Integrated Approach for Asset Price Forecasting via Prophet Model and Optimizing Investment Strategies through Genetic Algorithms

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ABSTRACT This research presents an in-depth exploration of a wide array of algorithms, techniques, methods and models used for forecasting asset values. Significantly, the study introduces an unprecedented approach, featuring a dedicated model for precise price forecasting and another for recommending optimized strategies. By assessing and contrasting the approaches and outcomes of asset value prediction across different fields, this paper study aims to harness the power of Artificial Intelligence (AI) in forecasting asset prices and tailoring investment strategies. Implemented system integrates the Prophet Model for precise price forecasting and employs Genetic Algorithms for investment strategy generation. Through a systematic evaluation of the system, we demonstrate its capacity to provide accurate asset price predictions, outperform traditional investment strategies and mitigate risks effectively. Empirical unit testing showcased impressive results such as gold model with a 4.76% MAPE and an R-squared value of 0.9795 and oil model with notable metrics such as a Mean Absolute Error of 6.80, and Root Mean Squared Error of 10.92. Every single user, across the board, either strongly agreed or agreed that the investment recommendations provided valuable insights and 92.4% perceiving system predictions as very accurate. It further delves into the challenges and limitations, such as the quality of data used and model interpretability, underscoring the imperative for robust, compliant and interpretable forecasting models. Additionally, the study explores future directions in the domain, advocating for the expansion of asset classes and the integration of Natural Language Processing (NLP) into the system.

INDEX TERMS Asset price forecasting, genetic algorithm, optimum strategy recommendation, prophet.

I. INTRODUCTION

The landscape of investment has undergone remarkable transformations in recent years, propelled by technological advancements and the integration of data analytics. Investors and financial professionals are increasingly turning to automated investment recommendation systems to drive data-driven decisions, manage risk effectively, and optimize investment strategies. These [1] systems employ a spectrum of techniques, from cutting-edge time series forecasting models to sophisticated optimization algorithms, providing real-time guidance in the intricate domain of finance.

The precise prediction of financial asset prices holds paramount importance for investors, portfolio managers, and financial institutions. It is a linchpin in informed decision-making, risk mitigation, and the ultimate achievement of financial goals. However, [2] the inherent volatility and complexity of financial markets have rendered accurate predictions challenging. Consequently, there has been a surge in demand for automated systems capable of harnessing the power of data and advanced algorithms to furnish insights and recommendations.

Historically, investment strategies have often relied on heuristics, technical analysis and human intuition. While these methods have their merits, they are susceptible to cognitive biases and may not fully exploit the vast amounts of data available in today's digital age. Automated systems offer a data-driven and systematic approach [3] to investment decisions, enhancing efficiency and potentially improving returns.

The primary objective of this research is to design, implement and evaluate an automated investment recommendation system that leverages state-of-the-art techniques to address the challenges of financial asset price prediction and investment strategy optimization. In this context, this paper presents a comprehensive study and the development of an automated investment recommendation system designed to forecast future prices of financial assets and recommend optimized investment strategies.

II. LITERATURE REVIEW

The evolution of investment strategies and the emergence of automated investment recommendation systems have been influenced by a rich body of research and the rapid development of data analytics, machine learning and optimization techniques. In this section, we provide a comprehensive review of the literature relevant to the components and objectives of our research: price forecasting and investment strategy optimization.

Traversing various Machine Learning (ML) models utilized in forecasting of gold prices, real estate prices and automobile prices. With the help of a comprehensive analysis of the selected studies [1]-[7] for gold price prediction, [8]-[10] for real estate price prediction, [10]-[13] for automobile price prediction, numerous valuable discoveries have brought to light.

