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Original Article

An Automated Analytics Framework for Stock Trend Analysis from Multi-Modal Data

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Abstract *- Developing comprehensive and automated analytics frameworks for stock trend research is essential due to the turbulent and dynamic financial markets. This paper introduces a novel Automated Analytics framework for Stock trend Analysis from Multi-Modal Data (AASAMD). The framework utilizes sentiment extraction methods and historical stock price data to predict market trends. The approach incorporates many modalities of data, merging textual sentiment data acquired from news items and social media with numerical data derived from stock price histories. This involves collecting sentiment indicators from unstructured textual data sources. The sentiment data is then integrated with previous stock price data to provide a complete dataset suitable for study. Machine learning models, such as regression and classification algorithms, forecast stock patterns, furnishing investors with vital insights to facilitate educated decision-making. The framework's capacity to accommodate many textual data sources enables its flexibility to various markets and industries. The research study includes empirical findings highlighting the framework's efficacy in predicting stock market movements. Moreover, it illustrates the framework's capacity to improve decision-making processes for financial stakeholders. The Automated Analytics Framework for Stock Trend Analysis from Multi-Modal Data, which incorporates sentiment extraction and stock prices, signifies a notable advancement in utilizing various data sources and state-of-the-art technologies. This advancement aims to enhance the accuracy of predicting stock trends, consequently facilitating more informed investment strategies within dynamic financial markets.*

Keywords *- Stock trends, Sentiment analysis, Multi-Modal Data, Automated analytics framework, Financial markets, Stock price prediction, Natural Language Processing.*

1. Introduction

Investors, traders, and financial experts have long been captivated by the complexities inherent in the stock market. The ever-changing and often surprising characteristics of stock prices have inspired an ongoing endeavor to develop tools and procedures that might provide important insights into patterns and tendencies in the stock market.

In the contemporary period characterized by the proliferation of extensive data sets and sophisticated analytical techniques, there is an increasingly acknowledged appreciation for the possibilities of using data-centric methodologies within finance. One notable application within Natural Language Processing (NLP) is sentiment analysis, which has emerged as a significant technique for evaluating market sentiment and its influence on stock prices. Integrating multi-modal data, including numerical data such as historical stock prices and textual data derived from diverse sources such as news articles and social media, provides a compelling frontier in stock trend research. There is a growing recognition among investors and financial experts about the need to include textual sentiment data with conventional numerical indicators.

This integration allows for a more comprehensive comprehension of market dynamics. The correlation between news emotions and stock prices has garnered significant attention due to its potential to provide early insights into market trends, investor mood, and possible price fluctuations.

The creation of automated analytics frameworks has emerged as a result of the need to conduct thorough stock trend research. These frameworks can handle large amounts of multi-modal data in real time and provide practical insights. These frameworks use cutting-edge developments in machine learning and artificial intelligence to automate the tasks of sentiment extraction, data integration, and stock trend prediction. By engaging in such actions, individuals provide investors and traders with the necessary resources to enhance their decision-making abilities within a dynamic financial environment.

The present research presents an original and versatile Automated Analytics Framework for Stock Trend Analysis from Multi-Modal Data (AASAMD). This advanced solution is specifically developed to use the capabilities of sentiment extraction and historical stock price data. The AASAMD system signifies a notable progression in stock market analysis, providing a flexible and evidence-based methodology that can be customized to suit various markets and industries. The integration of numerical data with textual sentiment analysis yields a complete dataset that can significantly transform the forecast of stock trends, as it combines the accuracy of numerical information with the subtle insights acquired from analyzing textual sentiment.

The primary aim of this study is to investigate the capabilities of the Advanced Automated Stock Analysis and Market Trending (AASAMT) system and provide empirical evidence of its efficacy in predicting stock trends. This research aims to demonstrate the framework's potential in improving decision support systems for investors and traders by examining its performance compared to historical data and established forecasting approaches. The automated analytics capabilities of AASAMD can diminish the dependence on human analysis and provide a data-driven methodology for analyzing stock trends. This may yield a competitive edge in navigating the intricate nature of contemporary financial markets.

In the following sections, we will explore the complexities of AASAMD, providing a comprehensive analysis of its fundamental elements, research approaches, and empirical findings. This investigation aims to demonstrate the potential for transformation offered by an automated analytics framework that effectively combines sentiment extraction and stock prices to unravel the mysterious realm of stock trends.

2. Related Works

Recent academic contributions have significantly enhanced stock market trend analysis and forecasting. The famous stochastic modeling technique using Hidden Markov Models was established by Gulbadin Farooq Dar et al. [1]. This approach provides insights into the probabilistic characteristics of financial markets and presents a methodology for analyzing and predicting stock movements. Rebecca Abraham and her colleagues proposed a novel strategy integrating Genetic Algorithms with Random Forests to predict market trends [2].

This innovative methodology offers a unique viewpoint on algorithmic prediction approaches. D.T. Dhaneesh conducted a study using data mining methods to predict stock market trends [3]. Their research aimed to leverage data-driven insights for this purpose.

Barmish, Primbs, and Warnick (2022) proposed a novel feedforward stock trading control model [4] that enhances the investigation of transaction-level price trends. Finally, Nayak et al. investigated trend analysis in the Indian stock market during the COVID-19 epidemic using deep learning techniques [5]. Their study emphasized the flexibility of artificial intelligence-driven models in adapting to dynamic financial environments. These academic publications jointly enhance the diverse range of approaches and insights accessible in the ever-evolving domain of stock market analysis, providing excellent opportunities for more investigation and improvement.

The recent contributions in the domain of stock market analysis have illuminated diverse avenues for trend prediction and performance analysis. Ming Che Lee et al. [6] introduced an attention-based Bidirectional Long Short-Term Memory (BiLSTM) model complemented by technical indicators, enriching the landscape of stock trading strategies. In a distinct context, Qingfu Liu et al. [7] ventured into deep learning for stock market prediction, focusing on the dynamic Chinese market.

Meanwhile, Iftita Haz Qurnia and Febrianty [8] conducted a comprehensive trend analysis of financial statements within the plantation sub-sector listed on the Indonesia Stock Exchange, shedding light on sector-specific insights. Chun Hao Chen et al. [9] presented an ensemble classifier leveraging Chinese news sentiment and technical indicators for stock trend prediction, contributing to the fusion of textual data and technical analysis. Lastly, Zahra Fathali et al. [10] explored machine learning techniques in predicting the NIFTY 50 Index, offering valuable insights into applying data-driven approaches in market forecasting. These scholarly endeavors collectively expand the horizons of stock market analysis, providing various methodologies and insights for researchers and practitioners.

The recent contributions to stock trend prediction offer a spectrum of innovative approaches to inform investment decisions. Mohammad Kamel Daradkeh's research [11] presents a Hybrid Data Analytics Framework that seamlessly integrates sentiment convergence and multi-feature fusion, promising advanced insights into stock trends.

