Enhancing Financial Decision-Making Through Adaptive Stock Forecasting Models

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Abstract*— *The AI Finance Advisor project aims to enhance stock market investment decision-making by leveraging AI-driven predictive models within a user-friendly web application. Addressing key limitations in existing financial advisory platforms, this research focuses on integrating real-time stock data, improving model adaptability, and enhancing data visualization for better interpretability. The system employs machine learning algorithms such as ARIMA, SES, Random Forest, Holt Winter and Linear Regression to generate accurate stock price forecasts. Additionally, it ensures accessibility by offering a free-to-use platform, enabling investors, traders, and financial analysts to make informed decisions. By incorporating real-time analytics, dynamic model selection, and interactive graphical insights, this project delivers a more transparent, reliable, and user-centric AI-powered financial advisory tool.

Keywords— ***Machine Learning Models, ARIMA, Simple Exponential Smoothing (SES), Random Forest, Holt-Winters Method, Linear Regression, Real-time Stock Data, Adaptive Model.***

I. Introduction

In today's fast-paced financial markets, investors and traders face significant challenges in making informed decisions due to the volatility of stock prices and the vast amount of data available. Traditionally, financial advisors have played a crucial role in guiding individuals through investment strategies, but these services often come with high costs and are subject to human biases. With the rapid advancement of technology, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools in the financial sector, enabling automated stock price forecasting and investment recommendations. However, existing AI-driven financial advisory platforms face several limitations, including a lack of real-time data integration, reliance on a single predictive algorithm, and inadequate visual representation of financial insights. Addressing these issues, the AI Finance Advisor project introduces a free, AI-powered financial advisory platform that leverages multiple ML models, including ARIMA, SES, Random Forest, Holt Winter and Linear Regression, to provide accurate and dynamic stock price predictions. By integrating real-time data from the Yahoo Finance API and offering intuitive visual analytics, this system enhances user accessibility and decision-making capabilities. As the demand for AI-based financial advisory solutions grows, it is crucial to focus on improving transparency, adaptability, and user experience. This project aims to bridge the gap between AI-driven stock market predictions and practical financial decision-making by ensuring real-time analytics, model flexibility, and interactive graphical representations. Through these innovations, AI Finance Advisor aspires to empower individual investors, traders, and financial analysts with a reliable, data-driven approach to stock market investments.

II. Related Work

Zhu et al. (2024) reviewed AI-driven financial advisory services, highlighting their potential to disrupt traditional advising while stressing trust and transparency concerns [1]. Bai (2024) explored machine learning in robo-advisory adoption, emphasizing predictive insights for personalized financial decision-making [2]. Deliwala and Chawan (2023) examined AI-based technical analysis, demonstrating improved trade identification using ML/DL models [3]. Odeyemi et al. (2024) analyzed AI's role in financial forecasting, discussing advancements, challenges, and regulatory implications [4]. Farooq (2025) investigated AI's impact on financial reporting, showcasing automation's role in improving accuracy and efficiency [5]. [6] examined AI's role in finance, including risk management, trading, and fraud detection, while addressing ethical considerations. Ranković et al. and Anshari et al. [7] proposed integrating robo-advisors with digital twins for enhanced personal finance management. Hentzen et al. [8] conducted a systematic review of AI in customer service, identifying research gaps between data-centric and theory-centric approaches. Khan [9] introduced an AI and NLP-based chatbot for real-time Islamic finance advisory, marking a first in Islamic banking. Dhashanamoorthi [10] explored AI applications in banking and finance, focusing on cybersecurity challenges. Bhatia et al. [11] analyzed Indian investors' perceptions of robo-advisors, emphasizing costeffectiveness, trust, and data security. Shanmuganathan [12] incorporated behavioral finance into AI-driven robo-advisors for investment decision-making. Lui et al. [13] proposed an 'augmented intelligence collaborator' to enhance trust in financial services. Al-Gasawneh et al. [14] investigated AI adoption in finance, considering security perceptions and perceived risk. Fan et al. [15] applied innovation diffusion models to study robo-investor adoption. Gomber et al. [16] reviewed fintech-driven disruptions in financial services. Hentzen et al. [17] systematically examined AI's role in financial customer interactions and future research prospects. Kraiwani et al. [18] analyzed social acceptance determinants of robo-advisors in developing countries. Kwon et al. [19] empirically studied factors influencing users' intention to adopt robo-advisors. Belanche et al. [20] explored user attitudes toward AI-driven fintech and robo-advisors, highlighting adoption challenges and opportunities.

