers monetary rewards for the winners. The challenges provide valuable experience to the competitors, hone their talents, and find novel career paths in quantitative finance.

RESULTS

An Intel (R) Core (TM) i3-6006U processor with a CPU operating at 2.00 GHZ and four gigabytes of RAM is used for all investigations. Our supervised learning approach allowed us to classify tweeter reviews with a fair degree of accuracy. In contrast to [6], we obtain higher accuracy. The outcomes are contrasted in the table I below:

Classifiers	Proposed Model	Existing State of Art
Naïve Bayes	**0.9973**	0.7912
Multinomial NB	**0.9970**	0.7892
Bernoulli NB	**0.9967**	0.7322
Logistic Regression	**0.9953**	0.7888
Linear SVC Classifier	**0.9967**	0.7532

Table 1: Result Comparison for implemented classifiers



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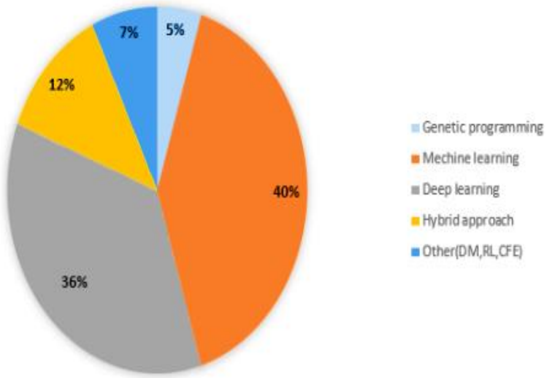

