Enhancing Stock Market Forecasting Through a Service-Driven Approach: Microservice System

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***Abstract*—Predicting stock market is a difficult task that involves not just a knowledge of financial measures but also the ability to assess market patterns, investor sentiment, and macroeconomic factors that can affect the movement of stock prices. Traditional stock recommendation systems are built as monolithic applications, with all components closely coupled within a single codebase. While these systems are functional, yet they are difficult integrating several services and aggregating data from diverse sources due to their lack of scalability and extensibility. A service-driven approach is needed to manage the growing complexity, diversity, and speed of financial data processing. However, microservice architecture has become a useful solution across multiple sectors, particularly in stock systems. In this paper, we design and build a stock market forecasting system based on the microservice architecture that uses advanced analytical approaches such as machine learning, sentiment analysis, and technical analysis to anticipate stock prices and guide informed investing choices. The results demonstrate that the proposed system successfully integrates multiple financial analysis services while maintaining scalability and adaptability due to its microservice architecture. The system successfully retrieved financial metrics and calculated key technical indicators like RSI and MACD. Sentiment analysis detected positive sentiment in Saudi Aramco's Q3 2021 report, and the LSTM model achieved strong prediction results with an MAE of 0.26 and an MSE of 0.18.**

Keywords—Stock market; microservice architecture; deep learning; technical indicators; sentiment analysis

I. Introduction

Analyzing the stock market to predict the price movement of shares is of interest to investors and traders. There is an extensive variety of interrelated factors affecting the stock price, including microeconomic considerations and geopolitical developments [1, 2]. A study found that psychological factors such as investor emotion and behavioral biases had a considerable impact on share prices [3]. Traditional methods for predicting stock prices depend on statistical models and technical analysis [4]. However, they are unable to completely comprehend the complex interdependencies and behavioral patterns that are inherent in investor psychology and market dynamics [5]. Consequently, deep learning has become recognized as a highly efficient tool for deriving meaningful insights from extensive, complex datasets [6].

The financial markets are very volatile and process intensive data [8]. Hence, they require sophisticated systems that can handle huge datasets, run complex analyses, and give real-time insights that can be used. Most traditional stock recommendation systems, on the other hand, are built as monolithic applications, with all components closely coupled within a single codebase. While these systems are functional, yet they are difficult in scalability, maintainability, and extensibility [7].

Also, it is critical for investors and financial analysts to be able to forecast stock movement with precision, as they must make informed decisions in a constantly changing environment. Forecasting systems that rely on monolithic architectural structures are difficult to adapt to ever-changing markets. These systems focus on limited data inputs, like historical price data, while overlooking critical factors such as real-time sentiment analysis and technical indicators, which play a significant role in market behavior. To the best of our knowledge, current approaches struggle to combine diverse analytical methods—like machine learning, sentiment analysis, and fundamental analysis—into a unified, effective system. This may lead to inconsistent performance and a lack of flexibility when applied to dynamic and complex market conditions.

Microservice architecture is now widely adopted across various sectors. Microservice divides a large system into small, self-contained services that provide benefits such as improved scalability, greater flexibility, and error tolerance [9]. The development of stock systems based on a microservice architecture enables the integration of various analytical functions such as artificial intelligence, technical analysis, sentimental analysis, portfolio management, and risk assessment. Using this modular strategy, traders and investors may precisely adjust market circumstances to make better-informed decisions.

Thus, this study proposes the design and implementation of a stock recommendation system based on microservices that use specialized services to deliver informed stock recommendations. The system's goal is to enhance the precision and relevance of stock recommendations by operating machine learning algorithms, fundamental and technical analysis, and sentiment analysis of financial reports. This research extends the existing literature on financial systems by examining how microservices can improve the efficiency, scalability, and usefulness of generating stock recommendations.

The paper is organized as follows: a literature review is conducted in Section II. Section III demonstrates the methodology, including the proposed system. Sections IV and

V present the study's results and discussion. Section VI presents the research conclusion and future work.

II. Background and Related Work

A. Microservice Architecture

Microservice architecture is becoming an effective solution across multiple sectors, particularly in stock systems because it excels at managing complex, large-scale applications that demand scalability, maintainability, and flexibility. Microservices empower teams to develop, deploy, and scale each component independently, enhancing efficiency and innovation by breaking down a system into smaller and independent components. Each service is designed to handle a certain business function and communicates with other services through lightweight protocols, typically using APIs [10].

Microservices systems can significantly improve the efficiency and responsiveness of financial trading systems. The shift from a monolithic architecture to a micro-services-based approach enables developers to create independent services that satisfy certain requirements, improving scalability and maintainability. For instance, a microservice reference architecture based on domain engineering can address the high complexity and maintenance costs associated with large-scale financial trading systems by providing a general solution for similar scenarios, allowing new microservices to coexist with legacy systems and supporting rapid business development through DevOps and other mechanisms [11].

Microservices in power trading platforms also highlight their ability to enhance load performance and scalability, which are critical for the real-time and complex nature of stock trading [12]. Furthermore, microservices can be integrated with IoT technologies to create efficient inventory management systems and benefit stock systems by ensuring real-time data processing and business logic execution [13]. Implementing microservices architecture within ERP financial systems showcases their ability to address complex business demands with exceptional availability, security, and scalability, which are crucial for stock systems managing substantial amounts of data and transactions [14].