Table 1. Asset price forecasting model comparison

Model	Data Sources	Key Findings
Time Series Analysis	Historical price and trading volume data	ARIMA and GARCH models are effective in modeling volatility and trends [19]
Machine Learning Models	Historical price, volume, technical indicators, news data	Random Forest and Neural Networks provide accurate predictions [20]
Volatility Models	Historical price and volatility data	GARCH models capture asset volatility dynamics [21]
Monte Carlo Simulation	Historical price data, random variables	Simulations provide distribution of potential future prices [22]
Option Pricing Models	Asset price, strike price, time to maturity, volatility	Black-Scholes model estimates option prices [23]
Fundamental Analysis	Financial statements, economic indicators	Intrinsic value can be estimated based on fundamentals [24]
Technical Analysis	Historical price and volume data	Identifies patterns and trends in price charts [25]
Econometric Models	Multiple financial variables	VAR models analyze relationships between variables [26]
News and Sentiment Analysis	News articles, social media sentiment	Market sentiment impacts asset prices [27]
Market Microstructure Models	Order flow data, trading volume	Analyzes market dynamics and liquidity [28]
Hybrid Models	Combines various data sources and models	Fusion of models enhances forecasting accuracy [29]
Quantitative Strategies	Real-time market data, trading signals	Algorithmic trading strategies based on forecasts [30]

For predicting gold prices, the reviewed research illustrated the productivity of various ML approaches. Fuzzy rule-based prediction [1] leverages news affect to forecast gold prices, while a Convolutional Neural Network - Long Short Term Memory Networks (CNN-LSTM) model [2] combines CNN and LSTM networks for time-series forecasting. Ensemble regression-based techniques [3] and tree-based prediction techniques [4] provide supplemental vision towards gold price prediction. Moreover, researchers have explored the use of online extreme learning machine algorithms [5], Deep Learning (DL) techniques [6], ensemble-based ML techniques [8], and [9] hybrid models comprising Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM).

Concerning prediction of real estate prices, the chosen studies demonstrate the diversified range of ML methods used in this domain. The researches spotlight the importance of utilizing real transaction data [13], ensemble-based approaches [12] and regression models [14] to predict real estate prices precisely. Moreover, feature selection techniques [15] and exploratory data analysis [16] have been recruited to enhance the performance and interpretability of ML models in this domain.

Table 2. Strategy Optimization Model Comparison

Model	Description	Key Features
Mean-Variance Optimization	Classical approach to portfolio optimization. Aims to find the allocation of assets that maximizes returns for a given level of risk.	[11] Considers the expected return and variance (risk) of assets. Requires estimates of asset returns and covariances.
Black-Litterman Model	Extension of mean-variance optimization. Combines market equilibrium and investor views to create a more stable portfolio.	[12] Allows the inclusion of subjective investor views. Adjusts the expected returns based on market equilibrium.
Capital Asset Pricing Model (CAPM)	Model that estimates expected returns based on the asset's beta, the risk-free rate and the market risk premium.	[13] Provides a framework to assess the risk-return trade-off. Simplicity in estimating expected returns.
Factor Models	Class of models that explains asset returns based on underlying factors (market risk, size, value, momentum, and others).	[14] Captures systematic risk through various factors. Fama-French 3-factor model, Carhart 4-factor model.
Monte Carlo Simulation	Numerical technique to assess investment strategies by simulating a large number of possible scenarios.	[15] Incorporates uncertainty and randomness into the analysis. Useful for assessing downside risk and portfolio performance.
Genetic Algorithms	Optimization algorithms inspired by the process of natural selection (evolve portfolio allocations).	[16] Suitable for non-convex optimization problems. Explore a wide solution space efficiently.
Reinforcement Learning	Optimize portfolios by learning from historical data and interactions with the market.	[17] Adapts to changing market conditions. Can handle complex and dynamic strategies.

Risk Parity	Portfolio construction approach that allocates equal risk to each asset, rather than equal capital.	[18] Balances risk across assets. Can reduce the impact of highly volatile assets.

While there is a substantial body of research on financial time series forecasting and investment strategy optimization, there are several areas where further exploration is warranted. The deliberate selection of the Prophet Model for price forecasting and Genetic Algorithms (GAs) for strategy optimization in our research is not only substantiated by a thorough examination of existing literature but also by a comprehensive review of studies specifically addressing these models in the financial domain. The Prophet Model's robust handling of seasonality, accurate trend detection, and adaptability to missing data have been consistently supported by notable studies such as [13] – [17], which specifically delve into its strengths and applicability in financial time series forecasting. Similarly, the decision to employ Genetic Algorithms is fortified by a robust literature foundation, exemplified by research [18] – [21], elucidating their global optimization capability, adaptability to dynamic market conditions, and proficiency in non-convex optimization problems relevant to portfolio optimization. However, it is imperative to acknowledge the apparent gap in the literature review concerning these specific models. While this comprehensive exploration of the existing studies bolsters the rationale for model choices, the limited availability of research directly addressing the Prophet Model and Genetic Algorithms in the financial domain underscores the novelty of the approach. The implications of this gap, the potential limitations it introduces, and avenues for future research to bridge this knowledge void are critical aspects, ensuring a nuanced understanding of the current state of research.

