StockGenie: AI-Driven Stock Market Assistant and Forecasting System

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***Abstract*—Stock market investing demands constant evaluation of extensive financial datasets, accurate recognition of market trends, and careful management of investment risks. These requirements often create significant challenges for beginner investors who may lack analytical expertise and access to advanced decision-support tools. While many existing trading platforms provide real-time market data, they frequently fail to offer intelligent forecasting mechanisms and structured learning environments that aid users in understanding market dynamics. This paper proposes StockGenie, an AI-driven stock market assistance system developed to facilitate informed investment decisions through predictive modeling, visual analytics, portfolio evaluation, and simulated trading experiences. The system utilizes time-series forecasting approaches, including Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks, to examine historical stock market data and generate future price predictions. In addition to forecasting capabilities, StockGenie incorporates an interactive visualization dashboard, a portfolio advisory component for risk-aware investment analysis, a virtual trading simulator for hands-on practice, and an AI-powered chatbot that provides instant guidance and explanations related to market behavior. Experimental evaluation using historical stock market datasets was conducted to assess forecasting performance. Quantitative metrics including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to compare ARIMA and LSTM models. The results indicate that the LSTM model achieves lower prediction error and improved trend prediction capability compared to traditional statistical approaches.**

***Index Terms*—Stock market forecasting, artificial intelligence, time-series prediction, LSTM networks, ARIMA models, portfolio management.**

I. INTRODUCTION

The stock market plays a critical role in modern financial systems by facilitating capital formation, investment growth, and wealth generation. It provides individuals and organizations with opportunities to participate in economic development through the buying and selling of financial securities. Despite these advantages, the stock market is highly volatile and influenced by a wide range of factors, including economic indicators, corporate performance, political events, and investor sentiment. These dynamic conditions make market behavior difficult to predict and require continuous analysis to make informed investment decisions.

Beginner investors often face significant challenges when navigating the stock market due to limited financial knowledge and insufficient experience in data interpretation. The availability of massive volumes of financial data, such as historical prices, technical indicators, and market news, can overwhelm new investors rather than assist them. As a result, many investors rely on intuition or incomplete information, which increases the likelihood of poor investment choices and financial losses.

Most existing stock trading platforms focus primarily on displaying raw market data, such as stock prices, charts, and basic indicators, without offering intelligent analytical support. Users are typically expected to manually analyze trends and predict future movements, which requires advanced domain knowledge. This lack of integrated forecasting tools and educational support limits the effectiveness of these platforms, especially for beginners who require guidance and learning

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resources.

Recent advancements in artificial intelligence and machine learning have significantly enhanced the ability to analyze complex financial time-series data. Predictive models can now identify hidden patterns, capture non-linear relationships, and generate forecasts with greater accuracy than traditional analytical methods. These technologies offer the potential to transform stock market analysis by automating trend identification and risk assessment, thereby supporting more informed investment decisions.

In response to these challenges, this paper introduces StockGenie, an AI-driven stock market assistant designed to provide a comprehensive decision-support and learning platform for beginner investors. StockGenie integrates predictive forecasting models, interactive data visualization, portfolio analysis, and virtual trading simulation into a unified system. The platform aims to simplify stock market analysis, deliver meaningful predictive insights, and offer a risk-free environment where users can practice trading strategies and improve their understanding of market dynamics. By combining intelligent analytics with user-centric design, StockGenie seeks to enhance investor confidence and promote informed participation in stock market activities.

The primary contributions of this work are summarized as follows:

1) Development of *StockGenie*, an AI-driven stock market assistant integrating forecasting, portfolio analysis, visualization, and educational simulation.
2) Integration of ARIMA and LSTM time-series forecasting models within a unified decision-support platform for beginner investors.
3) Implementation of a virtual trading simulation environment that enables risk-free learning of stock market strategies.
4) Design of a modular system architecture consisting of data acquisition, preprocessing, forecasting, advisory, and visualization modules.
5) Demonstration of the effectiveness of AI-based forecasting models through experimental evaluation using historical stock market datasets.