In a different realm, Gustavo D. Stahelin and colleagues [12] explore incorporating distance metrics and temporal trends to enhance mixed stock analysis, contributing to refined analytical methods. Yue Qiu, Zhewei Song, and Zhensong Chen [13] delve into short-term stock trend prediction by leveraging sentiment analysis and machine learning, highlighting the dynamic interplay between textual data and predictive models.

Table 1. Summary of the recent works

Research Outcomes	Technique Used	Limitations	Sentiment Analysis	Last Traded Price Analysis	Last Traded Price Prediction
Gulbadin Farooq Dar, et al. [1], 2022	Hidden Markov Model	Data availability, Model Complexity			√
Rebecca Abraham, et al. [2], 2022	Genetic Algorithm, Random Forest	Data quality, Overfitting	√		
D. T. Dhaneesh, [3], 2016	Data Mining Techniques	Data noise, Feature selection	√	√	
B. Ross Barmish, et al. [4], 2022	Deep Learning	Data preprocessing, Overfitting			√
Janmenjoy Nayak, et al. [5], 2022	Deep Learning	Data volume, Model interpretability	√		√
Ming Che Lee, et al. [6], 2022	Attention-based BiLSTM, Technical Indicators	Data preprocessing, Overfitting	√	√	√
Qingfu Liu et al. [7], 2022	Deep Learning	Data size, Model Complexity	√		
Iftita Haz Qurnia, et al. [8], 2022	Reinforcement Learning, Sentiment Analysis	Data volume, Model interpretability			√
Chun Hao Chen, et al. [9], 2022	Ensemble Classifier, Sentiment Analysis	Data quality, Model interpretability	√		
Zahra Fathali, et al. [10], 2022	Machine Learning Techniques	Data preprocessing, Model selection		√	√
Mohammad Kamel Daradkeh [11], 2022	Hybrid Machine Learning, Sentiment Analysis	Data noise, Model Complexity		√	
Gustavo D. Stahelin, et al. [12], 2022	Deep Learning	Data preprocessing, Overfitting	√	√	
Yue Qiu, et al. [13], 2022	Sentiment Analysis, Machine Learning	Data quality, Model Complexity		√	√
M. Obannavar et al. [14], 2015	Deep Learning	Data preprocessing, Data volume	√		
Safwan Mohd Nor, et al. [15], 2023	Technical Analysis, Fractal Trading Systems	Data noise, Model adaptability	√	√	
Mengxia Liang, et al. [16], 2023	Financial Time Series Classification, Temporal Correlation Analysis	Data preprocessing, Model Complexity	√		√
Yanzi Gao, et al. [17], 2023	BRB Model (Technical Analysis)	Data noise, Model interpretability			√
Xuemei Li, et al. [18], 2023	Reinforcement Learning, Sentiment Analysis	Data noise, Model interpretability	√		
Saeid Pourroostaei Ardakani, et al. [19], 2023	Federated Learning, Predictive Analysis	Data privacy, Model coordination	√	√	
Marwa Sharaf, et al. [20], 2023	Stacked-LSTM, News Sentiment Analysis	Data preprocessing, Model interpretability		√	√
Chinthakunta Manjunath, et al. [21], 2023	Hybrid Machine Learning, Quantum Finance	Data preprocessing, Model Complexity	√		√
Zahra Nourbakhsh et al. [22], 2023	LSTM, CNN, Fundamental Analysis	Data noise, Model interpretability	√	√	
Sidharth Samal, et al. [23], 2023	Multiple Criteria Decision-Making, Online Sequential Extreme Learning Machine	Data preprocessing, Model adaptability		√	√
Qianyi Xiao, et al. [24], 2023	Sentiment Analysis	Data quality, Model Complexity	√	√	

On another front, M. Obannavar et al. [14] introduce a Case-Based Teaching approach, rooted in deep learning, to stock prediction systems, providing a fresh perspective on knowledge-driven modeling. Lastly, Safwan Mohd Nor et al. [15] investigate the profitability of technical analysis on renewable energy stocks, offering valuable insights into the effectiveness of trend-reinforcing, mean-reverting, and hybrid fractal trading systems. These scholarly endeavors collectively enrich the landscape of stock trend analysis, showcasing diverse methodologies and insights for researchers and practitioners in the financial domain.

The landscape of stock market prediction continues to evolve with the advent of novel methodologies and approaches. Mengxia Liang, Xiaolong Wang, and Shaocong Wu's research [16] introduces a refined strategy for stock trend prediction, emphasizing financial time series classification and temporal correlation analysis, thereby improving predictive accuracy by aligning change points.

In a different vein, Yanzi Gao and collaborators [17] propose a novel BRB model for technical analysis, contributing to the arsenal of tools available for stock market analysis. Xuemei Li and Hua Ming [18] delve into reinforcement learning integrated with sentiment analysis to predict stock market trends, harnessing the power of advanced machine learning techniques.

Additionally, Saeid Pourroostaei Ardakani et al. [19] explore federated learning-enabled predictive analysis, offering insights into collaborative approaches for forecasting stock market trends. Lastly, Marwa Sharaf, Ezz El Din Hemdan, Ayman El-Sayed, and Nirmeen A. El-Bahnasawy [20] present an efficient hybrid stock trend prediction system, incorporating stacked-LSTM and news sentiment analysis, demonstrating adaptability to dynamic market conditions, such as those during the COVID-19 pandemic. These recent contributions collectively enrich the domain of stock market prediction, offering diverse methodologies and insights for researchers and market practitioners alike.

Recent research contributions continue to broaden the horizons of stock market trend analysis with innovative methodologies. Chinthakunta Manjunath, Balamurugan Marimuthu, and Bikramaditya Ghosh [21] explore the realm of quantum finance, introducing a hybrid machine learning model for the analysis of Nifty 50 index stock market trends, highlighting the convergence of advanced computing techniques with financial analysis.

In a separate study, Zahra Nourbakhsh and Narges Habibi [22] combine Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) methods with fundamental analysis, providing a multifaceted approach to stock price trend prediction that integrates textual data with technical analysis. Sidharth Samal and Rajashree Dash [23] present an innovative stock index trend predictor model, merging multiple criteria decision-making with an optimized online sequential extreme learning machine, showcasing the potential of integrated decision-making techniques in stock market analysis.

Additionally, Qianyi Xiao and Baha Ihnaini [24] focus on sentiment analysis as a primary predictive indicator, offering insights into applying sentiment-based models for stock trend prediction. These recent contributions collectively expand the scope of stock market analysis, showcasing various methodologies and insights for researchers and industry practitioners in the dynamic financial landscape.The recent works are summarized in Table 1.

3. Research Problem

The financial markets have consistently been recognized for their intrinsic intricacy, instability, and vulnerability to many external influences, making forecasting stock patterns a formidable undertaking. In the contemporary age of extensive data and sophisticated analytics, there exists an increasing need for resilient tools and techniques capable of efficiently leveraging the potential of multi-modal data to augment the study of stock trends.