Adopting microservice architecture in stock recommendation systems may offer numerous benefits, including improved scalability, maintainability, and responsiveness. Thus, making it a valuable approach for modern financial trading platforms and related applications. The effective management of systems based on micro-services is vital for ensuring service quality across various microservice components, which is particularly important in stock systems where resource demands and quality of service requirements are high [15]. Integrating microservices with social-media messaging bots for automated inventory management further illustrates their versatility and potential for enhancing customer and retailer connectivity in stock systems [16]. Additionally, microservices can be applied to assess the impact of news on the stock market, which makes the system respond to news events, analyze them, and predict their effects on market trends. Thus, it provides valuable insights for traders and investors. Additionally, microservices in asset tracking systems, such as those based on indoor positioning systems, showcase their potential for real-time data processing and resource-efficient operations, which can be applied to stock systems for tracking and managing assets efficiently [17].

The potential implications of a booming stock market prediction system through deep learning algorithms services built on microservice architecture are essential. Accurate forecasting could inform investment decisions and contribute to risk management strategies, portfolio optimization, and the development of automated trading systems. Furthermore, the valuable insights derived from this research have the potential to revolutionize financial forecasting and expand economic modeling applications.

B. Machine Learning Algorithms

Integrating machine learning and pattern recognition improved the accuracy of stock trading systems [18]. Esteemed machine learning methods have been utilized to predict fluctuations in stock prices. Some of these powerful algorithms are Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest, and Decision Tree, each algorithm offers unique advantages. LSTM, a recurrent neural network, demonstrates exceptional efficacy in encapsulating time-based dependencies and intricate patterns within stock market data, as shown by its exceptional forecasting accuracy compared to conventional models like ARIMA [19] [20]. Despite the complexity of machine learning models, it is suggested that straightforward strategies are effective for predicting price soaring. A study conducted by [21] evaluates the effectiveness of using deep learning and technical indicators to predict short-term stock price movements. The authors developed a four-layer Long Short-Term Memory (LSTM) model incorporating various technical indicators, achieving an impressive 83.6% accuracy in forecasting stock trends. Authors in study [22] offer a comprehensive comparative analysis of nine machine learning models and two deep learning methods. The RNN and LSTM with continuous data emphasized superior performance among others. It also demonstrated a notable improvement in accuracy across all models when technical indicators are converted to binary data inputs.

Numerous studies have generated precise estimations by detecting non-linear correlations in stock market data [23, 24]. Random Forest, an ensemble learning method, is particularly adept at managing large datasets and mitigating overfitting by aggregating multiple decision trees. Although Decision Trees are easy to interpret and implement, they are at risk of overfitting, especially with small datasets. Nonetheless, they can remain beneficial when integrated with other models or used with an ensemble technique like Random Forest [25]. Comparative studies have shown that advanced models like LSTM and SVM surpass decision trees in performance. Nonetheless, decision trees remain valuable for data exploration and feature selection [26]. However, the selection of a model typically relies on the requirements of the prediction task, including the dataset's size and design, the necessary balance between accuracy and interpretability, and the available computational resources [23]. Each model offers distinct advantages. In some cases, the most precise forecasts arise from a combination of these models, which integrate the optimal elements of each to mitigate the shortcomings [23, 25 - 27].

Disparate data sources, such as traditional time-series data and web platforms such as Google and Wikipedia, have been shown to greatly improve prediction accuracy [28]. The authors of study [45] emphasize the value of using NLP and finance to forecast stock prices. In their study, they emphasized the use of historical price data, text data from the news or social media, and their combination to improve accuracy. They discuss algorithms like RNN, GRU, and LSTM for price analysis, sentiment analysis for assessing investor emotions, and methods such as graph networks and event-driven approaches for identifying company correlations. A study investigates sentiment analysis of online investor opinions to support investment decisions and risk assessment. Using data from Sina Finance, it combines machine learning methods, like SVM and GARCH models, with sentiment analysis. Results show strong correlations between forum sentiment and stock price volatility, with machine learning outperforming semantic approaches and sentiment having a greater impact on value stocks than growth stocks [46].

The stock market is a complicated financial system with shifting prices, and investors seek to maximize gains while minimizing risks. Recent advances in neural networks and hybrid models have exceeded older approaches in terms of prediction accuracy. A study introduced the SMVF-ANP technique, which analyzes market transmission processes and financial aspects using multi-layer perceptron (MLP), dynamic artificial neural networks, and GARCH models. Results reveal that SMVF-ANP outperforms typical strategies and models, with a prediction accuracy of 97.2%, an efficiency rate of 96.9%, and higher returns [47]. Tong et al. studied the effect of social media mood on irrational herding behavior in the Chinese stock market. They discovered that emotion had a considerable impact on illogical conduct [48]. Furthermore, authors in study [49] extracted insights from unstructured financial text in quarterly company reports. They utilized FinBERT, a pre-trained language model based on the BERT framework. Their results demonstrate that FinBERT outperforms state-of-the-art methods, achieving an accuracy of 84.77% on quarterly reports.