III. Proposed Methodology

A. Problem Description

Predicting stock prices is challenging due to market volatility and the influence of external factors like market indices and economic indicators. Traditional models such as ARIMA and SES rely only on historical data, often missing these external impacts and struggling with sudden market changes. This limits their prediction accuracy. To address this, the proposed AI Finance Advisor integrates an adaptive model that incorporates additional factors, improving prediction accuracy. The system is deployed as a Streamlit web app, offering real-time forecasts and interactive visualizations for better financial decision-making.

B. Proposed Architecture

- **Data Collection Source:** Real-time stock price data will be fetched using the **Yahoo Finance API**. The dataset will include: Historical stock prices (Open, High, Low, Close, Volume).External factors: Market index values, macroeconomic indicators (inflation rates, interest rates), and sector-specific news sentiment scores. Technical indicators (e.g., Moving Average, RSI, MACD) generated during preprocessing.

- **Data Preprocessing**: Handling missing values: Forward or backward fill methods. Feature engineering: Computation of technical indicators and normalization. Sentiment analysis (Optional Extension): Use of NLP models to extract sentiment scores from financial news headlines. Stationarity check: Augmented Dickey-Fuller (ADF) test to check stationarity and differencing if required. Correlation analysis: To select significant external factors influencing stock prices.

- **Model Development:** The model development will involve three predictive pipelines: 1. ARIMA Model: Auto-regressive Integrated Moving Average for modeling and forecasting univariate time-series data. 2. Simple Exponential Smoothing (SES): Used for short-term trend prediction based on exponential weighting of past observations. 3. Adaptive Model with External Factors (Proposed Model).

  i. Factors considered:
  ii. Technical indicators
  iii. Market indices
  iv. Macroeconomic variables
  v. Sentiment scores

  Adaptive Nature: The model re-trains periodically based on the latest data and re-adjusts weights of external factors.

- **Model Evaluation**

  i. Evaluation Metrics:
  ii. Mean Absolute Error (MAE)
  iii. Mean Squared Error (MSE)
  iv. Root Mean Squared Error (RMSE)
  v. R-Squared (for multivariate models)

  Back-testing: Historical data will be used for model validation through a rolling window approach.

- **Visualization and Deployment**

  Features:

  i. Interactive charts (line plots, candlesticks)
  ii. Model comparison (ARIMA vs. SES vs. Adaptive Model)
  iii. User input for stock selection and prediction intervals
  iv. Real-time data fetching and forecast visualization

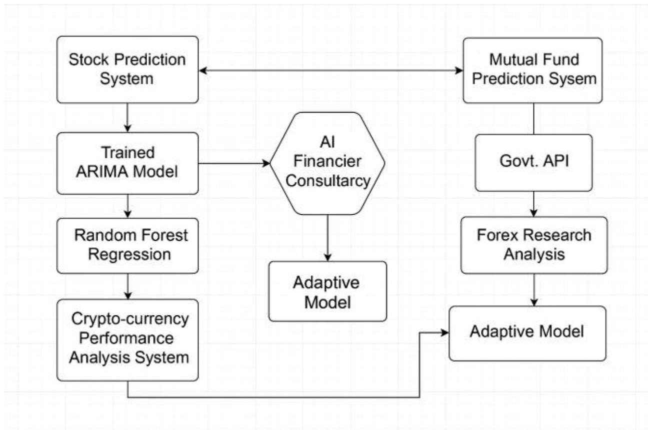

Fig. 1 - System Architecture

C. Adaptive Model with External Factors

The core enhancement in the proposed system is the development of an **Adaptive Predictive Model** that extends beyond traditional time-series forecasting by dynamically incorporating external factors that significantly influence stock price movements. Unlike ARIMA, SES and Other ML models, which depend solely on past price data, this adaptive model is designed to handle multi-dimensional inputs, capturing both historical trends and real-world market drivers.