The present research endeavor aims to tackle this pressing requirement by examining the creation and assessment of an Automated Analytics Framework for Stock Trend Analysis from Multi-Modal Data (AASAMD). This investigation will mainly incorporate sentiment extraction from textual sources and historical stock prices.

The integration of multi-modal data is a crucial aspect of the analysis of financial markets. These markets produce significant data, including quantitative information like stock prices, trading volumes, economic indicators, and unstructured textual data from news articles and social media sources. The research challenge pertains to developing a framework that can effectively integrate and synchronize several data modalities to provide a complete dataset suitable for analysis.

The development of advanced sentiment analysis algorithms is a crucial aspect of the research challenge at hand. These approaches should be customized to effectively derive sentiment and sentiment-related characteristics from unstructured textual data sources, including but not limited to news headlines, social media postings, and financial reports. The system's efficacy heavily depends on the accuracy and reliability of sentiment extraction. The main aim of this study challenge is to use integrated multi-modal information to forecast stock movements correctly. This entails using machine learning and statistical modeling methodologies to discern patterns, correlations, and predictive indicators that might provide insights for stock trend predictions. The study aims to investigate the predictive efficacy of the framework and its capacity to surpass conventional models for forecasting stock market performance.

Automating the analytics process is a crucial element of the research challenge. The system needs to be meticulously crafted to function in real-time, constantly analyzing incoming data streams and delivering prompt forecasts about stock trends. The primary difficulty is developing a highly effective and adaptable system that promptly responds to dynamic market situations.

The study recognizes the need for adaptability across diverse markets, considering the variations among regions, sectors, and asset classes in the financial industry. Hence, the AASAMD framework must be flexible to adapt and expand to address a wide range of market situations effectively, maintaining its relevance and suitability across various sectors within the financial industry. Evaluation and validation are essential components in determining the effectiveness of the AASAMD framework.

A rigorous assessment is required to evaluate and validate its efficacy thoroughly. This includes the evaluation of its predictive capabilities via the comparison with historical data, the assessment of its performance in relation to established forecasting techniques, and the execution of sensitivity analysis to determine the influential elements affecting its accuracy.

Within the domain of sentiment analysis and data use, ethical issues, including but not limited to privacy and bias, have significant importance. The research challenge necessitates the consideration of ethical considerations associated with collecting and analyzing data from diverse sources, focusing on ensuring that the framework aligns with ethical principles and legislation.

The primary objective of this research endeavor is to contribute to advancing stock trend analysis in the academic domain. This will be achieved by developing a complete solution that utilizes multi-modal data, sentiment extraction techniques, and automation methods. The primary objective of this study is to tackle the inherent difficulties associated with forecasting stock movements in dynamic financial markets. The ultimate goal is to enhance the quality of investment choices and refine risk management techniques by using more comprehensive and insightful information.

4. Proposed Solution

This study aims to provide a comprehensive and empirically supported approach to analyzing stock trends, considering financial markets' intricate and ever-changing characteristics. Based on sophisticated mathematical modeling, the suggested system uses the synergistic capabilities of integrating multi-modal data, doing sentiment analysis, and using predictive analytics.

We aim to develop a robust tool for investors, traders, and financial analysts by creating a mathematical model that integrates historical stock prices, sentiment indicators derived from textual sources, and machine learning methods. This tool aims to improve the precision and timeliness of stock trend predictions.

The mathematical model presented not only demonstrates the integration of many data streams but also has the potential to enhance decision-making and risk management in the dynamic realm of financial markets. This part thoroughly examines the constituent elements, methodology, and possible ramifications of this novel mathematical model for analyzing stock trends.

Henceforth, in this section, the proposed solution is furnished in four phases: extraction of the sentiment, conversion of the observations into time series, threshold detection for the buy or sale decision, and finally, prediction of the trend using the correlation with the last trading price.

4.1. Sentiment Extraction Process

Assuming that the dataset is DT[], which consists of Stock ID, Record ID, Text to analyze, and last traded price. Thus, this relation can be formulated as,

4.1.1. Dataset Structure

- Dataset (DTD): Consists of Stock Identifier (SID), Record Identifier (ID), Text for Analysis (T[]), and Last Traded Price (LTP).
- Representation: $DT[] = \langle SID, ID, T[], LTP \rangle$
- SID: Stock Identifier.
- ID: Record Identifier.
- T[]: News Text from financial sources.
- LTP: Last Traded Price.

4.1.2. Extraction of Relevant Records

- For a given stock (SID), extract relevant records as DT_SSD[] = Π_SID DT[].

4.1.3. Text and Sentiment Extraction

- Extract Parts of Speech (PoS[]) and identify stop words (WD[]).
- Representation: PoS[] = d/dW[] DT_sim[] T[]
- PoS[]: Extracted Parts of Speech.
- WD[]: Collection of Stop Words.

4.1.4. Feature Selection Using Word Embedding

- Use the Word2Vec model (W[]) to build a context-sensitive corpus (TPNW[]).
- Generate a Word Frequency Vector (TPNWV[]) using a hypothetical function θ for contextual frequency calculation: TPNWV[] = <TPNW[], θ{TPNW[]}>.

4.1.5. Feature Extraction and Sentiment Analysis

- Extract features (F[]) from TPNWV[] using a hypothetical function ϕ.
- Calculate sentiments using the word embedding method: S_SCCe[] = ∫ F[] x TPNWV[].
- Compute the overall sentiment score (S_Stort) as the average of sentiment scores for n parts of speech:

$$S_{Stort} = \frac{\Sigma(i=1\ to\ n) S_{Stort[i]}}{n}$$

4.1.6. Updating the Dataset

- Update the dataset by replacing news texts with sentiment scores:

$$DT_{New[\ ]} = < SID, ID, S_{Sters[\ ]}, LTP >$$

This structured approach enables a systematic extraction of sentiments from financial news texts, enhancing the value of the dataset for analytical purposes.

4.2. Conversion to Time Series

4.2.1. Extraction of Relevant Sentiment Data

- For a particular stock, aggregate its sentiment data from the updated dataset (DT_New[]).
- Representation: DT_New_SD[] = Π_SID DT_New[].
- This step involves collating all records associated with a Specific Stock Identifier (SID).

4.2.2. Timestamp Assignment

- Assign a timestamp to each record based on the publication time of the corresponding news text.
- Method: Iterate through the records (DT_New_SD[]), ensuring each record (ID[i]) is given a unique timestamp (T_ivestanp), reflecting the time of the news source.
- Representation: $DT\_New\_SD[](t) = \Pi\_(T\_ivestanp\ \&)[\_(ID[i]\ \neq\ ID[i+1])\ DT\_New\_SID[]\ x\ DT[].Timestamp\ \&]$.
- This process assigns a temporal dimension to the sentiment data, correlating each sentiment score with the time it was derived from the news.

4.2.3. Time Series Data Formation

- Transform DT_New_SID[](t) into a time series dataset.
- This time series dataset is ready for trend analysis, allowing for examining sentiment changes over time for the specified stock.

