© February 2025 | IJIRT | Volume 11 Issue 9 | ISSN: 2349-6002

Investment Advisory and Portfolio Management System: Leveraging Machine Learning for Enhanced Financial decision- Making

Ishaan Singh Arora[1], Kartik Jindal[2], Shristy Singh[3], Dr. N. Krishnaraj[4]
[1,2,3]*Networking & Communications, SRM Institute of Science and Technology,* Chennai, Tamil Nadu, India
[4]*AssociateProfessor, Networking and Communications, SRM Institute of Science and Technology,* Chennai, Tamil Nadu, India

***Abstract*—Portfolio Investment planning is the major and functional part of life in business environments. Financial investment and planning are the major problem where a complete detection over the best seems to be a problematic one. Mostly deciding Stock market, gold investments, Mutual Fund and real estate-based functioning is intense. Thus, a smart solution needs to be leverage on making a best recommendation approach using machine learning. Multiple variation analysis can be done using a smart algorithmic approach with a comparative analysis and research functioning. Machine Learning based ARIMA classification algorithm gives out an analytical system and investment planning. These algorithms analyze the real trend and historical data where the comparative study over linear and continuous values is known. Smart Service Oriented Architecture (SOA) will be implemented where the software implementation can enhance a best strategic system which shows a best functioning decision driven system. The implemented application lends AI driven recommendations for further decision making in portfolio work outs. Additional proposed system not only makes out decision on classified feature attributes but also enhances to find out the risk management over all various fields of findings. A visualization function can be lent over multiple systematic function which makes best financial path analysis. This improvement can lend a easiest handling SOA function with a wide approach.**

***Index Terms*—Portfolio Investment Planning, Service Oriented Architecture, ARIMA model classification.**

I. INTRODUCTION

In the ever-evolving financial world, managing investments in mutual funds, stocks, real estate, and diversified portfolios can be a daunting task for investors. The dynamic nature of markets requires constant monitoring, analysis, and timely decision-making to maximize returns and minimize risks. The project objective is to change the challenges by developing a predictive portfolio management system powered by the ARIMA (Auto-Regressive Integrated Moving Average) algorithm, a robust tool for time-series forecasting. ARIMA is specifically chosen for its efficiency in analyzing historical data and predicting future trends in financial markets. The system leverages ARIMA to forecast the performance of various investment categories, including stock prices, mutual fund returns, and real estate values. By using historical market data, ARIMA models can detect patterns, seasonal variations, and trends to generate accurate predictions of future investment performance.

Mostly investor’s real time analysis over their portfolio ideal comparison system on investment will be a problematic one. Thus, proposed work involves the charts with the portfolio maintenance on graph and charts analysis. Additionally, the risk assessment with futuristic maintenance where the complete analysis of the asset with each fund detection and investment functioning can be done. Thus, the proposed system makes out a research-based analysis and also multivariate functioning process where the investors with the risk assessment can be done. This topic mainly focuses on four main functions: Stock, Gold, Mutual fund and Real estate.

Stock: Stock Purchasing shares (or ownership holdings) in a business with the hope of earning profits over time is known as stock investing.

Purchasing stocks makes you a shareholder, or a portion owner, of the business, and the value of your investment may increase in response to market circumstances and the company's success.

Gold Investment: Purchasing gold as a financial asset to diversify an investment portfolio, protect wealth, and protect against inflation is known as gold investment. Because gold is rare, strong, and widely accepted, it has been a valuable repository of wealth for millennia.

Real Estate: Real estate is the one where it gives to make investment in properties and leasing for a good growth. Because of its capacity to generate long-term wealth and guard against inflation, it is regarded as one of the most stable investment options.

Mutual Fund: A mutual fund is a type of investment instrument that buys a range of stocks, bonds, and other assets by pooling the capital of multiple members. It is managed by qualified fund managers who select investments to reduce risks and maximize profits.

On these four main factors and attributes the modeling function with risk assessment can be noted with ARIMA and Random Forest Models.

II. RELATED WORKS

In [1] Markowitz, H. (1952)

Markowitz introduced the Modern Portfolio Theory (MPT), The goal of portfolio selection is to create portfolios that maximize expected returns while preserving levels of risk that each individual can tolerate. Modeling techniques are used in portfolio selection to evaluate "acceptable levels of portfolio risk" and "expected portfolio returns" based on investor expectations of future returns and historical data. After that, it provides methods for selecting the optimal portfolio. It wouldn't be an overstatement to say that modern portfolio theory has revolutionized the field of investment management. The ability to quantify the investment risk and expected return of a portfolio has allowed managers to add a scientific and objective element to the subjective art of investment management.