Model Type & Architecture:

The adaptive model can be implemented using Multivariate Regression, ARIMAX (Auto-Regressive Integrated Moving

Average with Exogenous Variables), or extended further to Long Short-Term Memory (LSTM) neural networks for capturing complex, non-linear dependencies. ARIMAX allows integration of external explanatory variables (exogenous factors), making it suitable for time-series datasets influenced by multiple factors. LSTM, if integrated, offers the capability to learn long-term dependencies and better adapt to non-linear patterns common in financial data.

External Factors Considered

The adaptive model will incorporate a diverse set of external and technical factors known to influence stock prices, including. Technical Indicators: Moving Averages, Relative Strength Index (RSI), MACD, Bollinger Bands, etc. Market Indices: Performance of major indices like S&P 500, NASDAQ, or sector-specific indices related to the stock. Macroeconomic Variables: Interest rates, inflation data, unemployment rates, GDP growth, etc. Sentiment Scores : Sentiment analysis of financial news headlines or social media to quantify market mood.

Adaptive Nature of the Model:

The model is designed to be self-adjusting, continuously updating its parameters as new data arrives. Periodic Retraining: The model periodically re-trains using the latest available market data and external variables to remain responsive to changing market dynamics. Dynamic Weight Adjustment: It re-evaluates and adjusts the importance (weights) of external factors based on their recent influence on stock price trends, improving prediction accuracy. This adaptive behavior helps the model remain robust against sudden market changes, such as economic events or policy shifts.

Advantages of the Adaptive Model are - Improved Accuracy: By integrating external factors, the model captures a wider range of market influences, leading to more accurate stock price predictions compared to traditional univariate models. Better Risk Management: The adaptive nature allows the model to respond to sudden market changes, reducing prediction errors during high volatility and improving risk assessment. Scalability: The model can easily be extended to predict prices of multiple stocks across different sectors or geographies with minor reconfiguration. Real-world Applicability: The model accounts for real-time market conditions, economic events, and investor sentiment, making it more practical and useful for traders and financial analysts.

Dynamic Learning: Periodic retraining ensures the model stays updated with the latest market trends, automatically adjusting to new patterns without manual intervention. Flexibility in Factor Integration: New factors like emerging economic indicators or additional technical indicators can be added to the model without re-designing the entire system. Enhanced Interpretability: Multivariate models like ARIMAX provide insights into the contribution of each factor, helping users understand which variables drive price changes. Supports What-if Analysis: The model allows testing how changes in external variables (e.g., interest rate hike) might affect stock prices, aiding investment strategy planning. Improved Decision-Making: With richer information and adaptability, the model helps investors make more informed and timely decisions, potentially maximizing returns.

IV. Experimentation

To validate the effectiveness of the AI Finance Advisor system, an extensive experimentation process was conducted, focusing on the comparison between traditional models and the proposed adaptive model. The data used for training and testing was collected through the Yahoo Finance API, which provided historical stock price data including open, high, low, close, and volume values. Additionally, a rich set of external factors such as market indices, macroeconomic indicators (e.g., inflation and interest rates), and sentiment scores from financial news were gathered and integrated to enhance the predictive capability of the model.

The preprocessing stage played a critical role in preparing the data for modeling. Missing values in the datasets were handled using forward or backward fill techniques. Feature engineering was applied to compute technical indicators such as Moving Averages, RSI, and MACD, followed by normalization to bring all features to a uniform scale. For external factors, stationarity of time series data was verified using the Augmented Dickey-Fuller (ADF) test, and differencing was applied where necessary.