To meet the varied demands of investors, advanced stock recommender systems have been expertly developed, which utilize techniques such as K-Nearest Neighbor, Singular Value Decomposition, and Association Rule Mining, all of which take into account investors' unique preferences and risk profiles to maximize portfolio returns [29]. Multi-agent recommender systems utilizing hybrid filtering techniques and involving collaborative and content-based filtering have been designed to adaptively recommend profitable stocks based on investor preferences and macroeconomic factors [30]. Incorporating social media text and company correlations into stock movement prediction models has enhanced the ability to capture multimodal signals, providing a robust tool for investment decision-making [31]. A systematic review of recent developments in machine learning methods, such as deep learning and ensemble methods, highlights the importance of these technologies in improving stock market movement forecasts and reducing investment risks [32]. In addition, a deep reinforcement learning approach that combines artificial neural networks (ANN), long short-term memory (LSTM), natural language processing (NLP), and deep Q networks (DQN) was proposed to forecast the next day's stock price. The proposed model outperforms standard algorithms in terms of accuracy, demonstrating its efficacy in automating stock market in-vestment decisions [33]. Thus, the remarkable innovations in stock recommendation systems highlight their extraordinary sophistication, empowering them to deliver precise, timely, and personalized investment guidance that perfectly aligns with the dynamic needs of investors and traders.

C. Technical Analysis

Technical indicators are vital in forecasting stock market movements that offers valuable insights into market trends and behaviors. The metrics are typically divided into two primary classifications: trend indicators and volume indicators. Trend indicators play a pivotal role in revealing not only the direction but also the strength of a market trend, which is essential for crafting savvy investment choices. Noteworthy in-stances of trend indicators encompass Moving Averages (MA), Moving Average Con-vergence Divergence (MACD), and Exponential Moving Average (EMA) [34]. These indicators are utilized to smooth out price data, facilitating the detection of trends over a designated timeframe. For example, the MACD, a momentum indicator, illustrates the correlation between two moving averages of the price of an asset trend. At the same time, the EMA assigns greater importance to the most recent prices, increasing its sensitivity to new information [35].

On the other hand, volume indicators are crucial as they reveal the true power behind price movements by examining trade volume. They assist investors in understanding the degree of interest surrounding a specific stock or market. Common volume indicators include Relative Volume (RVOL), Volume Weighted Average Price (VWAP), and Chaikin Money Flow (CMF) [34]. RVOL compares the current volume to the average volume over a specific period, indicating whether a stock is actively traded. The VWAP determines the mean price at which a security was traded during the day, considering volume and price, in contrast, the CMF assesses buying and selling pressure over a specific period.

The precision of stock predictions could be increased by combining these metrics with sophisticated machine learning algorithms. Combining technical indicators with ensemble learning methods like Random Forest and Gradient Boosting has improved predictive precision, attaining a success rate of 91.45% in forecasting the opening price of stock [36]. Similarly, using LSTM models with technical indicators as voters have demonstrated high accuracy in stock market predictions, with RMSE values indicating strong performance [34]. Jaideep and Matloob developed a machine learning classifier using five technical and 23 fundamental indicators. Their findings highlight the importance of analyst ratings in predicting stock prices [37]. Thus, these methods emphasize the need of selecting the proper set of technical indicators to improve the efficacy of prediction models. Furthermore, utilizing correlation-based feature selection models to identify crucial technical indicators has undeniably revolutionized the forecasting capabilities of deep learning algorithms, particularly Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) [38].

Hybrid machine learning models that integrate various classifiers and optimization strategies have successfully forecasted stock price fluctuations, especially in volatile market conditions affected by external elements such as political turmoil and pandemics [39]. However, the strategic use of trend and volume indicators, along with advanced machine learning techniques, provides a robust framework for predicting stock market movement; thus, they offer rich visions for investors and financial analysts [4, 34-36, 38, 40, 41-43].

However, existing systems focus on historical price data and fail to integrate other valuable inputs, such as sentiment analysis, machine learning algorithms, and technical indicators. Despite their effectiveness, these systems' advanced technologies are often used in isolation. In response to these limitations, we propose a microservice-based architecture that brings together modularity, scalability, and advanced analytics.

III. METHODOLOGY

A. The Proposed System

Making well-informed investment choices is challenging due to the total volume of data accessible to investors. These data sources range from historical stock prices and technical indicators to company fundamentals and sentiment extracted from news articles and financial reports. The ability to process, analyze, and interpret these data effectively is crucial for investors. Hence, we propose a microservice-driven stock prediction system to address this need. Designing the system to provide investors with comprehensive stock analysis and actionable recommendations can optimize their portfolios and minimize risks as well.

The proposed system is built on microservices architecture, and each service was designed to handle a distinct part of the stock analysis process. These microservices operate independently while effortlessly communicating with one another through RESTful APIs. This architecture ensures the system is scalable, efficient, and adaptable to future enhancements. The proposed system was tested using real-world stock data to assess its effectiveness in response to each service and providing initial and informed stock recommendations. The system's performance was evaluated based on its ability to retrieve stock data, generate reliable technical and fundamental insights for traders, and summarize a semantic analysis for a given financial report. (The source code for the system can be accessed through the fine-grained personal access token link provided in the footer at the bottom of the page or by clicking on this link).