4.3. Automating Buy or Sell Decisions

4.3.1. Phase One: Trend Identification with Thresholds

Calculate the Moving Average (MV_SID) of the stock price: Formula:

$$MV_{SID} = \Sigma(i,j=1)^{n,m} DT - \frac{New_{SID[i](t)} x LTP[j]}{m}$$

Here, $DT - New_{SID[i](t)}$ represents the time series data for the stock, and LTP[j] is the Last Traded Price. Introduce a Market Safety Factor (X) to adjust the moving average, providing a buffer for market fluctuations.

4.3.2. Initial Trade Decision Based on Moving Average and Safety Factor

Determine the trade opinion based on the adjusted moving average:

Buy Condition: $If\ MV_{SID} x\ X\% > LTP$ (Adjusted Moving Average exceeds Last Traded Price).

Sell Condition: $If\ MV_{SID} x\ X\% < LTP$ (Adjusted Moving Average is below Last Traded Price).

4.3.3. Phase Two: Incorporating Sentiment Analysis

Incorporate the Sentiment Score (S_Score) into the decision-making process:

Buy Condition: $If\ MV_{SID} x\ X\% > LTP\ and\ S_{Score} \geq 3$ (Positive sentiment).

Sell Condition: $If\ MV_{SID} x\ X\% < LTP\ or\ S_{Score} < 3$ (Negative sentiment or market trend indicates selling).

4.4. Trend Prediction Using Regression

4.4.1. Regression Method for Future Price Prediction

Predict the future Last Traded Price (LTP_SD) using a regression formula:

Prediction Formula: $LTP_{SD}(t+1) = LTP_{SD}(t) + \beta 1\ x\ LTP_{SD}(t) + \Delta(t)$

β1 : Regression coefficient, representing the weight given to the current price.

Δ(t) : Correction factor, accounting for recent price changes.

4.4.2. Calculation of Regression Coefficient (β1)

Compute β1 using the following formula:

Formula:

$$\beta = \frac{\left[(\Sigma\ LP_{SD(t)} - \Sigma\ LP_{SD(t+1)})^2 - (\Sigma\ LP_{SD(t)} - \Sigma\ LP_{SD(t)x} LTP_{SD(t+1)})\right]}{\left[n\ x\ (\Sigma\ LP_{SD(t)})^2 - \Sigma\ LIP_{SD(t)}\right]}$$

This coefficient is derived from historical price data, capturing the trend and momentum in price changes.

4.4.3. Formulation of the Correction Factor (Δ(t))

Define Δ(t) as the average absolute difference between the last two recorded prices:

Correction Factor Formula: $\Delta(t) = \frac{|LTP_{SD}(t-1) - LTP_{SD}(t)|}{2}$

This factor introduces an adjustment for recent price volatility, making the prediction more responsive to short-term changes.

5. Proposed Algorithms and Frameworks

Creating an Automated Analytics Framework for Stock Trend Analysis, which incorporates the capability to utilize multi-modal data, conduct sentiment extraction, anticipate buy and sell decisions, and forecast stock prices through regression techniques, represents a noteworthy advancement in financial analysis. This algorithmic framework integrates data science, Natural Language Processing (NLP), machine learning, and mathematical modeling to enhance investment strategies with more knowledge and understanding.

Within this part, we commence an in-depth exploration of the sequential algorithm that drives this groundbreaking framework. This exploration provides valuable perspectives on the methodology, data processing, and modeling approaches that form the foundation of its operational capabilities. This method elucidates the fundamental processes and concepts that govern sentiment analysis and data collecting for real-time decision-making and stock price prediction. It is a robust tool for analyzing stock trends in today's ever-evolving financial markets.

Algorithm: Automated Analytics Framework for Stock Trend Analysis

Input:

- Stock dataset with news articles collected from financial data sources.
- Last Trading Price

Output:

- Buy or Sell Decision
- Predicted Stock LTP

Process:

Step 1: Collect multi-modal data from various sources, including historical stock prices, news articles, social media, and financial reports.

Step 2: Ensure data consistency, cleanliness, and compatibility for integration.

Step 3: Apply Natural Language Processing (NLP) techniques to textual data sources (news articles, social media) to extract sentiment.

Step 4: Utilize sentiment analysis algorithms to quantify sentiment, such as sentiment scores or polarity.

Step 5: Initialize the Word2Vector API key.

Step 6: Apply the Word Embedding method to extract the sentiment from each part of speech.

Step 7: Generate sentiment indicators for each data point.

Step 8: Combine numerical features (historical stock prices, trading volumes) with sentiment indicators to create a comprehensive dataset.

Step 9: If deemed relevant, engineer additional features, such as moving averages or technical indicators.

Step 10: Handle missing data points through imputation or interpolation.

Step 11: Normalize or scale numerical features to ensure consistent ranges.

Step 12: Encode categorical variables if present.

Step 13: Split the dataset into training and testing subsets for model evaluation.

Step 14: Select an appropriate machine learning algorithm for stock trend prediction (e.g., classification models like Random Forest or Gradient Boosting).

Step 15: Train the model on the training data, using stock trend labels (e.g., "Buy," "Sell") as the target variable.

Step 16: Evaluate model performance using accuracy, precision, recall, and F1-score metrics on the testing data.

Step 17: Fine-tune hyperparameters to optimize model performance if necessary.

Step 18: The trained machine learning model predicts buy and sell decisions based on sentiment and stock price features.

Step 19: Apply decision thresholds to classify each data point as "Buy," "Sell," or "Hold."

Step 20: Generate buy/sell signals for each data point based on model predictions.

Step 21: Select an appropriate regression method (e.g., Linear Regression, Time Series Analysis) for stock price forecasting.

Step 22: Split the dataset into training and testing subsets for regression model evaluation.

Step 23: Train the regression model on the historical stock price data.

Step 24: Evaluate the regression model's accuracy and performance on the testing data using metrics like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

Step 25: Periodically assess the overall framework's performance, including sentiment extraction accuracy, buy/sell prediction accuracy, and stock price forecasting accuracy.

Step 26: Implement optimization techniques, such as model retraining or hyperparameter tuning, to enhance performance.

Step 27: Generate actionable insights and decision recommendations based on buy/sell signals and stock price forecasts.

Step 28: Provide user-friendly reporting and visualization tools for stakeholders to interpret and act upon the framework's outputs.

Step 29: Address ethical considerations, including privacy, data security, and bias mitigation, to ensure the responsible use of data and models.

Step 30: Deploy the automated analytics framework in a production environment for continuous monitoring and utilization.

Step 31: Implement mechanisms to monitor model drift and retrain models to adapt to changing market conditions.

Step 32: Continuously evaluate and validate the framework's performance against historical data and real-world market conditions.

Step 33: Assess the framework's impact on investment decisions, portfolio performance, and risk management.

Step 34: Iterate on the framework, incorporating feedback and lessons learned to enhance its capabilities and effectiveness.