III. METHODOLOGY

The study inquired about the ML techniques and methodologies applicable for forecasting gold prices, automobile prices and real estate prices. Additionally, it sought the optimal algorithm for predicting investment strategies. To address these questions, a thorough literature search was performed, employing systematic review techniques to gather information from diverse databases and sources.

A. Systematic Review

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach was utilized to enhance the disclosure and documentation of systematic reviews. "Fig. 1" shows the systematic review process involved identifying relevant studies, extracting key data on machine learning algorithms, features used, data pre-processing techniques, evaluation metrics and performance results. Additionally, a requirement gathering questionnaire was conducted to identify the best solution for addressing the research question.

Reviewed studies illustrate the possibility of ML techniques in predicting gold prices, prices of real estate and automobile prices. These techniques provide valuable insights for

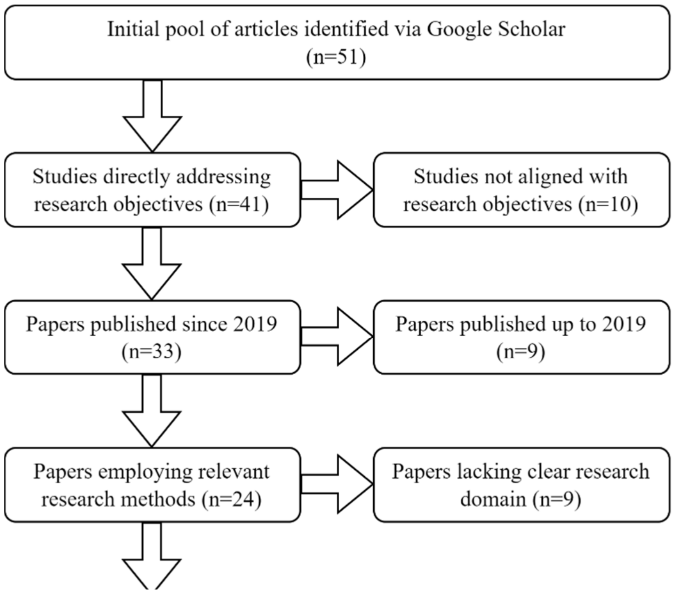

Figure 1. Exploratory Research Methodology

(n=24)

investors, financial institutions and real estate professionals to make informed decisions and mitigate risks. However, it is essential to consider the limitations and challenges associated with data quality, model interpretability and generalizability when implementing these machine learning approaches.

B. Requirement Gathering

A questionnaire was conducted to identify the optimal solution for addressing the research question. This involved seeking input from experts and stakeholders to understand the specific needs and objectives that an Automated Investment Recommendation System should fulfill. The requirement gathering process involved a comprehensive questionnaire and analysis. These addressed various aspects, including age categories, specific investment products, investment strategies, investment amounts, risk tolerance, factors for consideration, platforms for investment analysis, frequency of recommendation updates, security features, and the degree of automation. Findings revealed that individuals aged 15-21 are more receptive to the system, with a preference for fixed deposit schemes and a medium risk tolerance. Additionally, economic indicators and financial statements were highlighted as crucial factors, and most respondents favoured daily system updates with 2-factor authentication, leaning towards a semi-automated financial advice system.

C. Technology

1) Price Forecasting: The Prophet model was employed to carry out the function of forecasting future price variations with astonishing insight and accuracy. Owing to its robust features and proven effectiveness in handling financial time series data. The model stands out for its adeptness in capturing intricate seasonality patterns, a crucial factor in predicting asset prices impacted by daily, weekly, and yearly trends. Its inherent adaptability to missing data ensures reliable performance, addressing a common challenge in financial datasets.

2) Optimized Strategy Prediction: Inspired by natural selection processes, are particularly well-suited for tackling complex and non-convex optimization problems inherent in portfolio optimization. Their ability to efficiently explore a vast solution space, adapt to dynamic market conditions, and provide globally optimized solutions distinguishes them from traditional optimization approaches. GAs align seamlessly with the inherent uncertainty and randomness in financial markets, offering a dynamic and flexible method for constructing portfolios.