The system combines essential financial metrics, sophisticated machine learning algorithms, and sentiment analysis to provide a strong data-informed decision. Each microservice is responsible for a particular function or task in the stock recommendation process, enabling efficient real-time processing of large data sets. Fig. 1 presents the architecture of the system. The major components of the system are detailed as follows:

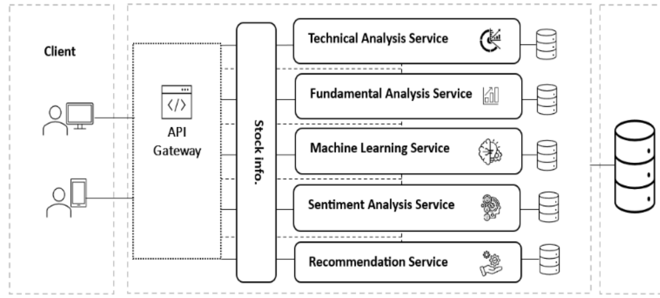

Fig. 1. The architecture of the proposed system.

1) Stock data and fundamental analysis services: The first step in the system involves collecting financial data from publicly available sources. This microservice retrieves vital financial metrics for individual stocks, including historical prices and trading volumes. The fundamental analysis microservice can process the data to compute key financial metrics like Market Capitalization, Dividend Yield, Earnings Per Share (EPS), and Revenue. These metrics help evaluate the financial health and performance of the selected company. We used the Yahoo Finance API in our system.

2) Technical analysis service: The system's technical analysis microservice calculates a range of widely used technical indicators that assist in identifying trends, momentum, and market conditions. To detect price trends and possible reversals, we run indicators such as moving averages (MA), the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD). Also, this component employs volume-based indicators like On-Balance Volume (OBV) and volatility indicators like the Average True Range (ATR). Thus, these technical indicators are important for traders and investors to determine a stock's price shifts and the overall direction of the trend.

3) Sentiment analysis service: Sentiment analysis has become an important tool in predicting stock market trends, given that news and financial reports can greatly affect investor actions and stock valuations. The sentiment analysis process was developed using a Flask-based API that integrates the FinBERT model, a variant of BERT specifically fine-tuned for sentiment analysis in financial contexts. The FinBERT, which is available via Hugging Face's model repository, is known for its domain specific capabilities in financial sentiment classification [48]. It is initialized in the application through the transformers pipeline with a sentiment analysis task. The model outputs predictions across three sentiment categories: positive, negative, and neutral. It processes the text data to determine whether the general sentiment is positive, negative, or neutral, providing a complementary perspective to the technical and fundamental analyses.

4) Machine learning predictions service: In its early version, the system uses an LSTM (Long Short-Term Memory) model to estimate future stock values, which is a recurrent neural network designed to manage time-series data. The LSTM model predicts future stock swings using previous

https://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@github.com/aalgarni2/Stock_Market_Forecasting_Microservice_System.git stock prices and other services. This approach identifies long-term linkages and patterns in stock price data. It aids in providing short-term projections, which are critical for making buy, sell, or hold choices. The model is designed to react dynamically to new data, gradually improving the accuracy of its predictions as time progresses. The system scales and normalizes historical stock data, technical indicators, and semantic analysis findings before passing them through an LSTM model for training. After completion, the model produces forecasted stock values, which are then compared to the current market price to inform the recommendation service. During model execution, we divided the dataset into training (80%) and testing (20%) sets. We set up the model with 50 epochs, a batch size of 32, and an Adam optimizer with a learning rate of 0.001. The model's performance was assessed using Mean Absolute Error (MAE) and Mean Squared Error (MSE). Other machine learning approaches such as Support Vector Machine, Random Forest, and Decision Tree will be implemented in future work. Thus, this modular approach makes it easier to update and expand the system with new capabilities as they become available.

5) Recommendation service: The recommendation microservice will integrate the outputs of the fundamental analysis, technical indicators, and machine learning predictions to deliver a final recommendation. The algorithm would be designed to aggregate results from four microservices, fundamental analysis, technical indicators, machine learning predictions, and sentiment analysis, to generate a final stock recommendation. Each service's output is weighted, combined, and compared against set thresholds. Then, the service determines whether the recommendation is to 'Buy,' 'Hold,' or 'Sell'.

6) User interaction via streamlit interface: The system's user interface is designed to let investors enter stock ticker symbols, select a date period for analysis, and upload a financial report for sentiment evaluation. The interface retrieves and shows results based on the services that have been selected. The modular architecture also can enable future integration of additional analytical services or advancements with minimal disturbance.

IV. Result

A. *Fundamental Analysis and Technical Analysis Performance*

The component of fetching the historical stock data was tested with several stocks by entering the ticker, start date, and end date. All runs demonstrated that stock data can be retrieved successfully from the Yahoo Finance API. For the fundamental analysis service, it successfully retrieved financial metrics. Additionally, the proposed system effectively calculated and returned multiple technical indicators such as RSI, and MACD. These indicators effectively identified trends, overbought and oversold conditions, and market volatility. The ability to visualize these indicators over a selected date range helped investors gain deeper insights into price movements and market dynamics. Indicators like MACD and RSI provided actionable insights into buying or selling opportunities. Thus, the system's technical indicators are aligned with known market trends, providing an additional layer of validation to the stock's performance.

During testing of the three components, we entered the stock ticker "2222.SR" (Saudi Arabian Oil Company); the system retrieved stock data for the specified date. Also, when we run the fundamental analysis, the system provides the available and accessible data. For unavailable metrics, it shows 'N/A'. The accuracy and reliability of this data depend on the real-time updates provided by Yahoo Finance, which proved to be timely and comprehensive during testing. Fig. 2 illustrates the system's interface after fetching the stock data.