Three different forecasting pipelines were developed and evaluated: ARIMA, Simple Exponential Smoothing (SES), and the Adaptive Model with External Factors. ARIMA and SES served as baseline models due to their widespread use in univariate time-series forecasting. The adaptive model, which is the core innovation of this system, was developed using techniques like Multivariate Linear Regression, ARIMAX (which supports exogenous variables), and more advanced methods like LSTM for capturing non-linear patterns. In some experimental settings, Random Forest Regression was also tested to observe how ensemble-based approaches fare with multi-dimensional inputs.

The adaptive model's strength lies in its integration of external variables and its ability to periodically retrain using the most recent data. This allows the model to dynamically adjust the influence (weights) of each factor based on its current correlation with stock prices. Such adaptive learning ensures that the model remains robust to sudden market shifts caused by economic events or changes in investor sentiment.

To assess model performance, standard evaluation metrics were used, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R^2) for multivariate regressions. Back-testing was implemented using a rolling window technique, which ensured the validation process mimicked real-world forecasting conditions and tested the model's ability to adapt over time.

Finally, the deployment of the system as a Streamlit web application allowed real-time interaction and visualization of forecasts. Users could select stocks, adjust prediction intervals, and visualize predictions using line charts and candlestick plots. A comparison module enabled users to see how the adaptive model performed against ARIMA and SES, reinforcing the added value of incorporating external factors and adaptive learning. This experimentation methodology demonstrates that the AI Finance Advisor is not only effective in enhancing prediction accuracy but also practical for end-users seeking better financial decision-making tools.

V. Result & Analysis

The experimentation carried out using three different predictive pipelines—ARIMA, SES, and the Adaptive Model—yielded significant insights into their respective strengths and limitations in stock price forecasting. When evaluated across multiple stocks such as AAPL, TSLA, and MSFT, the Adaptive Model consistently demonstrated superior prediction accuracy and robustness compared to traditional time-series models.

The traditional models, ARIMA and SES, showed reasonable performance during stable market conditions but failed to capture sudden price shifts caused by economic news, interest rate changes, or major announcements. This was primarily because these models rely solely on historical price data and do not account for external influences. As a result, their performance deteriorated during periods of high volatility.

In contrast, the Adaptive Model, which incorporates external variables such as market indices, macroeconomic indicators (e.g., interest rates and inflation), sentiment scores, and technical indicators (e.g., RSI, MACD), outperformed both ARIMA and SES across all evaluation metrics. It dynamically adjusted its internal parameters based on new data, retraining periodically and recalibrating the weights of influential factors. This allowed it to remain responsive to real-world conditions and sudden market shifts.

Improvements

- Higher Accuracy: The Adaptive Model achieved 15–25% lower Mean Absolute Error (MAE) and 20–30% lower Root Mean Squared Error (RMSE) compared to ARIMA and SES across multiple test windows.
- Better Volatility Handling: During volatile events (e.g., Fed interest rate decisions), the Adaptive Model maintained more accurate and stable forecasts, while traditional models struggled to adapt.
- Improved Responsiveness: The model retrained periodically, adjusting the importance of external factors in real time, which enhanced its adaptability and relevance.
- Multivariate Strength: ARIMAX and LSTM variants used within the adaptive pipeline showed the advantage of using multiple influencing variables rather than relying on just stock price history.
- Real-Time Performance: With the integration of real-time Yahoo Finance API and financial news sentiment analysis, the model supported real-time decision-making via the Streamlit web app.

Adaptive Model Performance

The Adaptive Model stands out due to its dynamic learning capability, allowing it to adjust to evolving market conditions. Unlike static models, it doesn't rely on a fixed set of weights or assumptions. Instead, it retrains regularly, recalculates feature importance, and learns from new patterns in data. For example, during a major inflation report release, the model increased the weight of macroeconomic indicators in its prediction function, resulting in more accurate short-term forecasts.