Figure 4: AI-type Implementation in reference articles

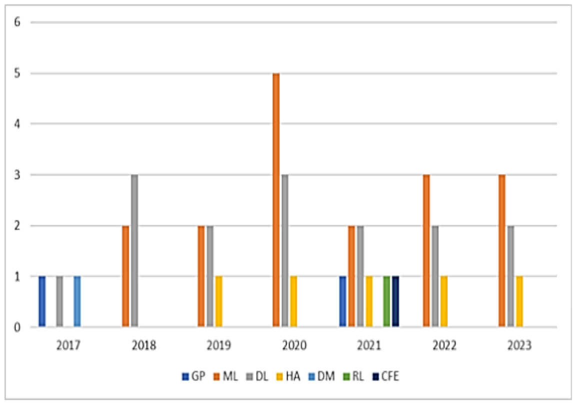

Figure 5: AI Implementation Type per year

Fig 6: AI Algorithms type by year

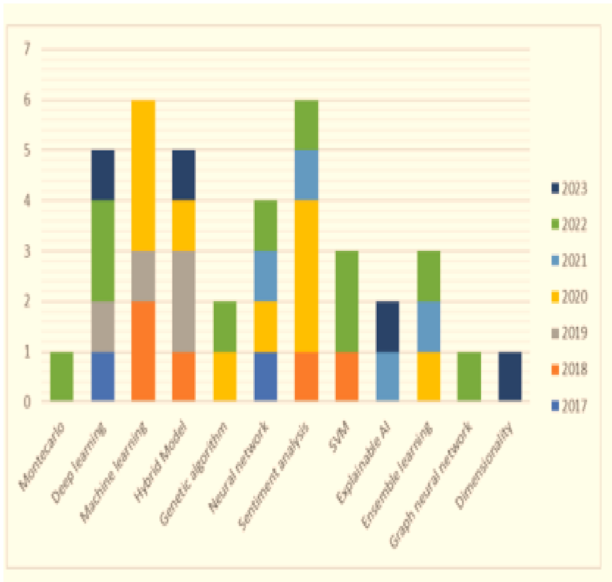

Fig 7: Comparison of Accuracy prediction metrics

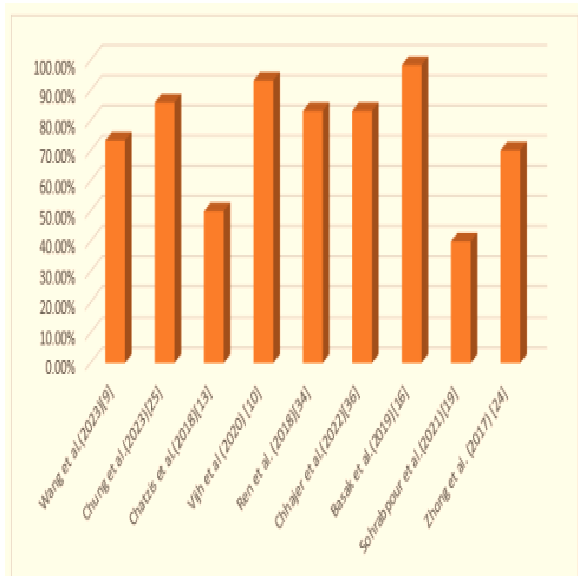

Figure 4 shows the several AI implementation types used in stock market prediction research. With barely 5% of individuals utilizing it, genetic programming is the least popular tactic out there. The most widely used method for categorizing enormous data sets and identifying patterns for predictive analysis is ML. DL, which models complex associations in data using neural networks, is the second largest. To increase forecast accuracy, hybrid systems use AI methods including extensive feature extraction, reinforcement learning, and dimension reduction. The data recognizes the usefulness of hybrid models and specialized methodologies and emphasizes the significance of ML and DL in modern stock market forecasting. For stock market forecasting between 2017 and 2023. Considering a peak in 2020 the algorithms for ML is the most popular strategy. The application of neural networks in financial forecasting is developing, partly due to the increased use of DL. Hybrid models (HA), which are sporadic but reliable, propose merging multiple AI techniques to improve forecast accuracy. Figure 5 shows the distribution of AI techniques for stock market forecasting from 2017 to 2023. ML, DL, ensemble learning, explainable AI, graph neural networks, dimensionality, sentiment analysis, hybrid models, GAs, neural networks, and SVM are the most widely used techniques. Monte Carlo is rarely utilized, whereas DL, which reached its peak in 2020, is widely used. In 2020 and 2021, ML will also be a popular approach. In addition to neural networks, other techniques employed include graph neural networks, SVM, ensemble learning, dimensionality, explainable AI, sentiment analysis, and GAs. The graph shows the increasing variety and sophistication of AI techniques for stock market prediction.

DISCUSSION

Sentiment detection is a novel activity that faces several challenges. The aim of this effort is to investigate methods and approaches that ensure automatic classification of emotions into positive or negative polarity. This article uses a number of different approaches. The most recent ones are based on data from the 30,000 tweet samples currently available in NLTK's Twitter corpus. We convert all tweets to lowercase after pre-processing the data using tokenization, lemmatization, and the elimination of stop words, URLs, @ mentions, punctuation, and special characters. The data is then prepared by transforming the cleaned tokens into a Python dictionary, where True is used as a value and words are utilized as keywords. After that, the data is split 70:30 between training and test data. We used supervised machine learning algorithms to classify our tweets into positive and negative categories, and then we compared the accuracy of each.

In addition to discussing various prospective research avenues, the review paper addresses some application cases for AI-based stock market forecasting techniques and the associated challenges. It goes on to say that overall, this subject has made great strides thanks to the numerous creative ideas and methods proposed, which usually outperform conventional forecasting methods. It illustrates how the use of AI techniques could significantly improve forecasts for inventory markets. It is no longer unusual because research articles have often noted the use of neural networks, sentiment analysis, reinforcement learning, multimodal inputs, and even hybrid models to increase prediction accuracy and minimize problems like overfitting and volatility. Apart from being superior to the traditional buy-and-hold strategy techniques, These AI-powered strategies provide investors with practical resources to assist them understand intricate market dynamics and, consequently, act more sensibly. Despite these features, AI systems used to forecast the stock market still encounter difficulties. Overfitting, version interpretability, very good facts, and market inefficiencies are examples of constant bounds. There are additional levels of complexity due to legal obligations and ethical issues. These difficult circumstances must be resolved in order to guarantee the moral, open, and trustworthy use of AI in the financial markets. It is impossible to exaggerate the significance of AI methods for inventory market forecasting. Investors are able to strengthen and enhance their position in the market thanks to AI's dependable supply of precise, data-driven market knowledge, which is made possible by the more complicated financial markets. One has a distinct advantage when it comes to distributing finances, especially when artificial intelligence models are developed to collect and analyse massive amounts of data and generate real-time feeds.

FUTURE SCOPE

AI models that incorporate behavioural finance insights may be able to better understand market movements that are influenced by sentiment and human psychology. Research conducted in conjunction with behavioural economists and AI specialists may lead to trends that more accurately capture the subtleties of market behaviour, particularly during periods of market pressure or irrational exuberance. Block chain and Internet of Things technologies can be combined with AI to create intelligent energy management systems. Similar to this, IoT devices can supply real-time streams of data, while blockchain technology can provide transparent and unchangeable data for the financial markets. Because of this multidisciplinary teamwork, a more robust, dependable, and real-time model for stock market forecasting would be produced. Developments in neuroscience and cognitive technology may also offer fresh perspectives on how to represent decision-making processes. AI models will become more accurate and intuitive predictors and far closer approximations of human decision-making through collaborative work with neuroscientists.

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