The concept of portfolio selection has, more importantly, shifted the focus of portfolio management from the risk of individual assets to the risk of the entire portfolio. According to this hypothesis, it is possible to mix hazardous assets to produce a portfolio that has much lower risk but still represents the expected returns of its components. In other words, it is possible to construct a portfolio whose risk is less than the sum of its constituent parts.

In [2] Fama, E.F. (1970)

Fama's Efficient Market Hypothesis (EMH) The current study investigates the efficiency of the foreign exchange market in Mauritius, a developing and multicultural African country, using the Efficient Market Hypothesis as a foundation. The case of the nominal spot rate daily data for the Mauritian currency market—that is, EUR/MUR, USD/MUR, GBP/MUR, and JPY/MUR—over a five-year period from 2012 to 2016 is therefore examined in this paper. First, the analytical approach uses the Augmented-Dickey Fuller (ADF) and Philips Peron (PP) unit root to test the weak-form of efficiency. Second, the existence of semi-strong form efficiency in the Mauritian foreign exchange market is examined using the Granger Causality Test, the Johansen Co-integration Test, and Variance Decomposition. Second, the Johansen Co-integration test indicates that there are no long-term correlations between the foreign exchange variables. However, the Granger causality test confirmed both unidirectional and bidirectional connections between the various exchange rates. Additionally, the Variance Decomposition confirmed that there were long-term co-movements among the currency rates. Consequently, the semi-strong form market is not supported by either test. Since it suggests that one exchange rate may foresee one or more exchange rates, this contradicts the semi-strong form market theory. Thus, it may be concluded that the foreign market in Mauritius is inefficient in the semi-strong form but efficient in the weak form.

In [3] Box, G.E.P., & Jenkins, G.M. (1970) The current work developed multiple Autoregressive Integrated Moving Average (ARIMA) models to mimic carbon dioxide emissions using time series data covering 44 years, from 1972 to 2015. The performance of these generated models was assessed using a number of selection criteria, and the best forecasting model was determined to be the one with the lowest score on these criteria. The results show that, out of the many ARIMA models, ARIMA (0, 2, 1) fits the data the best for predicting carbon dioxide emissions in Bangladesh. According to ARIMA (0, 2, 1), Bangladesh's carbon dioxide emissions for 2016, 2017, and 2018 were anticipated to be 83.94657 Metric Tons.

In [4] Lopez-de-Lacalle, J. (2019)

Lopez-de-Lacalle developed the R library ‘TSstudio’ for time-series analysis and visualization. This tool simplifies implementing ARIMA models for forecasting financial data. It includes features for handling data preprocessing, diagnostics, and evaluating model performance. The library’s user-friendly interface and integration with machine learning tools have made it a popular choice for analyzing stock prices, mutual funds, and real estate trends. This work highlights the importance of combining predictive analytics with visualization for portfolio management.

In [5] Black, F., & Scholes, M. (1973)

Black and Scholes summarize the black school’s model where the pricing options are well known and derived with some mathematical functions. The underscore predictive model with work load in financial marketing is the major functional work which needs to be promised. The implementation of this model is changed with the statistical functioning where he used ARIMA model in trend analysis. The statistical inputs are volatility, risk free rates, aligns the method with trend setter. Market involvement with complimentary tool for analyzing the models and predicting the risk factor using ARIMA.

In [6] Engle, R.F. (1982)

Engle shows an ARCH model where the financial risk assessments are well analyzed. Mainly regression analysis is the main functional system where the complete functions are known. The market fluctuations on the past and historical data analysis can be done in which the complete maintenance and functional orientation can be processed. The ARCH model gives the trend forecasting functional in which the model of portfolio function can be maintained and loaded with low level of integration. Mainly this paper shows the risk assessment recommendations which helps in identifying the periods of investments with volatility.

In [7] Bollerslev, T. (1986) The author offered an ARCH model, which is a logical extension of the ARCH (Autoregressive Conditional Heteroskedastic) process initially introduced by Engle (1982), to account for prior conditional variances in the current conditional variance equation. The autocorrelation structure and stationarity requirements are derived for this new class of parametric models. Additionally, testing and maximum likelihood computation are considered. Finally, an empirical case pertaining to the uncertainty of inflation rates is shown.

In [8] Chen, K., & He, X. (2018)

Since the current study lacked a longitudinal design, various conflict resolution techniques were used. Blake and Mouton's 1964 model is "the most extended model" in light of this (Aritzeta et al., 2005, p. 162). In accordance with this methodology, Rahim (1983) used the two dimensions of "concern for others" and "concern for self" to establish his five conflict management styles (see Figure 1). His paradigm identifies five conflict management styles: obliging, dominating, avoiding, integrating, and compromise. According to Rahim and Bonoma (1979), the firstdimension gauges how much a person watches out for their own interests, while the second dimension looks at how much they care about other people.