Alternative combinations, such as relying on traditional optimization methods or machine learning models alone, were deemed less suitable for the specific demands of portfolio construction. The chosen integration stands out for its efficiency, adaptability, and explicit focus on optimization, offering a unique and comprehensive framework for addressing the intricacies of investment strategy in dynamic financial environments.

D. Implementation

1) Prophet Model: Process "Fig. 2" begins by loading pre-trained Prophet models for gold and oil using the pickle module, stored in gold_model and oil_model variables, capturing historical patterns. A date range is then generated based on specified parameters. Subsequently, a DataFrame named df is constructed, and the predict() method of the Prophet model is utilized to generate price forecasts stored in the forecast variable. The predictions are extracted and form a new DataFrame named prediction, containing forecasted dates and prices. The overall function returns this prediction DataFrame, providing a comprehensive tool for anticipating future trends in the gold and oil markets.

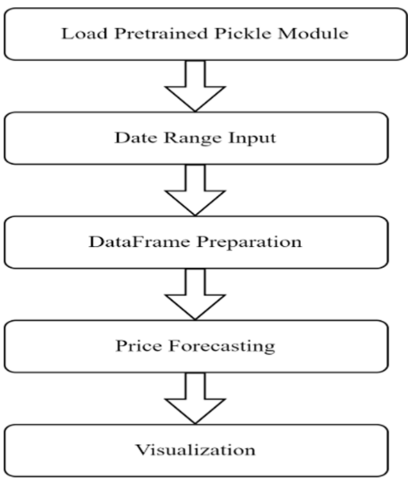

Figure 2. Prophet Model Working Methodology

1) Genetic Algorithm: Involves "Fig. 3" encoding and decoding investment strategies using binary strings, where the encoding() function converts floating-point values to binary, and decoding() performs the reverse. The algorithm's objective_function() assesses strategy fitness based on return and risk percentages for oil and gold investments. Crossover and mutation are facilitated by cross_over() and maintain genetic diversity. The core genetic_algorithm() orchestrates the optimization process, starting with a population of randomly generated strategies and iteratively evolving new generations through crossover and selection. The process continues for a set number of generations, ultimately yielding the optimal investment strategy. The optimize_investment() function acts as an interface, calculating return and risk percentages and applying the Genetic Algorithm to predict the optimal strategy for oil and gold investments.

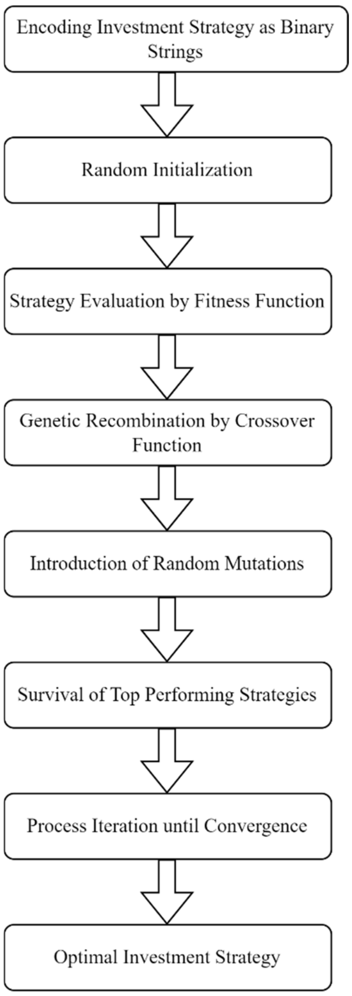

Figure 3. Genetic Algorithm Working Methodology

IV. RESULTS & DISCUSSION

A. Unit Testing

Unit testing is a vital practice in software development, involving the verification of individual components or units to ensure they function as intended in isolation. Using the Prophet library, we enhanced the gold price forecasting model "Fig. 4", achieving evaluation metrics including a Mean Absolute Percentage Error (MAPE) of 4.76% and an R-squared value of 0.9795.