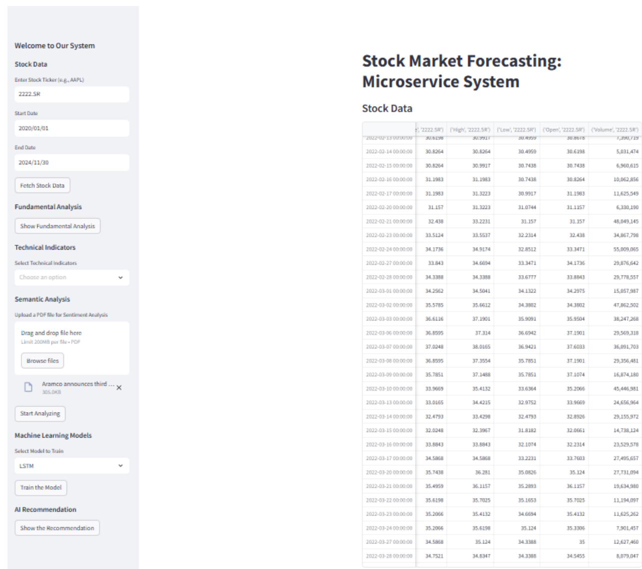

Fig. 2. The proposed system main interface.

B. *Sentiment Analysis Services Performance*

The sentiment analysis services perform sentiment analysis on any uploaded PDF document. Sentiment analysis is increasingly used in financial prediction. Incorporating news sentiment or financial report analysis improves accuracy in forecasting stock trends [44]. For our proposed system, we implemented the FinBERT model for the sentiment analysis microservice. We tested this service by uploading several PDF files.

The sentiment analysis service uses FinBERT to analyze text from PDF documents. The FinBERT tokenizer divides the text into pieces using tokens. The FinBERT algorithm evaluates each segment to identify the sentiment labels (positive, neutral, or negative), which are then accepted to obtain a sentiment measurement. In an analysis of Saudi Aramco's third-quarter report for 2021, the sentiment analysis service detected positive sentiment. Fig. 3 shows the sentiment analysis of the report. The sentiment analysis was instrumental when applied to earnings reports. Positive sentiment can be associated with subsequent price increases. In contrast, negative sentiment may correlate with price declines. However, while sentiment extracted from financial documents can predict short-term stock price movements, external market factors and investor behavior may influence price fluctuations.

Fig. 3. Sentiment analysis report.

C. Machine Learning Service and Recommendation System

The machine-learning service is designed to employ various machine learning algorithms for stock price prediction. They are LSTM, Support Vector Machine (SVM), Random Forest, and Decision Tree. In this early development, we only implemented LSTM. Other algorithms are left for future work. During testing the service, the LSTM model achieved a Mean Absolute Error (MAE) of 0.26 and a Mean Squared Error (MSE) of 0.18 for predicting the stock price of 2222.SR (Saudi Aramco). The results demonstrate the potential of LSTM for forecasting in financial markets. Fig. 4 show the result of MAE and MSE after training the model.

Fig. 4. The result of MAE and MSE of the model..

The recommendation engine service will integrate the results of fundamental analysis, technical indicators, and semantic analysis and pass them on to the machine learning algorithm service. The recommendation engine's strength is its ability to integrate several types of information which helps in producing a comprehensive insight of the stock's performance. This guarantees that the recommendation is well-rounded and takes into account both quantitative and qualitative considerations. Also, it limits the risk of making decisions that are based on only one factor. The full implementation of this service is left for future work.

V. Discussion and Limitation

The results of testing the system imply that the proposed system can be an effective tool for providing data-driven stock recommendations based on multiple sources. The system offers a comprehensive stock analysis approach by integrating fundamental analysis, technical indicators, sentiment analysis, and machine learning predictions. The modular design of the services facilitates integration with other components of the stock recommendation system. Also, the modular approach allowed for a flexible selection of technical indicators [50]. Extending support for more complex strategies or combining indicators could enhance the analytical capability of the system further. FinBERT's pre-training on financial data provided domain-specific sentiment analysis, making the results relevant for stock market insights. The service's modular design supports easy scaling, such as adding more sentiment categories or integrating additional pre-trained models. Future work could focus on improving sentiment granularity and analyzing sentiment trends across sections of a document to uncover deeper insights. The LSTM model's architecture can capture temporal dependencies; hence, it is suitable for time-series data like stock prices. However, the ability to choose among models provided flexibility for different user requirements and computational resources. Future improvements include implementing additional time-series-specific models and enabling hyperparameter optimization for models.

Furthermore, the proposed system demonstrates that its internal structure is scalable and efficient. Each microservice operated independently. The utilization of RESTful APIs allows services to communicate without interruption as well as ensures that changes to one service do not impact the overall system. Hence, the system's modularity increases its flexibility and usability by making it simple to add or improve current services.

There are specific constraints that need to be defined. First, there is a need for stress testing to assess performance under high-load conditions. Second, sentiment analysis is heavily dependent on the quality of the input data. Hence, the outcomes of the results can be affected if there are specific constraints that need to be defined. First, there is a need for stress testing to assess performance under high-load conditions. Second, sentiment analysis is heavily dependent on the quality of the input data. So, the outcomes of the results may be affected negatively if there is any biased data.