In [9] Patel, J., Shah, S., & Thakkar, P. (2015) The stock market prediction and analysis were identified by the writers. The study's primary focus is on the job of predicting future stock market index values. The CNX Nifty and the S&P Bombay Stock Exchange (BSE) Sensex are two Indian stock market indices that have been selected for experimental evaluation. The experiments were based on ten years of historical data for these two indicators. The projections are made one to 10, fifteen, and thirty days in advance. This work proposes a two-stage fusion strategy, where the first step is Support Vector Regression (SVR). In the second step of the fusion approach, SVR–ANN, SVR–RF, and SVR–SVR fusion prediction models are created using Artificial Neural Networks (ANN), Random Forests (RF), and SVR. The prediction performance of these hybrid models is compared to single-stage scenarios that use ANN, RF, and SVR separately.

In [10] Jain, R., & Jain, K. (2020)

A country's social and economic structure depends on its stock market, which the Jain and Jain created. Stock market forecasting is the most challenging and demanding task for investors, professional analysts, and academics in the financial sector because of the highly noisy, nonparametric, volatile, complicated, non-linear, dynamic, and chaotic nature of stock price time series. Stock market prediction is a significant endeavor and a primary area of study in the financial field since stock market trading involves a greater degree of risk. However, the introduction of computationally complex devices can reduce much of the hazard. Fuzzy logic, genetic algorithms, artificial neural networks, and other evolutionary techniques are among the computationally intelligent approaches used for stock market forecasting.

III. EXISTING SYSTEM

The existing portfolio management system mostly identifies the static investment tracking which will be predicted on profit and loss functions. Mostly the long-term prediction will not be done in this system where the complete detection and prediction are unknown. Mostly historical value functions can be identified with the forecasting prediction with visualizations. But still this platform includes time consuming process and output performing errors. The existing system mostly performs the ARIMA model with real estate functioning with some personalized recommendation. Multiple error zones can be identified in the existing functional system where the property value changes can be accessible in this maintenance. Stock and mutual funds can be implemented here with ARIMA functional system where a normal identification can be done in these insights. Normal Enterprise architecture can be done in the existing system where the ARIMA identify the mutual fund, real estate and stock investment functions where a normal maintenance can be done.

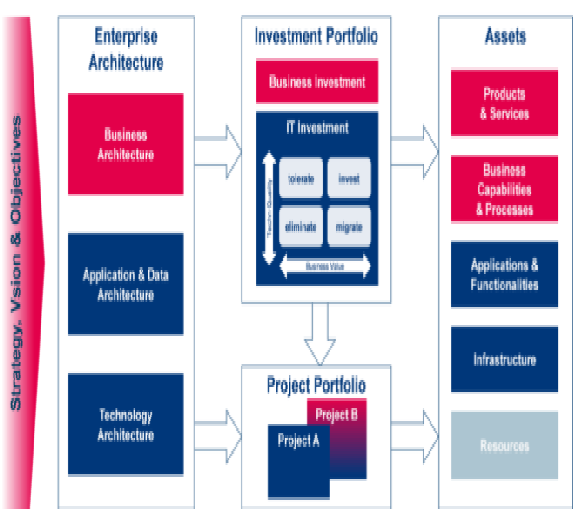

Fig 1 Existing system Portfolio Investment Planning

In the existing architecture, normal product and service-based infrastructure is only identified where the analysis of risk assessment over the past history data and recommendations are not done. On analyzing these challenges over the existing functional system, the implemented system needs to be more efficient with a smart investment panning portfolio maintenance approach.

IV. MATERIALS AND METHODS USED

The proposed system is a predictive portfolio management platform that utilizes the ARIMA algorithm to analyze historical investment data and forecast future performance. It offers real-time tracking and detailed insights for portfolios, including mutual funds, stocks, real estate, and other assets. The system compares invested amounts with current values, highlights profit or loss, and predicts future trends to guide investment decisions. A user-friendly dashboard visualizes data with graphs and charts, enabling easy portfolio monitoring and analysis. The platform provides personalized recommendations, such as diversification strategies and high-performing sectors, based on market trends and risk assessments. It also incorporates real estate valuation using dynamic geographic and economic indicators. By leveraging ARIMA's predictive capabilities, the system ensures accurate forecasts, empowering investors to make informed, data-driven decisions. This comprehensive solution bridges the gap between static tracking systems and intelligent investment tools, enhancing portfolio optimization and financial growth.