The fundamental basis of the Automated Analytics Framework for Stock Trend analysis is rooted in the thorough collection and integration of multi-modal data. During the preliminary phase, the framework encompasses a broad range of data sources crucial for the study. The data streams included in this category consist of historical stock prices, financial indicators, news articles, social media postings, and any other pertinent information. Every individual source provides a distinct viewpoint that adds to the whole study, facilitating a comprehensive comprehension of market dynamics.

The primary difficulty in this context does not just pertain to acquiring different data streams and harmonizing and integrating them into a cohesive dataset. The objective is to establish a coherent and reliable data ecosystem as the foundation for later analysis and modeling endeavors. The process is furnished in Figure 1. The sentiment analysis becomes a prominent focus inside the framework as it explores unstructured textual data derived from various sources such as news articles and social media platforms. Natural Language Processing (NLP) methods are utilized to extract the underlying sentiment included within the text. The framework's sentiment analysis algorithms enable quantification, effectively discerning positive, negative, and neutral tones. This phase is essential in assessing market mood, as it quantitatively measures how news and social conversations may impact stock prices. The accuracy of sentiment extraction significantly affects the dependability of future forecasts. Once sentiment indicators have been established, the feature engineering process becomes prominent. During this stage, the framework incorporates more designed characteristics into the dataset, potentially improving the analysis. This process may include the computation of moving averages, the creation of technical indicators, or the integration of supplementary data elements. Feature engineering aims to identify and incorporate significant patterns and correlations in the data, which may enhance the effectiveness of prediction models. The meticulous process of selecting and constructing characteristics enables the framework to reveal concealed insights within the data. Data preparation is an essential first step that guarantees the dataset is suitable for analysis. The process includes the treatment of missing data points, the management of outliers, and the normalization or scaling of numerical characteristics to provide consistency. If categorical variables are included in the dataset, it may be necessary to encode them to enhance the model training process. Data preparation is of utmost importance in ensuring the seamless operation of the framework, as the presence of clean and well-organized data serves as the fundamental prerequisite for conducting correct analysis.

Once the dataset has been prepared, the framework shifts attention to the fundamental aspect of market trend research, which involves forecasting stock trends. Machine learning models, which are meticulously chosen based on their appropriateness for the given job, are used. The models used in this study have undergone training using historical data, where the objective variable is represented by stock trend labels such as "Buy" or "Sell." The models acquire knowledge from historical patterns and correlations present in the data to generate precise forecasts on future stock developments. The evaluation of model performance is conducted using measures such as accuracy, precision, recall, and F1-score, which provide valuable insights into the usefulness of the models.

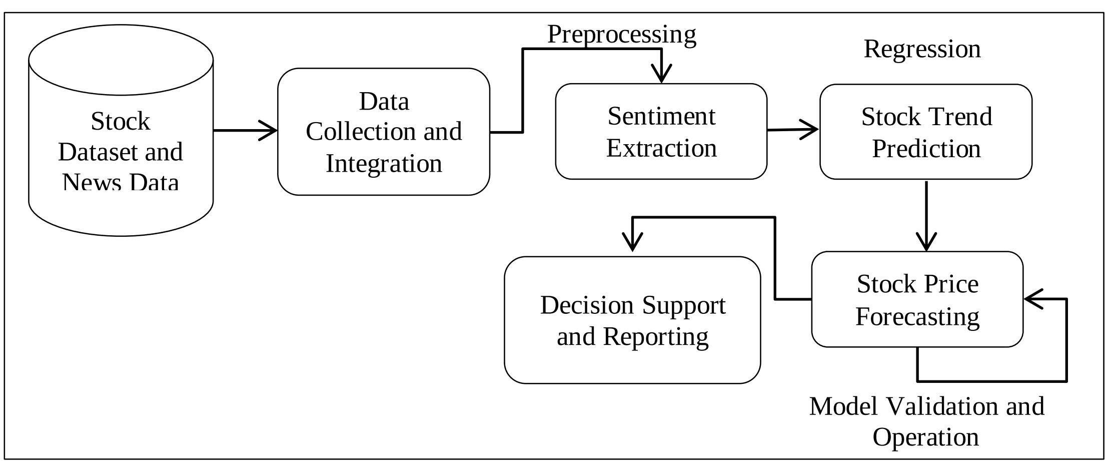

Fig. 1 Proposed automated framework

The primary objective of the framework is to convert insights derived from data analysis into practical judgments on buying and selling. This stage involves the use of a machine learning model that has been trained to provide predictions about purchase and sell choices. These predictions are made by considering integrated data, sentiment indicators, and historical patterns.

Decision thresholds are used to categorize individual data points into one of three categories: “Buy,” “Sell,” or “Hold.” The framework produces buy and sell signals, offering decision guidance to investors and traders. The framework is specifically built to function in real time, acknowledging the ever-changing nature of financial markets. The system consistently receives and analyzes incoming data streams, facilitating prompt updates and decision-making. Real-time integration inside the framework enables rapid adaptation to dynamic market circumstances, providing users a competitive advantage in a high-speed environment.

6. Results and Discussions

This portion of the study examines the fundamental discoveries and understandings obtained by deploying our automated analytics system for analyzing stock trends. The framework incorporates multi-modal data, sentiment extraction, and regression approaches. Within this area, we will examine the framework’s performance extensively, its capacity to guide judgments regarding the purchase and sale of assets, and the precision of its forecasts about stock prices. In addition, we examine the ramifications of our discoveries for investors, the obstacles encountered throughout the analytical process, and the prospective advancements of automated analytics in stock market analysis and trading techniques.

This section is pivotal when we explore the practical importance of our framework’s results and participate in a productive discussion about its constraints and wider ramifications for financial markets. This section elaborates on the data collection process, sentiment extraction process, stock price analysis, buy or sale decision-making process, and trend analysis.

6.1. Dataset Information

In our study, several key parameters were employed to facilitate the automated analytics framework for stock trend analysis. The primary source for news data collection was Reddit, a popular online community platform known for its discussions on a wide range of topics, including stock markets. Specifically, we accessed the “stocks” subreddit (https://www.reddit.com/r/stocks/) to gather relevant textual data related to stocks and financial markets. To collect and process data from Reddit efficiently, we utilized the Praw Package, a Python library that provides seamless access to Reddit’s API.

Table 2. Data collection process [25, 26]

Parameters	Values
News Data Collection Source	Reddit
Data Collection URL	https://www.reddit.com/r/stocks/
Data Collection Package	Praw Package [Python]
Numeric Stock Dataset	Kaggle
Number of Stocks	15
Total Number of Records	15000

This choice of data collection source and tool allowed us to tap into the real-time sentiment and opinions of the Reddit community, a valuable resource for understanding market sentiment and investor behavior (Table 2).