II. Related Work

Stock market forecasting has been widely studied using statistical and artificial intelligence–based approaches. Early research primarily relied on classical time-series models such as the Autoregressive Integrated Moving Average (ARIMA), which has been effectively used for short-term stock price prediction due to its ability to model linear trends and temporal dependencies [16], [17]. However, these methods often struggle to capture the non-linear and highly volatile nature of real-world financial markets [2], [4].

To address these limitations, machine learning techniques were introduced for stock market prediction. Several studies and surveys have reviewed the application of machine learning models, highlighting improvements over traditional statistical approaches while noting challenges related to feature engineering and scalability [3], [10], [12]. Data mining and big-data-driven approaches further enhanced forecasting performance by enabling large-scale financial data analysis [4], [9].

Recent advances in deep learning have significantly improved stock price forecasting accuracy. Long Short-Term Memory (LSTM) networks have demonstrated strong capability in modeling long-term dependencies and non-linear relationships in financial time-series data [15]. Empirical studies show that deep learning–based models outperform traditional methods, particularly in complex and dynamic market conditions [7], [13]. Hybrid forecasting frameworks combining statistical and deep learning models have also been proposed to improve robustness and prediction consistency [8].

Beyond forecasting accuracy, research has emphasized the importance of user-centric financial systems. Virtual trading platforms and stock market simulators have been shown to enhance learning and reduce financial risk for novice investors [1], [5]. More advanced systems incorporate multi-agent architectures and intelligent simulations to support real-time decision-making [6].

Additionally, conversational AI and intelligent advisory systems have gained attention in financial applications. Hybrid AI chatbots and LLM-based tools have been introduced to provide accessible market insights, personalized recommendations, and interactive learning support for investors [11], [14].

Despite these developments, many existing systems focus primarily on prediction performance while offering limited integration of education, portfolio analysis, and experiential learning. The proposed StockGenie platform addresses these gaps by combining AI-based forecasting, portfolio risk evaluation, virtual trading simulation, and an AI-powered advisory interface within a unified framework

III. Proposed System

The proposed system, referred to as StockGenie, is an artificial intelligence–based stock market assistance platform developed to guide beginner investors in understanding and analyzing market behavior. The system brings together intelligent price forecasting, interactive data visualization, portfolio assessment, and experiential learning components within a single, cohesive framework. The core aim of StockGenie is to reduce the complexity associated with stock market data by converting large volumes of financial information into clear, interpretable insights. In addition, the platform provides a secure and risk-free environment that enables users to explore investment strategies and enhance their decision-making abilities without financial exposure.

StockGenie is built upon a modular and scalable system architecture that supports efficient data acquisition, advanced predictive analytics, and intuitive user interaction. Each functional module is designed to operate independently while remaining tightly integrated within a centralized processing workflow. This design approach improves system flexibility, simplifies maintenance, and allows for future enhancements

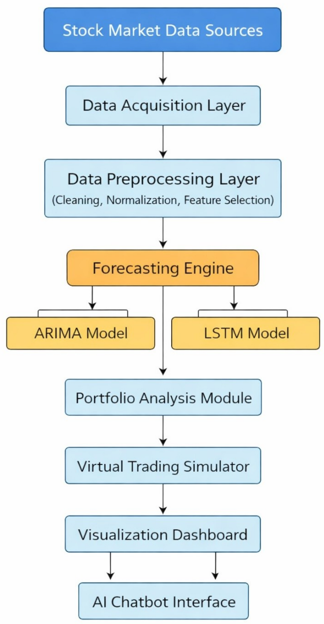

Fig. 1. Architecture of the StockGenie AI-driven stock market analysis platform

without disrupting existing functionality. The platform is capable of processing both historical and near real-time stock market data, which is analyzed using artificial intelligence techniques to generate meaningful predictions and analytical outcomes.