The proposed architecture clearly depicts the step-by-step functional system where the complete functional investment decision on gold, real estate, Mutual Funds and stock decision where the highest and lowest funds with SOA visualization can be done. The dataset can be processed from kaggle and some other sources of functions. The implementation will be further analyzed with ARIMA classification algorithm.

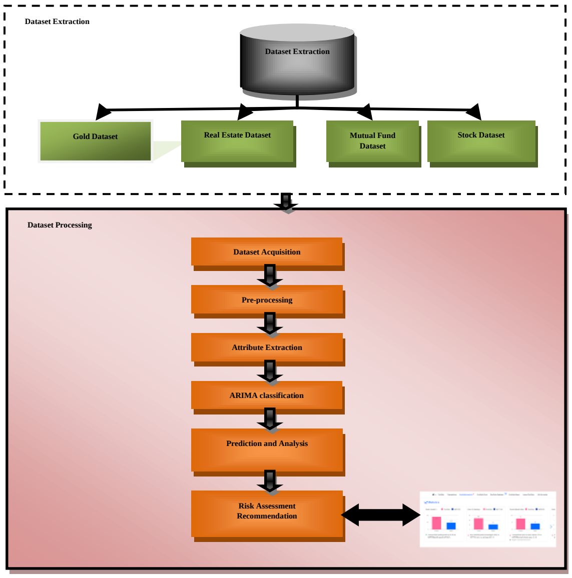

Fig 2 Proposed Architecture of Portfolio Investment Decision making

a) Dataset Acquisition

To construct a portfolio management system involving gold stocks real estate and mutual funds you need high-quality financial Information sets. Under are around true sources and methods for getting such as Information sets.

1. Publicly Available Datasets (Free Sources)

Gold Price Data

- World Gold Council – Historical and live gold price data.
- LBMA (London Bullion Market Association) – Gold and silver prices.
- Federal Reserve Economic Data (FRED) – Daily gold price dataset.

Stock Market Data

- Yahoo Finance – Free stock price data with API access.
- Alpha Vantage – Provides free stock data via API.
- Quandl – Historical stock and financial datasets.
- Google Finance – Stock prices and market trends.

Real Estate Data

- Zillow Research – US housing prices, rent trends, and real estate index.
- Redfin Data Center – Home sales, median prices, and inventory levels.
- Realtor.com Data – Market insights on real estate trends.
- CoreLogic – Mortgage and home price indices (paid access).

Mutual Fund Data

- Morningstar – Mutual fund NAVs, performance, and risk metrics.
- Mutual Fund Data from AMFI (India) – NAVs, fund performance, and AUM data.
- SEC's EDGAR Database – US mutual fund filings and disclosures.
- Lipper by Refinitiv – Global mutual fund data (paid).

b) Pre-Processing

One challenging stage in guaranteeing precise and insightful portfolio management analysis is preprocessing financial information sets. apt that the Information set involves aggregate plus classes including amber pillory material land and common finances information integration is performed away confluence disparate sources founded along amp green timestamp such as arsenic. Handling missing values is essential due to factors like market holidays and Information discrepancies. Techniques like interjection and arsenic clever take back take are useful for filling up these gaps. Additionally, to improve representation effectiveness, normalization techniques like Z-score normalization and Min-Max scaling are used to bring disparate financial data into a consistent range. Have Tech foster Improves the Information set away incorporating fiscal indicators care roll averages unpredictability measures and everyday take calculations which render Understandings into grocery trends and chance prediction. These preprocessing steps ensure the Information set is clean structured and Improved for Foretelling representation and portfolio optimization.

c) Attribute Extraction

Attribute extraction is the process in which the unwanted data will be eliminated where the complexity reduction can be made. Still a large amount of dataset has been extracted with multiple attributes NP problem will create a time complexity. Thus, on analyzing the usage of the attributes the unwanted attributes will be eliminated.

1. Gold Attributes:

- Price Trends: Historical price movements, seasonality
- Volatility: Fluctuations in gold prices
- Inflation Hedge: Correlation with inflation rate

- Supply & Demand: Mining output, central bank reserves
- Geopolitical Influence: Impact of global events

2. Real Estate Attributes:

- Property Valuation: Price per square foot, appreciation rate
- Rental Yield: Annual rental income / Property price
- Liquidity: Time to sell a property
- Market Demand: Vacancy rates, urbanization trends
- Location-Based Factors: Proximity to infrastructure, economic growth