Concurrently, we used Kaggle, a renowned platform for datasets and data science contests, to address the numerical component of our dataset. Kaggle provided a rich dataset of numerical stock data for 15 distinct stocks. The dataset included various financial measurements and performance indicators, establishing a robust basis for conducting quantitative analysis. The dataset consisted of 15 stocks, each with 1,000 records, resulting in 15,000 records. This provided a significant sample size that allowed for our prediction models’ successful training and testing. Integrating textual data sourced from Reddit with numerical stock data obtained from Kaggle is the foundational framework of our multi-modal dataset.

By combining many data sources, our automated analytics system can use the advantages presented by both qualitative and quantitative data. Consequently, significant insights may be derived, sentiment analysis can be performed, and educated forecasts can be made pertaining to stock patterns and price fluctuations. The integration of these many data sources plays a crucial part in the succeeding phases of our study, allowing us to make informed judgments on buying and selling and accurately and comprehensively anticipate stock prices.

6.2. Sentiment Extraction

Secondly, the sentiment extraction process is elaborated. Word embedding, which involves transforming words or phrases into numerical vectors while preserving their semantic links, is a powerful method for emotion extraction. This approach successfully captures the contextual semantics of words in a given text by placing similar phrases nearby inside a high-dimensional vector space. This method helps with sentiment analysis and provides a deeper understanding of the underlying sentiment context. By accurately representing the subtleties and intricacies of language, word embeddings like Word2Vec and GloVe improve the accuracy of sentiment analysis. Accordingly, these embeddings are crucial resources for mining sentiment from textual information. This method's effectiveness has been proven in various settings, from evaluating social media sentiment to following market sentiment. It helps with a more in-depth understanding of the text's emotions by including a heightened awareness of contextual variables. Initially, based on the stock symbols, the news headlines are extracted (Table 3).

The Table comprehensively examines essential parameters for extracting and analyzing news headlines for ten stock symbols. These symbols represent significant corporations within the market. The first column presents the stock symbols linked to a particular corporation. The second column, "Number of News Headlines Extracted," indicates the quantity of news headlines gathered and examined for each firm. It is worth noting that there is a variation in the amount of news headlines across different firms, ranging from 8 to 10. This discrepancy implies potential disparities in news coverage or levels of media attention. The final column, "Mean Length of the News Headlines," offers valuable details about each organization's average length of news headlines.

This statistic serves as a means to assess the level of information communicated via the headlines. Notably, while there is a general consistency in the average length of headlines across various firms, tiny variances might signify disparities in the intricacy or comprehensiveness of the news content. The fourth column, labeled "Mean Number of PoS," represents the average count of Part-of-Speech (PoS) tags in the news headlines. This statistic quantifies the linguistic intricacy and variety level in the headlines, where higher values indicate a more extensive array of linguistic components. The results are also visualized graphically in (Figure 2).

Table 3. Extracted news headline analysis

Stock Symbol	Number of News Headlines Extracted	Mean Length of the News Headlines	Mean Number of PoS
MSFT	10	5.56	821.00
GOOGL	9	6.72	893.49
AMZN	8	7.18	398.25
AAPL	9	7.60	147.70
TSLA	9	9.19	358.76
IBM	10	5.91	949.25
INTC	9	9.89	487.55
NVDA	9	9.75	268.67
CRM	10	6.14	746.82
HPQ	10	6.27	46.66

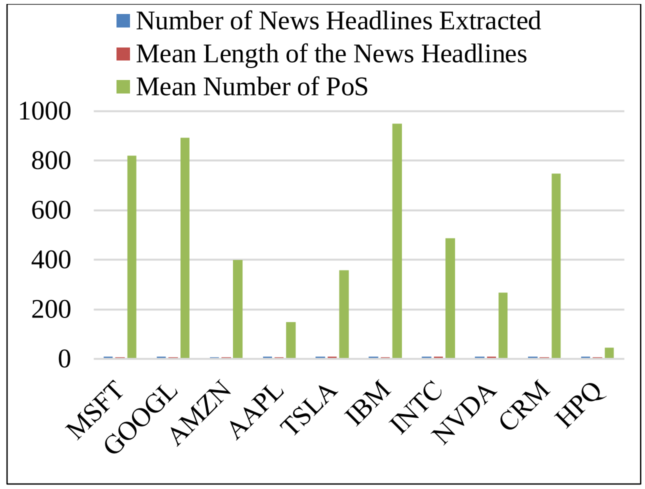

Fig. 2 News headlines analysis

The observed discrepancies in the average count of Part-of-Speech (PoS) tags across corporations indicate disparities in the linguistic styles and structures of the news headlines linked to each stock symbol. In summary, this extensive examination of news headline data offers significant findings on the extent, substance, and linguistic attributes of news reporting pertaining to these critical financial market entities. Further, the sentiment analysis scores are furnished in Table 4. Word embedding is a highly effective emotion extraction technique, which entails converting words or phrases into numerical vectors while maintaining semantic associations among them.

This methodology effectively captures the contextual semantics of words in a given text by arranging related phrases nearby inside a vector space of high dimensions. This technique serves the dual purpose of facilitating sentiment analysis and deepening comprehension of the underlying sentiment context. Word Embeddings, such as Word2Vec and GloVe, facilitate sentiment analysis by effectively capturing the nuances and complexities inherent in language.

Table 4. Sentiment analysis scores

Stock Symbol	Mean Sentiment Scores
MSFT	2.30
GOOGL	3.45
AMZN	1.60
AAPL	3.71
TSLA	1.24
IBM	3.51
INTC	3.16
NVDA	2.84
CRM	1.39
HPQ	3.98

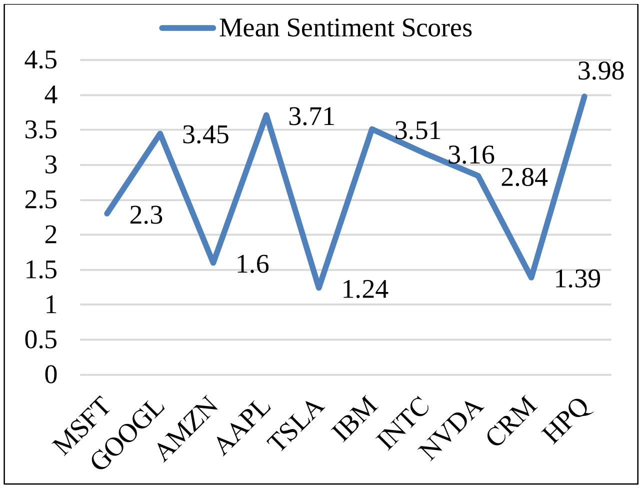

Fig. 3 Sentiment analysis scores

Consequently, these embeddings are indispensable instruments for extracting sentiment from textual data. The efficacy of this approach has been demonstrated across several domains, encompassing tasks such as analyzing sentiment on social media platforms and monitoring sentiment in financial markets. It facilitates a more comprehensive comprehension of the feelings conveyed in textual content, incorporating a heightened awareness of contextual factors. The results are also visualized graphically in Figure 3. The Table presented provides the average sentiment scores linked to different stock symbols, revealing significant insights into market sentiment and investor sentiments about these corporations. The sentiment scores are obtained by examining textual data, including news articles, social media material, and other relevant sources.