By leveraging machine learning–based forecasting models and interactive analytical tools, StockGenie transforms raw financial data into actionable knowledge. The system not only assists users in identifying potential market trends and investment opportunities but also encourages learning through exploration and simulation. Through its integrated design and user-focused features, StockGenie serves as both a decision-support system and an educational platform tailored to the needs of novice investors.

A. Overall System Architecture

The architecture of StockGenie is structured into multiple functional layers, each responsible for a specific role within the data processing and analysis pipeline. These layers include the Data Acquisition Layer, Data Preprocessing Layer, Forecasting and Analytics Layer, Application Services Layer, and User Interface Layer. This layered architecture ensures efficient data flow, scalability, and a clear separation of responsibilities among system components.

The Data Acquisition Layer is responsible for collecting both historical and real-time stock market data from reliable financial data sources. The collected data typically includes stock prices, trading volume, and other relevant market indicators. This layer ensures continuous data availability and timely updates, forming the foundation for subsequent analytical processes.

The Data Preprocessing Layer prepares the collected data for analysis by performing cleaning and transformation operations. Financial datasets often contain missing values, noise, and inconsistencies that can adversely affect prediction accuracy. This layer applies data cleaning, normalization, feature selection, and time-series transformation techniques to ensure that the data is suitable for training forecasting models.

The Forecasting and Analytics Layer serves as the core intelligence of the system. It utilizes advanced time-series prediction models, including Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks, to analyze historical stock price patterns and generate future price forecasts. ARIMA is employed to model linear trends and short-term market behavior, while LSTM captures complex non-linear relationships and long-term dependencies. The combined application of these models enhances forecasting robustness across varying market conditions.

B. Portfolio Analysis and Risk Evaluation Module

The Portfolio Analysis Module assists users in evaluating their investment decisions by analyzing asset allocation, diversification levels, and potential risk exposure. By utilizing historical price data and forecasted values, the system provides insights into portfolio performance and identifies risks associated with specific stocks or investment strategies.

Risk evaluation is performed by examining volatility measures and price fluctuations over time. The system presents risk indicators alongside predicted returns, enabling users to understand the trade-off between risk and reward. This module is particularly beneficial for beginner investors who may have limited experience in assessing financial risk.

C. Virtual Trading Simulation Module

To support experiential learning, StockGenie incorporates a Virtual Trading Simulation Module that allows users to practice stock trading without real financial involvement. The simulator mimics real market conditions using historical and near real-time data, enabling users to execute buy and sell operations, monitor portfolio performance, and evaluate different trading strategies.

The simulation environment provides immediate feedback on user actions, allowing investors to observe the outcomes of their decisions. This risk-free setting enhances learning, builds investor confidence, and reduces the likelihood of costly mistakes when transitioning to real-world trading.

D. AI-Powered Advisory and Chatbot Module

StockGenie integrates an AI-powered chatbot to provide instant assistance and educational support to users. The chatbot interacts with users through natural language queries and responds to questions related to stock market concepts, system functionalities, and forecast interpretations. This conversational interface improves accessibility and user engagement by delivering explanations in a simplified and intuitive manner.

In addition, the advisory module provides contextual recommendations based on user behavior, portfolio composition, and market trends. These suggestions assist users in interpreting analytical results and refining their investment strategies over time.

E. Visualization and User Interface Module

The User Interface Module serves as the primary interaction layer between the system and the user. It presents stock trends, forecast results, portfolio insights, and simulation outcomes through interactive dashboards and visual elements. Charts such as line graphs, candlestick representations, and performance metrics enable users to interpret complex financial data effectively.

The interface is designed with a user-centric approach, ensuring clarity, responsiveness, and ease of navigation. Interactive features allow users to customize visualizations, select stocks of interest, and seamlessly switch between analysis and simulation modes.

F. System Workflow and Integration

The operational workflow of StockGenie begins with data acquisition, followed by preprocessing and forecasting. The generated prediction results are then utilized by the portfolio analysis and simulation modules to provide comprehensive insights. User interactions through the dashboard and chatbot dynamically influence system outputs, creating an adaptive and responsive learning environment.