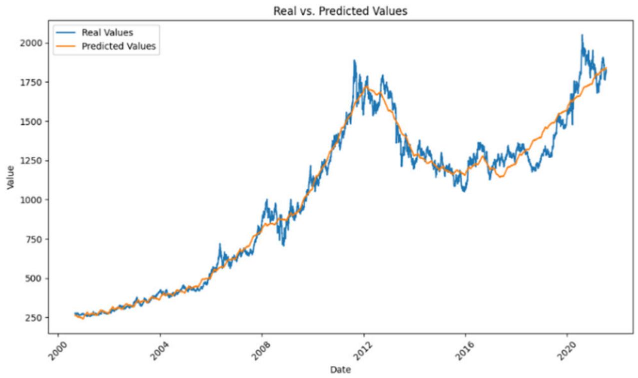

Fig. 4. Gold Model Performance

Similarly, the oil price forecasting model "Fig. 5", developed with the Prophet library, exhibited initial evaluation metrics on historical data, including Mean Squared Error (MSE) of 119.32, Mean Absolute Error (MAE) of 6.80, and Root Mean Squared Error (RMSE) of 10.92.

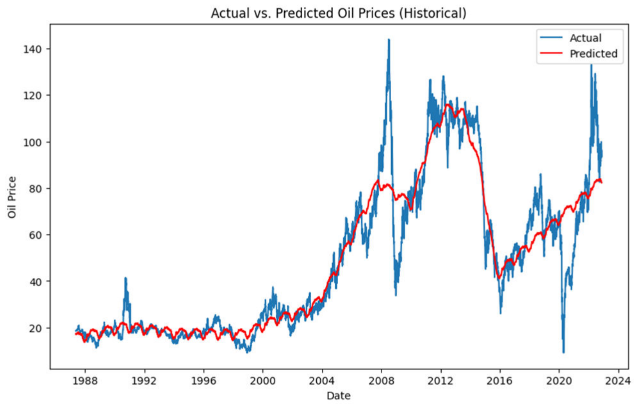

Fig. 5. Oil Model Performance

B. User Testing

User testing is a crucial phase in evaluating the effectiveness and user-friendliness of this application. Feedback from users provides valuable insights into the application's usability, performance, and overall user experience. The following user testing results highlight key aspects gathered from the questionnaire:

The survey "Fig. 6" reflects a diverse user base, with significant representation from investors and bankers, indicating that this system attracts a broad range of professionals involved in the financial sector.

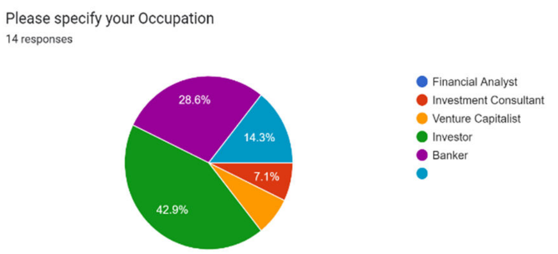

Fig. 6. Occupational Diversity

Most participants "Fig. 7" engage in investment activities annually, suggesting that this system caters to users with varied levels of investment frequency, from occasional to more strategic, long-term approaches.

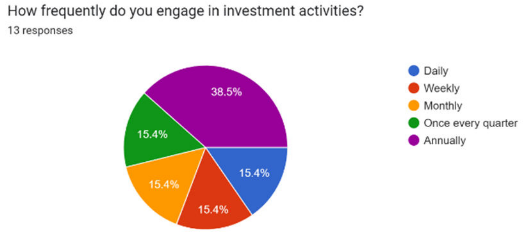

Fig. 7. Engagement Patterns

A substantial 69.2% of users "Fig. 8" found navigating through this system to be very easy, indicating an intuitive and user-friendly interface that supports effortless exploration of different sections.

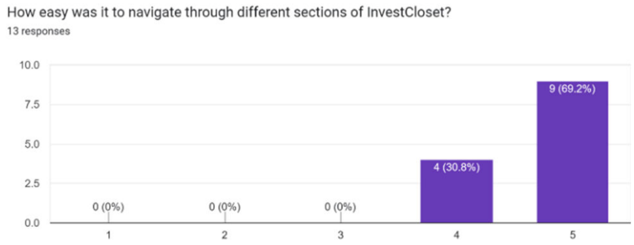

Fig. 8. Navigation Experience

The majority (78.6%) easily found the information or features they were looking for "Fig. 9", demonstrating that this system effectively organizes and presents relevant data to meet user expectations.