However, the system's modular architecture allows for future enhancements, such as incorporating more advanced sentiment analysis models, employing advanced machine learning approaches to better account for market volatility, and leveraging recommendation services with explainable AI. This system has the potential to significantly aid investors in making well-informed decisions while also being adaptable to future advancements in financial technology.

VI. Conclusion and Future Work

The proposed system adopts a comprehensive methodology for stock market analysis, integrating traditional financial metrics with contemporary machine-learning approaches. The system assists investors in making informed decisions by offering services like fundamental analysis, technical indicators, sentiment analysis, and machine learning algorithms. However, this paper presents a microservice-based architecture that embeds state-of-the-art technologies, such as LSTM for time-series prediction and FinBERT for sentiment analysis in stock price forecasting. By comparison, the LSTM model generates smaller error metrics than traditional baselines and thus has demonstrated the capability of learning and representing the complex, nonlinear stock price pattern. The value added to the system for further processing was done by the incorporation of FinBERT, through the analysis of the financial reports based on sentiment analysis. The paper's parameter optimization will be expanded to capture more market scenarios and embed additional analysis tools for the betterment and adaptability of the system.

The recommendation service developed in this version is still on a very high level of abstraction and, hence, is left for further research and development. Also, we aim, in future work, to introduce Explainable AI (XAI) into the stock trading systems to make the predictions transparent and explain why they are predicted this way. It will be interesting to see whether XAI can be integrated into microservice architecture. The other related research direction could try to investigate how the XAI modules connect with the existing services and, more importantly, provide explanations that are correct, understandable, and trusted.

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REFERENCES

[1] Zhang, Y. The impact of stock price fluctuations on the financial market. *Highlights in Business Economics and Management* 2024, *39*, 638–643. https://doi.org/10.54097/rcy13226.

[2] Sundar, S.; Dhyani, B.; Chhajer, P. Factors Affecting Stock Market Movements: An Investors Perspective. *European Economic Letters (EEL)* 2023. https://doi.org/10.52783/eel.v13i1.172.

[3] East, R.; Wright, M. Taming the Animal Spirits: Predicting Psychologically Based Stock Price Movements. *Research Square (Research Square)* 2022. https://doi.org/10.21203/rs.3.rs-2090235/v1.

[4] Jose, N. J.; P, N. V. Integrating Technical Indicators and Ensemble Learning for Predicting the Opening Stock Price. *International Journal of Information Technology Research and Applications* 2024, *3* (2), 1–15. https://doi.org/10.59461/ijitra.v3i2.96.

[5] Ho, T.-T.; Huang, Y. Stock Price Movement Prediction Using Sentiment Analysis and CandleStick Chart Representation. *Sensors* 2021, *21* (23), 7957. https://doi.org/10.3390/s21237957.

[6] Badhan, A. K.; Bhattacherjee, A.; Roy, R. Deep Learning Techniques in Big Data Analytics. In *Studies in big data*; 2024; pp 171–193. https://doi.org/10.1007/978-981-97-0448-4_9.

[7] Nassima, A. M.; Hanae, S.; Karim, B. Dynamic Decomposition of Monolith Applications Into Microservices Architectures. *2024 Mediterranean Smart Cities Conference (MSCC)*, 2024, 1–4. https://doi.org/10.1109/mscc62288.2024.10697026.

[8] Dimov, A.; Emanuilov, S.; Bontchev, B.; Dankov, Y.; Papapostolu, T. Architectural Approaches to Overcome Challenges in The Development of Data-Intensive Systems. *AHFE International* 2022. https://doi.org/10.54941/ahfe1002521.

[9] Blinowski, G.; Ojdowska, A.; Przybylek, A. Monolithic vs. Microservice Architecture: A Performance and Scalability Evaluation. *IEEE Access* 2022, *10*, 20357–20374. https://doi.org/10.1109/access.2022.3152803.

[10] Oyeniran, N. O. C.; Adewusi, N. A. O.; Adeleke, N. A. G.; Akwawa, N. L. A.; Azubuko, N. C. F. Microservices architecture in cloud-native applications: Design patterns and scalability. *Computer Science & IT Research Journal* 2024, *5* (9), 2107–2124. https://doi.org/10.51594/csitrj.v5i9.1554.

[11] Sheng, X.; Hu, S.; Lu, Y. The Micro-service Architecture Design Research of Financial Trading System based on Domain Engineering. *Proceedings of the 2018 International Symposium on Social Science and Management Innovation (SSMI 2018)* 2019. https://doi.org/10.2991/ssmi-18.2019.32.

[12] Yang, N.; Liu, Y.; Lv, W.; Gao, C.; Zheng, S.; Zhang, Q. Application of microservices in power trading platforms. In *CRC Press eBooks*; 2022; pp 176–183. https://doi.org/10.1201/9781003330165-25.

[13] Sithiyopasakul, P.; Piyatananugoon, C.; Chaowalittawin, V.; Krungseanmuang, W.; Sathaporn, P.; Kanjanasurat, I.; Purahong, B.; Archevapanich, T.; Lasakul, A. Inventory Management System based on IoT and Microservices Architecture Design. *2022 International Electrical Engineering Congress (iEECON)* 2023. https://doi.org/10.1109/ieecon56657.2023.10126548.