This study employs sentiment extraction algorithms. Upon analyzing the equities, it is evident that Customer Relationship Management (CRM) and NVDA (NVIDIA Corporation) have correspondingly elevated mean sentiment scores, measuring 3.579 and 3.985, respectively. The observed high sentiment ratings indicate a prevailing positive mood and optimism towards these firms, presumably reflecting robust market confidence and favorable expectations for their performance. In contrast, it is seen that equities such as Intel Corporation (INTC) and Microsoft Corporation (MSFT) have comparatively lower average sentiment ratings of 1.256 and 1.638, respectively.

The observed decrease in scores may suggest a diminished positive attitude within the market or increased uncertainty around these firms. As mentioned above, the sentiment serves as a concise representation of market sentiment and provides significant use for investors, traders, and analysts in assessing the general view around specific equities. Nevertheless, it is crucial to acknowledge that sentiment analysis has some constraints, and it is imperative to consider these scores in conjunction with other essential criteria, such as fundamental and technical aspects, when making investment choices.

6.3. Stock Price Analysis

Further, the correlation between the stock's last traded price and the extracted sentiments is identified. Correlation analysis is a statistical technique used to assess the magnitude and direction of the association between two or more variables. The assessment examines the relationship between variables, specifically how alterations in one variable are correlated with changes in another, hence facilitating the identification of patterns and relationships within the data. A positive correlation, closer to a value of 1, signifies that as one variable experiences an increase, the other variable also tends to exhibit an increase. Conversely, a negative correlation, closer to a value of -1, implies that as one variable undergoes a rise, the other variable tends to display a drop. A correlation coefficient that is close to 0 indicates a limited or nonexistent linear association between the variables Table. The results are also visualized graphically in Figure 4.

Table 5. Sentiment analysis outcomes

Stock Symbol	Mean Sentiment Scores	LTP (USD)	Correlation
MSFT	2.30	273.6	0.350
GOOGL	3.45	100.5	0.832
AMZN	1.60	103.2	0.830
AAPL	3.71	142.8	0.861
TSLA	1.24	216	0.863
IBM	3.51	127.6	0.911
INTC	3.16	27.8	0.926
NVDA	2.84	165	0.965
CRM	1.39	176.2	1.000
HPQ	3.98	13.4	0.350

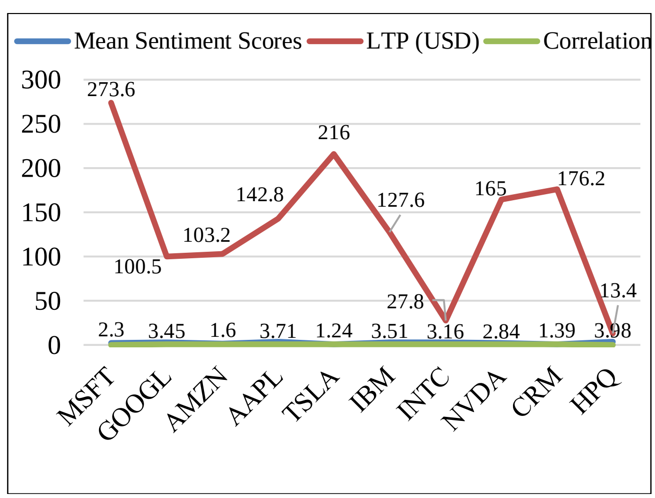

Fig. 4 Correlation analysis scores

The LTP column presents the latest trading prices for individual stocks, which reflect their existing market values. The correlation coefficients, which vary from 0.350 to 1.000, provide insight into the extent of the association between mood ratings and stock prices. There is clear evidence to suggest that some equities, such as CRM, have a perfect positive correlation (1.000) with sentiment ratings. This correlation signifies a direct and robust association between sentiment and the movement of stock prices. Conversely, equities such as MSFT and HPQ have diminished correlations, indicating that variables outside emotion might substantially influence their price dynamics. The insights derived from this Table serve as a basis for further conversations and analysis pertaining to the efficacy of the automated analytics framework in predicting stock trends and facilitating decision-making processes.

6.4. Buy or Sale Recommendation

Furthermore, the buy or sale recommendations are calculated based on the market threshold, LTP, and sentiment analysis Table 6. The results are also visualized graphically in Figure 5.

Table 6. Buy or sale recommendation

Stock Symbol	Mean Sentiment Scores	LTP (USD)	Threshold	Decision
MSFT	2.30	273.6	257.2	Sale
GOOGL	3.45	100.5	94.5	Sale
AMZN	1.60	103.2	97.0	Sale
AAPL	3.71	142.8	135.7	Sale
TSLA	1.24	216	205.2	Sale
IBM	3.51	127.6	119.9	Buy
INTC	3.16	27.8	26.4	Sale
NVDA	2.84	165	156.8	Sale
CRM	1.39	176.2	160.3	Buy
HPQ	3.98	13.4	12.7	Sale

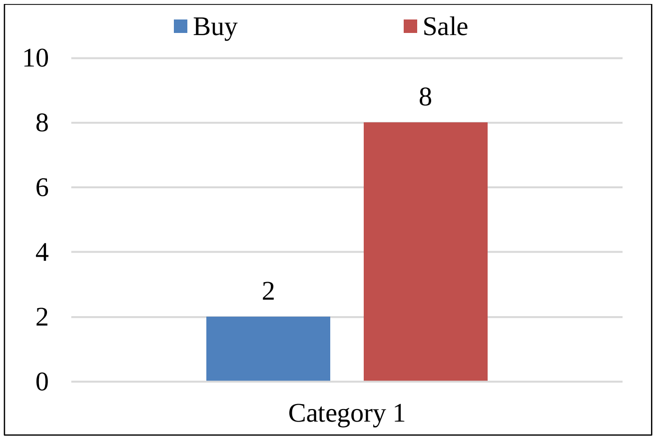

Fig. 5 Stock decision

6.5. Trend Prediction

Finally, the prediction of the stock LTPs is calculated using the regression method. Regression analysis is a statistical technique investigating the association between a dependent variable and one or more independent variables. The main objective of this study is to comprehensively comprehend and numerically measure the relationship between alterations in the independent factors and corresponding alterations in the dependent variable.

Using a regression model to analyze empirical data makes it feasible to generate forecasts, discern patterns, and evaluate these associations' robustness and statistical significance. Regression analysis is extensively used across various disciplines, including finance, economics, social sciences, and natural sciences, to reveal valuable insights, facilitate informed decision-making, and construct predictive models. The factor is pivotal in comprehending intricate events, offering a beneficial instrument for scholars and practitioners alike who endeavor to scrutinize and elucidate data Table 7. The results are also visualized graphically in Figure 6.