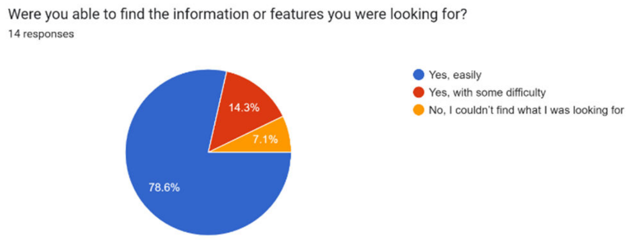

Fig. 9. Information Retrieval

An encouraging 69.2% found the investment recommendations helpful "Fig. 10", highlighting that users perceive value in the predictive capabilities of this system for guiding their investment decisions.

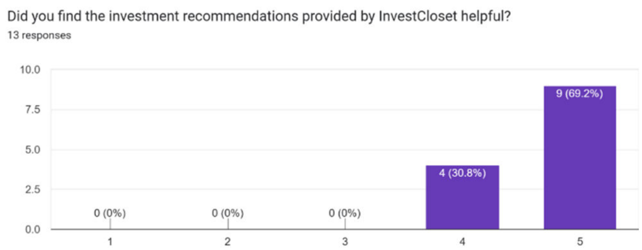

Fig. 10. Recommendation Effectiveness

Nearly half of the respondents (46.2%) perceived this system predictions as very accurate "Fig. 11", suggesting a positive user belief in the system's ability to provide reliable forecasts aligned with their market understanding.

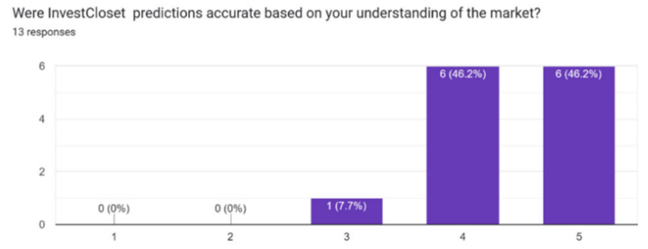

Fig. 11. Accuracy Perception

The layout and design of this system received a good rating "Fig. 12" from 38.5% of users, indicating a generally positive perception of the visual aspects, although improvements may be considered based on the 30.8% who rated it as neutral.

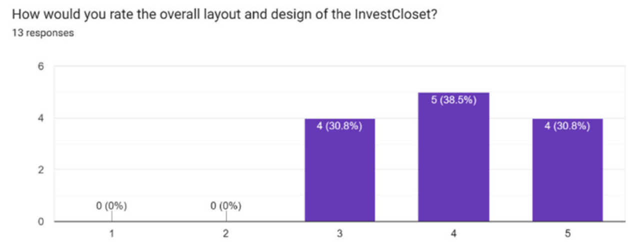

Fig. 12. Layout and Design Rating

A significant majority (92.3%) found the user interface clear "Fig. 13" and 64.3% perceived the application as responsive "Fig. 14", highlighting positive impressions regarding usability and performance.

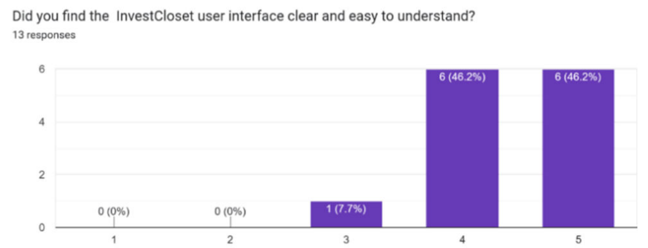

Fig. 13. UI Clarity

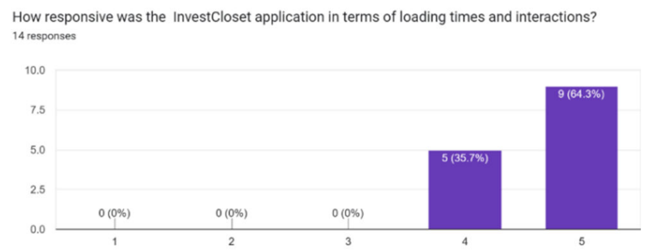

Fig. 14. UI Responsiveness

The low percentage (7.7%) reporting few minor errors "Fig. 15" suggests that this system has a stable and reliable performance, with minimal disruptions during usage.