[14] Yan, W.; Shuai, F. Application of Microservice Architecture in Commodity ERP Financial System. *International Journal of Computer Theory and Engineering* 2022, *14* (4), 168–173. https://doi.org/10.7763/ijcte.2022.v14.1324.

[15] Xu, M.; Dustdar, S.; Villari, M.; Buyya, R. Special issue on efficient management of microservice-based systems and applications. *Software Practice and Experience* 2023, *54* (4), 543–545. https://doi.org/10.1002/spe.3298.

[16] M, D.; Raswanth, S. R.; Chaitanya, V. S. S. K.; Kalavalapalli, V. S. S.; Kumar, P.; Srivastava, G. Secure Automated Inventory Management system using Abstracted System Design Microservice Architecture. *2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)* 2023. https://doi.org/10.1109/icccnt56998.2023.10306924.

[17] Sasmita, D.; Kusuma, G. P. Microservices for Asset Tracking Based on Indoor Positioning System. *International Journal of Computing and Digital Systems* 2024, *15* (1), 861–873. https://doi.org/10.12785/ijcds/160162.

[18] Lokesh, D.,; Aravind, V.; Vani, V.; Karthik, N. Stock Recommendation System for Better Investment Plan. *2024 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT)*, 2024, 1–6. https://doi.org/10.1109/iconscept61884.2024.10627901.

[19] Ruke, A.; Gaikwad, S.; Yadav, G.; Buchade, A.; Nimbarkar, S.; Sonawane, A. Predictive Analysis of Stock Market Trends: A Machine Learning Approach. *2024 4th International Conference on Data Engineering and Communication Systems (ICDECS)*, 2024, 1–6. https://doi.org/10.1109/icdecs59733.2023.10503557.

[20] Liu, L. A Comparative Examination of Stock Market Prediction: Evaluating Traditional Time Series Analysis Against Deep Learning Approaches. *Advances in Economics Management and Political Sciences* 2023, *55* (1), 196–204. https://doi.org/10.54254/2754-1169/55/20231008.

[21] Lee, M.-C.; Chang, J.-W.; Hung, J. C.; Chen, B.-L. Exploring the Effectiveness of Deep Neural Networks with Technical Analysis Applied to Stock Market Prediction 2021, https://doi.org/10.2298/CSIS200301002L.

[22] Nabipour, M.; Nayyeri, P.; Jabani, H.; S., S.; Mosavi, A. Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data: A Comparative Analysis. *IEEE Access* 2020, 8, 150199–150212. https://doi.org/10.1109/ACCESS.2020.3015966.

[23] Zhang, X. Stock price prediction of PayPal by Linear Regression, SVM, Random Forest and LSTM. *Applied and Computational Engineering* 2024, *52* (1), 201–207. https://doi.org/10.54254/2755-2721/52/20241568.

[24] Nabipour, M.; Nayyeri, P.; Jabani, H.; S, S.; Mosavi, A. Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis. *IEEE Access* 2020, *8*, 150199–150212. https://doi.org/10.1109/access.2020.3015966.

[25] Halder, S.; Bagchi, D.; Samanta, A.; Mondal, D.; Samanta, S.; Hati, S.; Kundu, A. Strategic Selection of Machine Learning Models for Short-term Trading Optimization. *International Journal for Multidisciplinary Research* 2024, *6* (3). https://doi.org/10.36948/ijfmr.2024.v06i03.20529.

[26] Kotapati, L.; Sajjala, R. B.; Gudi, S.; Hareesh, B. V. N.; Tokala, S.; Enduri, M. K. Forecasting Stock Markets Trends using Machine Learning Algorithms. *2023 IEEE 15th International Conference on Computational Intelligence and Communication Networks (CICN)*, 2023, 278–282. https://doi.org/10.1109/cicn59264.2023.10402238.

[27] Sonkavde, G.; Dharrao, D. S.; Bongale, A. M.; Deokate, S. T.; Doreswamy, D.; Bhat, S. K. Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review, Performance Analysis and Discussion of Implications. *International Journal of Financial Studies* 2023, *11* (3), 94. https://doi.org/10.3390/ijfs11030094.

[28] Weng, B.; Ahmed, M. A.; Megahed, F. M. Stock market one-day ahead movement prediction using disparate data sources. *Expert Systems With Applications* 2017, *79*, 153–163. https://doi.org/10.1016/j.eswa.2017.02.041.

[29] Gonzales, R. M. D.; Hargreaves, C. A. How can we use artificial intelligence for stock recommendation and risk management? A proposed decision support system. *International Journal of Information Management Data Insights* 2022, *2* (2), 100130. https://doi.org/10.1016/j.jjimei.2022.100130.

[30] Taghavi, M.; Bakhtiyari, K.; Scavino, E. Agent-based computational investing recommender system. *RecSys '13: Proceedings of the 7th ACM Conference on Recommender Systems*, 2013. https://doi.org/10.1145/2507157.2508072.

[31] Sawhney, R.; Agarwal, S.; Wadhwa, A.; Shah, R. R. Deep Attentive Learning for Stock Movement Prediction From Social Media Text and Company Correlations. *Conference on Empirical Methods in Natural Language Processing*, 2020. https://doi.org/10.18653/v1/2020.emnlp-main.676.

[32] Bustos, O.; Pomares-Quimbaya, A. Stock market movement forecast: A Systematic review. *Expert Systems With Applications* 2020, *156*, 113464. https://doi.org/10.1016/j.eswa.2020.113464.