The modular integration of forecasting, analysis, simulation, and advisory components ensures efficient system performance and real-time responsiveness. This holistic design enables StockGenie to function effectively as both a decision-support system and an educational platform.

IV. Methodology

This section describes the methodology adopted for designing and implementing the StockGenie system. The proposed approach integrates data acquisition, preprocessing, time-series forecasting, portfolio analysis, and system integration to provide accurate predictions and meaningful investment insights. The methodology is designed to ensure reliability, scalability, and real-time responsiveness.

A. Data Collection

The initial stage of the methodology involves collecting historical and near real-time stock market data from publicly available and reliable financial data sources. The collected dataset typically includes attributes such as opening price, closing price, highest and lowest prices, and trading volume. These attributes are essential for analyzing market behavior and training forecasting models. Continuous data updates ensure that the system remains relevant to current market conditions.

B. Data Preprocessing

Raw stock market data often contains missing values, noise, and inconsistencies that can negatively impact model performance. To address these issues, a preprocessing pipeline is applied to clean and transform the data. This process includes handling missing values, removing anomalies, normalizing numerical features, and converting the data into time-series sequences. Feature selection techniques are also applied to retain only the most relevant attributes, thereby improving forecasting accuracy and computational efficiency.

C. Time-Series Forecasting Models

StockGenie employs a combination of statistical and deep learning–based forecasting models to predict future stock price movements.

1) ARIMA Model: The Autoregressive Integrated Moving Average (ARIMA) model is used to capture linear trends and short-term dependencies in stock price data. The model parameters are selected based on data stationarity and autocorrelation analysis. ARIMA is particularly effective for short-term forecasting and provides a baseline prediction for market behavior.

2) LSTM Model: The Long Short-Term Memory (LSTM) network is used to model complex non-linear relationships and long-term dependencies within financial time-series data. LSTM networks are well-suited for stock market prediction due to their ability to retain historical context over extended sequences. The model is trained using sequential input data and optimized through multiple training iterations to improve prediction accuracy.

D. Model Evaluation

The performance of the forecasting models is evaluated using error metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These metrics provide quantitative measures of prediction accuracy by comparing forecasted values with actual market prices. Comparative analysis is conducted to assess the effectiveness of ARIMA and LSTM models under different market conditions.

E. Portfolio Analysis and Risk Assessment

Forecasted stock prices are utilized by the portfolio analysis module to evaluate investment performance and risk exposure. The system analyzes diversification, asset allocation, and volatility measures to estimate potential risk levels. By combining historical trends with predicted values, the system assists users in understanding the trade-off between expected returns and associated risks.

F. Virtual Trading Simulation

The virtual trading module integrates forecasted and historical data to simulate real-world trading scenarios. Users can execute simulated buy and sell operations, monitor portfolio performance, and analyze the outcomes of different trading strategies. This module enables experiential learning by allowing users to experiment with investment decisions without financial risk.

G. System Integration and Workflow

All system components are integrated through a centralized workflow that ensures smooth data flow and synchronized operation. Data collected from financial sources is processed, analyzed, and passed to forecasting and analytical modules. The results are then displayed through interactive dashboards and made accessible via the chatbot interface. This integration ensures real-time responsiveness and seamless user interaction.

V. Results and Discussion

The forecasting performance of the StockGenie platform was evaluated using historical stock market data obtained from publicly available financial datasets. The models were trained using historical closing prices and tested on unseen data to assess predictive accuracy. Two evaluation metrics were used: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which are widely used for time-series forecasting evaluation.

TABLE I
Forecasting Model Performance

Model	RMSE	MAE	Prediction Accuracy
Moving Average	4.82	3.91	81.5%
ARIMA	3.27	2.64	87.2%
LSTM	2.14	1.78	92.6%

Table I shows the comparative forecasting performance of different models. The LSTM model achieved the lowest RMSE (2.14) and MAE (1.78), indicating higher prediction accuracy compared to traditional statistical approaches such as Moving Average and ARIMA. This improvement can be attributed to the ability of LSTM networks to capture complex temporal dependencies and nonlinear patterns present in stock market time-series data.