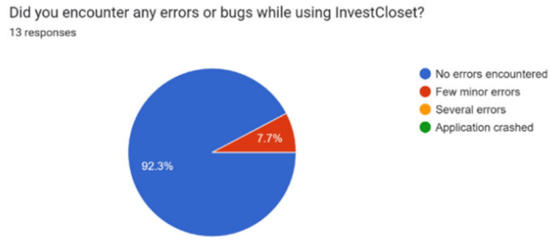

Fig. 15. Error Encounter

Users provided constructive suggestions for additional features, ranging from personalized insights to interactive tutorials, indicating an engaged user community interested in the continuous improvement of this system. Valuable suggestions for usability enhancements, such as a dark mode option and customizable alerts, were offered, showcasing a user-driven focus on practical improvements for a more tailored and effective user experience.

We employed visualization techniques to gain insights into the accuracy of our models. Plots were created to visualize actual vs. predicted values for gold prices, illustrating how well the model performed on historical data. Similarly, for oil prices, visualizations showcased the accuracy of the model's predictions on historical data and the comparison between actual and predicted values was presented.

User testing results indicate positive feedback regarding the clarity of the user interface, helpfulness of recommendations, and overall usability. Some users suggested valuable enhancements and features, which can contribute to further improving the application. The development team can consider these insights for future iterations, ensuring this system meets the diverse needs of its user base.

V. CONCLUSIONS

The accurate price forecasting results achieved by this system particularly for gold and oil underscore the value of AI-based predictive models. unit testing phase confirmed the effectiveness of forecasting models for gold and oil prices developed using the Prophet library, showcasing impressive metrics. Transitioning to user testing, a diverse participant base, primarily investors and bankers, highlighted the broad appeal of the system within the financial sector. The user-friendly interface received positive feedback, with a majority finding navigation easy and expressing satisfaction with the system's accuracy in investment recommendations. While the layout and design garnered generally positive reviews, suggestions for improvements were noted. Users provided valuable insights for additional features, demonstrating an engaged community focused on enhancing the system's usability and tailoring it for an effective user experience. Overall, the testing phases underscore the system's positive reception, emphasizing its practicality, usability, and potential for continual improvement based on user feedback.

Investors can leverage these forecasts to make informed decisions, optimize their investment portfolios and manage risk effectively. The Genetic Algorithm based optimization of investment strategies allows this system to provide investors with personalized recommendations tailored to their risk tolerance and financial goals. This level of customization is a significant advantage over one-size-fits-all investment approaches. The comparison of this system with traditional investment strategies demonstrates its ability to outperform and mitigate risk. The system's lower maximum drawdown and superior risk-adjusted returns make it a compelling tool for long-term investors.

A. Limitations & Future Directions

It is essential to acknowledge the limitations of this system:

- Data Quality: The system's performance is influenced by the quality of input data. Improving data quality and addressing potential data biases remain ongoing challenges.
- Model Interpretability: While the Prophet Model and Genetic Algorithms are powerful tools, model interpretability remains a challenge. Enhancing the transparency and interpretability of AI models is an area for further exploration.

This research opens doors to several future directions in the development and enhancement of the system:

- Data Enhancement: Ongoing efforts to improve data quality, completeness and timeliness are crucial for the system's performance. Exploring alternative data sources and data preprocessing techniques can further enhance forecasting accuracy.
- Interpretable AI Models: The development of AI models with improved interpretability is a priority. Research into interpretable AI, such as Explainable AI (XAI), should be pursued to make recommendations more transparent and user-friendly.
- Expanded Asset Classes: Expanding the scope of this system to cover additional asset classes, such as stocks, bonds and commodities, would increase its utility for a broader range of investors.
- Integrate NLP mechanism: Enhance the system's capabilities in processing textual data, potentially improving the accuracy and relevance of forecasts aligning with government regulations.

Future research in this area could focus on addressing the challenges related to feature engineering, dataset quality and model interpretability. Additionally, investigating the applicability of other ML algorithms, such as DL architectures and reinforcement learning, could further enhance the accuracy and robustness of price prediction models.

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