[33] Awad, A. L.; Elkaffas, S. M.; Fakhr, M. W. Stock Market Prediction Using Deep Reinforcement Learning. *Applied System Innovation* 2023, *6* (6), 106. https://doi.org/10.3390/asi6060106.

[34] Vincent, N.; Saputra, B. J.; Izzatunnisa, S. Y.; Lucky, H.; Iswanto, I. A. Stock Market Prediction System Using LSTM with Technical Indicators as Voters. *2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, 2023, *3*, 229–234. https://doi.org/10.1109/aidas60501.2023.10284633.

[35] Ramakrishnan, S.; Devi, K. R.; E, Y.; T, V.; C, T. A. Ensemble Algorithm to Speculate Stock Trend by Analyzing Technical Indicators on Historical Data. *2022 International Conference on Inventive Computation Technologies (ICICT)* 2023, 970–975. https://doi.org/10.1109/icict57646.2023.10134017.

[36] Jose, N. J.; P, N. V. Integrating Technical Indicators and Ensemble Learning for Predicting the Opening Stock Price. *International Journal of Information Technology Research and Applications* 2024, *3* (2), 1–15. https://doi.org/10.59461/ijitra.v3i2.96.

[37] Singh, J.; Khushi, M. Feature Learning for Stock Price Prediction Shows a Significant Role of Analyst Rating. *Applied System Innovation* 2021, *4* (1), 17. https://doi.org/10.3390/asi4010017.

[38] Ifleh, A.; Kabbouri, M. E. Stock price indices prediction combining deep learning algorithms and selected technical indicators based on correlation. *Arab Gulf Journal of Scientific Research* 2023. https://doi.org/10.1108/agjsr-02-2023-0070.

[39] Zouaghia, Z.; Aouina, Z. K.; Said, L. B. Stock Movement Prediction Based On Technical Indicators Applying Hybrid Machine Learning Models. *2022 International Symposium on Networks, Computers and Communications (ISNCC)* 2023, *1823*, 1–4. https://doi.org/10.1109/isncc58260.2023.10323971.

[40] Chang, V.; Xu, Q. A.; Chidozie, A.; Wang, H. Predicting Economic Trends and Stock Market Prices with Deep Learning and Advanced Machine Learning Techniques. *Electronics* 2024, *13* (17), 3396. https://doi.org/10.3390/electronics13173396.

[41] Borkar, S. N.; Jadhav, A.; Dhablia, A.; NandkishorAher, R.; Aher, N. D.; Aware, A. A. Selection of Technical Indicators for Stock Market Prediction: Correlation Based Approach. *2022 6th International Conference on Computing, Communication, Control and Automation (ICCUBEA* 2023, 1–6. https://doi.org/10.1109/iccubea58933.2023.10391999.

[42] Rouf, N.; Malik, M. B.; Arif, T.; Sharma, S.; Singh, S.; Aich, S.; Kim, H.-C. Stock Market Prediction Using Machine Learning Techniques: A Decade Survey on Methodologies, Recent Developments, and Future Directions. *Electronics* 2021, *10* (21), 2717. https://doi.org/10.3390/electronics10212717.

[43] Fei, Y.; Zhou, Y. Intelligent Prediction Model of Shanghai Composite Index Based on Technical Indicators and Big Data Analysis. Highlights in Business Economics and Management 2023, 17, 370–389. https://doi.org/10.54097/hbem.v17i.11486.

[44] Antweiler, W.; Frank, M. Z. Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *The Journal of Finance* 2004, *59* (3), 1259–1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x.

[45] Choi, J.; Yoo, S.; Zhou, X.; Kim, Y. Hybrid Information Mixing Module for Stock Movement Prediction. *IEEE Access* 2023, 11, 28781–28790. https://doi.org/10.1109/ACCESS.2023.3258695.

[46] Wu, D.D.; Zheng, L.; Olson, D.L. A Decision Support Approach for Online Stock Forum Sentiment [2] Analysis. *IEEE Trans. Syst. Man Cybern. Syst*. 2014, 44, 1077–1087. https://doi.org/10.1109/TSMC.2013.2295353.

[47] Guan, Z.; Zhao, Y. Optimizing Stock Market Volatility Predictions Based on the SMVF-ANP Approach. *Int. Rev. Econ. Financ*. 2024, 95, 103502. https://doi.org/10.1016/j.iref.2024.103502.

[48] Li, T.; Chen, H.; Liu, W.; Yu, G.; Yu, Y. Understanding the Role of Social Media Sentiment in Identifying Irrational Herding Behavior in the Stock Market. *Int. Rev. Econ. Financ*. 2023, 87, 163–179. https://doi.org/10.1016/j.iref.2023.04.016.

[49] Galphade, M.; Nikam, V.B.; Yedurkar, D.; Singh, P.; Stephan, T. Semantic Analysis Using Deep Learning for Predicting Stock Trends. *Procedia Comput. Sci.* 2024, 235, 820–829. https://doi.org/10.1016/j.procs.2024.04.078.

[50] Yang, J.; Wang, Y.; Li, X. Prediction of Stock Price Direction Using the LASSO-LSTM Model Combines Technical Indicators and Financial Sentiment Analysis. *PeerJ Comput. Sci.* 2022, 8, e1148. https://doi.org/10.7717/peerj-cs.1148.

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