Comparative benchmarking was conducted to evaluate the effectiveness of deep learning approaches relative to traditional statistical models. While the Moving Average model provides a simple baseline for forecasting, it fails to capture long-term dependencies in financial data. ARIMA improves performance through statistical time-series modeling, but its linear assumptions limit predictive capability. The LSTM model significantly outperforms both approaches due to its recurrent architecture, which enables effective learning of sequential patterns and long-term dependencies.

The ARIMA model provided reasonable accuracy for short-term price prediction by capturing linear trends, but its performance declined during periods of high market volatility. In comparison, the LSTM model demonstrated better capability in learning complex and non-linear patterns, resulting in more consistent and accurate forecasts, particularly for long-term trend analysis.

The visualization module effectively presented historical and predicted data through interactive charts, enabling users to interpret market trends with ease. Portfolio analysis results showed that the system successfully evaluated diversification

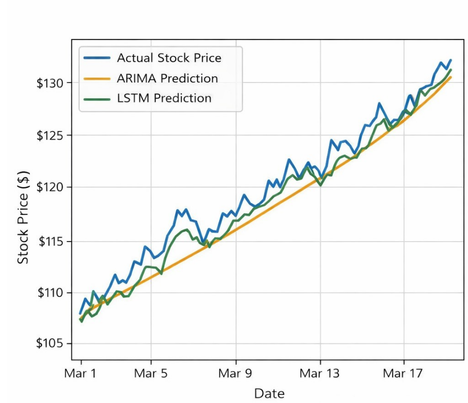

Fig. 2. Comparison between actual stock prices and predicted values using ARIMA and LSTM models

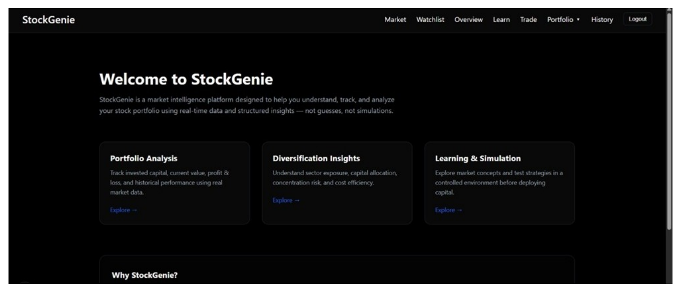

Fig. 3. Visualization dashboard of the StockGenie platform showing stock trend analysis and portfolio insights

and risk exposure, helping users understand the balance between potential returns and associated risks.

The virtual trading simulator allowed users to practice trading strategies without financial risk, offering immediate feedback and improving user confidence. Overall, the system exhibited efficient performance, low response latency, and an intuitive user experience, demonstrating that StockGenie functions effectively as both a decision-support tool and a learning platform for novice investors.

VI. Conclusion and Future Work

Experimental evaluation using RMSE and MAE metrics demonstrates that the LSTM forecasting model provides improved predictive accuracy compared to traditional statistical approaches such as Moving Average and ARIMA. The system integrates time-series forecasting models such as ARIMA and Long Short-Term Memory (LSTM) networks with interactive data visualization, portfolio analysis, and virtual trading simulation. By transforming large volumes of stock market data into meaningful insights, StockGenie simplifies complex financial information and provides users with a risk-free environment to learn and experiment with investment strategies. The experimental evaluation demonstrates that the proposed system delivers reliable trend forecasts, effective portfolio insights, and an intuitive user experience, making it suitable as both a decision-support tool and an educational platform.

Future work will focus on enhancing forecasting accuracy through the incorporation of hybrid and advanced deep learning models, as well as the inclusion of additional financial indicators. Integrating sentiment analysis based on financial news and social media data can further improve the system's ability to capture market dynamics. The platform can also be extended to support real-time trading integration, mobile application deployment, and cloud-based scalability to accommodate a broader user base. These improvements will enhance the robustness, accessibility, and practical applicability of StockGenie in real-world investment scenarios.

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