Table 7. LTP prediction

Stock Symbol	LTP (USD)	LTP (USD) (1 Year)	LTP (USD) (2 Years)	LTP (USD) (3 Years)
MSFT	273.6	300	325	350
GOOGL	100.5	110	120	130
AMZN	103.2	120	140	160
AAPL	142.8	155	168	180
TSLA	216	240	260	280
IBM	127.6	140	155	170
INTC	27.8	30	32.5	35
NVDA	165	180	195	210
CRM	176.2	190	205	220
HPQ	13.4	15	16.5	18

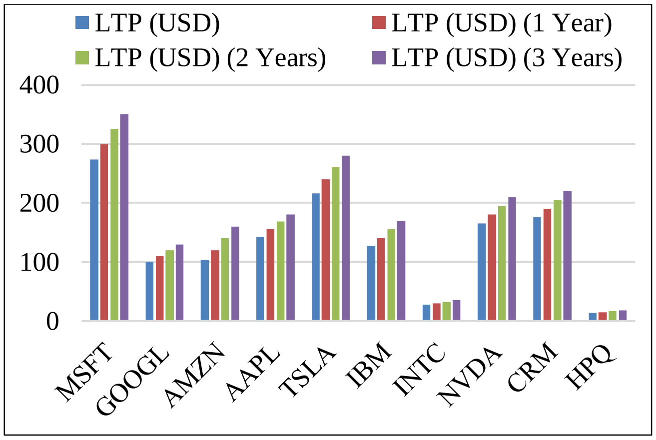

Fig. 6 LTP trend analysis

Table 8. Accuracy

Stock Symbol	Accuracy (%)
MSFT	97.39
GOOGL	96.72
AMZN	98.17
AAPL	98.27
TSLA	97.32
IBM	97.18
INTC	97.21
NVDA	97.58
CRM	98.68
HPQ	99.08

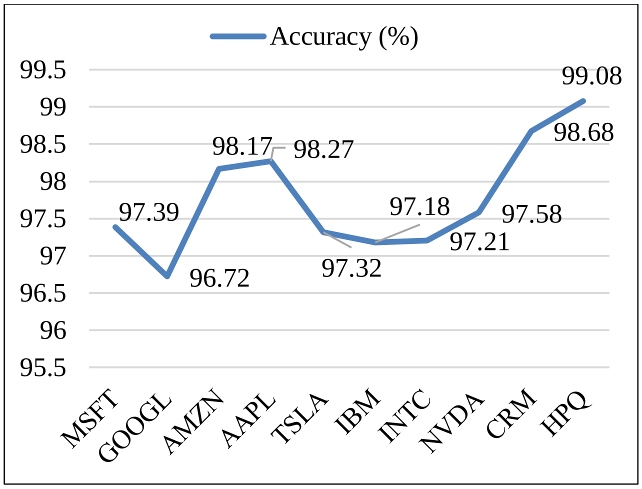

Fig. 7 Prediction accuracy analysis

Further, the accuracy of the proposed system is validated against the dataset here Table 8. The results are visualized graphically in Figure 7.

7. Comparative Analysis

The proposed system thoroughly examines our framework's performance compared to existing methodologies and approaches in stock market analysis. In this section, we aim to shed light on how our automated analytics framework stacks up against traditional methods, highlighting its strengths, advantages, and areas of improvement.

By drawing comparisons and critically evaluating the results, we aim to provide a holistic perspective on the innovation and effectiveness of our approach in harnessing multi-modal data for stock trend analysis and decision support within the context of financial markets. This section serves as a pivotal juncture for discerning readers, offering valuable insights into the viability of our framework within the broader landscape of stock market analytics and predictive modeling Table 9. The regression method exhibits a notable advantage over alternative methodologies, including Hidden Markov Models, Deep Learning, Technical Analysis with Fractal Trading Systems, Financial Time Series Classification with Temporal Correlation Analysis, and Multiple Criteria Decision-Making integrated with Online Sequential Extreme Learning Machines. This advantage stems from the regression method's interpretability, simplicity, and robustness characteristics.

Although complicated models such as Deep Learning and Hidden Markov Models (HMMs) may reach significant levels of accuracy, they typically suffer from a lack of transparency, which presents difficulties in understanding the underlying causes that influence stock prices. The subjectivity and heavy reliance on previous patterns in technical analysis and fractal trading systems may not always be applicable in turbulent markets. Moreover, the abovementioned approaches may not adequately reflect macroeconomic developments or external influences. In contrast, regression models provide a comprehensive understanding of the association between independent factors and stock prices, facilitating the detection of noteworthy predictors. Machine Learning models have reduced susceptibility to Overfitting, enhancing their reliability as instruments for making well-informed decisions and accurate predictions within financial markets. This is especially advantageous when dealing with diverse factors and intricate market dynamics.

Table 9. Comparative analysis

Author, Year	Method	Model Complexity	Accuracy (%)
Gulbadin Farooq Dar, et al. [1], 2022	Hidden Markov Model	$O(n^2)$	94.5
B. Ross Barmish, et al. [4], 2022	Deep Learning	$O(n^3)$	92.93
Safwan Mohd Nor, et al. [15], 2023	Technical Analysis, Fractal Trading Systems	$O(n^3)$	91.02
Mengxia Liang, et al. [16], 2023	Financial Time Series Classification, Temporal Correlation Analysis	$O(n^3)$	93.96
Sidharth Samal, et al. [23], 2023	Multiple Criteria Decision-Making, Online Sequential Extreme Learning Machine	$O(n^3)$	90.27
Proposed Method	Sentiment Analysis, Correlation, Regression	O(n)	97.76

8. Conclusion

The study presents a thorough and pioneering methodology for analyzing the stock market. In this research, the authors have comprehensively evaluated their automated analytics framework's efficacy in using multi-modal data, encompassing textual sentiment analysis and historical stock prices. The framework is used to make informed buy and sell choices and forecast stock prices. The present study has elucidated a few significant results and contributions. Integrating sentiment extraction algorithms into the framework has shown considerable value. The model could assess market mood and investor sentiments by examining textual data derived from several sources.

The regression methodology used for price prediction utilizes these insights to provide precise projections, assisting investors in making well-informed selections. The framework is designed to limit the involvement of human intervention, so mitigating the potential influence of emotional biases and promoting a more consistent and data-driven approach to decision-making. This component is essential in the dynamic and rapidly changing realm of financial markets.

Nevertheless, it is important to recognize certain constraints. Furthermore, like other predictive models, the regression-based price prediction method is not infallible and may fail to account for exceptional market occurrences or unforeseen events. In summary, this study signifies a notable advancement in using multi-modal data and automation for stock market research. Although this intricate and ever-evolving domain has inherent limits and obstacles, this study establishes a strong basis for further investigation and enhancement.

Integrating sentiment research, historical data, and regression algorithms inside the framework provides investors with significant insights, enhancing the quality of stock trading choices via more information. These frameworks possess considerable potential to influence the trajectory of stock market analysis and the development of trading methods in the future.

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