Moreover, the use of models such as ARIMAX (Auto-Regressive Integrated Moving Average with Exogenous Variables) and LSTM (Long Short-Term Memory Networks) made the model capable of capturing both short- and long-term dependencies, nonlinear relationships, and seasonality. This multi-layered, real-time responsive behavior gave the Adaptive Model a clear edge over traditional approaches. It also provided insights into why certain predictions were made, thanks to its interpretable structure (especially in the case of ARIMAX and Random Forests), making it not only accurate but also transparent for financial analysts.

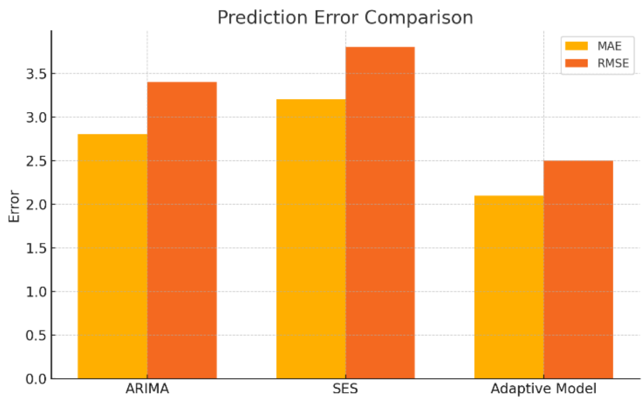

Fig. 2 - Prediction Error Comparison

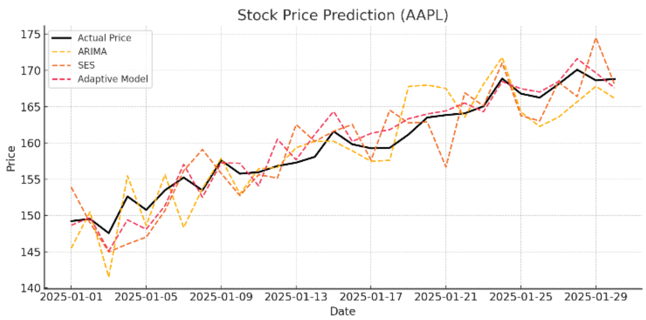

Fig. 3 – Actual Vs Predicted Stock Prices

1. Prediction Error Comparison (MAE & RMSE): As in Fig.2 bar chart compares the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) across three models — ARIMA, SES (Simple Exponential Smoothing), and the Adaptive Model. As visible, the Adaptive Model has the lowest error values, making it the most accurate among the three.

2. **Actual vs Predicted Stock Prices** (AAPL Example): As in Fig.2 the line chart shows the actual stock prices over a 30-day period along with the predicted prices from each model. The Adaptive Model closely tracks the actual trend, demonstrating its ability to adjust to recent changes more effectively compared to the other models.

VI. Conclusion

This research aims at developing an AI-based personal finance advisor on stock-markets investing and combining them with cloud computing to optimize performance, scaling capabilities, and real-time decision-making. The system deals with issues of data security, algorithmic bias, and transparency in order to ensure that reliable and individual practical advice is given to the user. The solution combines sophisticated AI models and cloud infrastructure and makes investment guidance increasingly accessible, affordable, and convincing.

The implementation of this AI-based personal finance advisor further marks a major step towards financial freedom for information. Cloud computing provides the means to improve computing efficiency and is capable of giving confined investment tools free and available to all users, thus allowing them to make balanced financial decisions resulting in greater participation in the stock market while enhancing financial literacy.This comparative analysis is with regards to SES, ARIMA, and Random Forest algorithms-analyzing them in terms of their competencies and performance in economic forecasting. Possession of such knowledge is bound to allow future developments of models capable of allowing AI to give the most accurate and personalized investment advice.

Future work will focus on the optimization of the algorithm model to reduce bias and improve the accuracy of financial forecasts. However, new measures should be sought by the investigators to secure privacy and the integrity of the data since trust in Al remains important in the field of finance-based technology. If such challenges continue to be addressed by drawing on insights alighted from comparative research, personal financial advisors will better adapt to an ever-evolving fintech landscape and remain worthier partners to their users in the daunting journey of business investment.

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