3. Stock Attributes:

- Price & Returns: Stock price movement, dividend yield
- Volatility (Beta): Sensitivity to market changes
- Sector Performance: Industry trends and economic cycle
- Earnings Metrics: P/E ratio, EPS, ROE, etc.
- Liquidity: Trading volume and bid-ask spread

4. Mutual Fund Attributes:

- NAV (Net Asset Value): Fund price per unit
- Expense Ratio: Management fees and expenses
- Risk & Volatility: Standard deviation, Sharpe ratio
- Portfolio Composition: Asset allocation, sector exposure
- Fund Manager Performance: Historical returns, consistency

Prioritizing the attributes mention remaining unwanted will be left over and the main attribute will be extracted.

d) Classification

Classification is the process on which it predicts the trends on future enhancements. The classification proceeds with ARIMA model and Random Forest.

1. ARIMA Model

ARIMA Model identify time series forecasting where the price trends, fluctuations, Risk volatility, Expense Ratio, Net asset value, etc can be assessed.

Multiple asset identification has been ensemble in this model where the unique price trend and the volatility are taken into considerations.

ARIMA can be represented with three model selection function ARIMA(p,d,q)

Were,

- p=Past value auto regressive features
- d=difference of each feature attributes
- q=Final moving average date from the past errors

Mostly the p and q values will be the Auto Correlation function and the Partial plots can be determined with multiple optimal parameters.

The classification can be termed with training and testing functioning. Getting out this p,d,q as a model attribute the complete function can be trained and 6 months based forecasting the future value can be done. Each model and the quality can be determined with three main factors:

1. Trend Analysis:

In the trend analysis the growth asset, declining asset and safe asset are known where the complete uptrend, downtrend and the stable trend can be predicted using ARIMA model

2. Volatility Analysis:

Volatility analysis is the risk factor prediction where a standard deviation of the high risk and low risk of the asset with the error terms are known.

3. Return Prediction:

On comparing out the historical data each return asset are computed with the high threshold and low threshold.

The optimization result is classified with ARIMA model with three investors risk averse, Moderate Risk, High risk investors where each investment function planning.

Investor Type	Gold	Real estate	Stocks	Mutual Funds
Risk Averse	Stable Investment	Low level volatility	Avoid Stock	Conservative System
Moderate Risk	Investment ok	Investment ok	Stable stocks	Balanced Funds
High Risk	No investment	Flipping investment	Growth Stock	Aggressive funds

Table 1 Optimization and results optimization result

The ARIMA model can be classified with the multiple level of analysis where the investors risk assessment can be predicted and visualization can be done. Each level of risk assessment can be completely identified and a graph prediction has been made with factors that investors plan to invest over Real estate, Mutual Fund, Gold and stock maintenance. Multiple level of maintenance can be processed where the complete assessment can be determined.

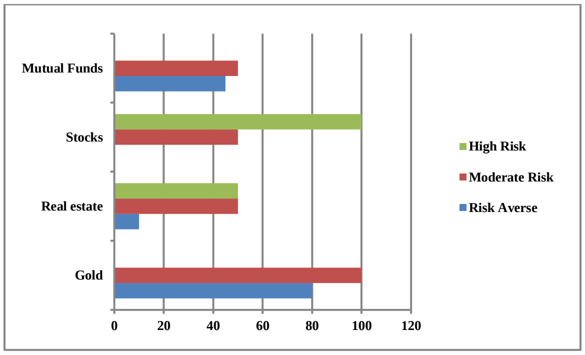

Fig 3 Assessment of risk with Visualization system

Thus, the ARIMA function can be predicted with these external values and the attribute extracted modeling.

2. Random Forest Classification

Random Forest (RF) is a supervised machine learning algorithm that has the ability to group assets (gold real estate, stocks, and mutual funds) into categories. It does this by looking at past data and key features. While ARIMA predicts future trends, Random Forest puts things into groups. This helps to sort assets by looking at many different aspects.

Random Forest figures out the risk factor in portfolio management by looking at past financial data and picking out key things like volatility, liquidity, Sharpe ratio, beta (which shows systematic risk), and how much assets return. To classify, it trains many decision trees on different parts of the data then combines what they predict. This helps make sure the results are strong and don't over fit. To assess the risk factor, Random Forest uses a method based on probability. It works out how important each feature is for deciding the risk level. The model then sorts assets into set risk levels (Low, Medium High) based on decision lines it's learned. You can show the way it classifies with a math formula:

$R=f(v,l,s,b,r_t)$ (1)

Were,

R= Risk classification

V=volatility

L=Liquidity

S=sharp ratio

B= beta systematic risk

R_t=historical returns

A decision tree can be created with the random forest where the impurity granules can be gathered with the purity of risk analysis. The entropy value gives the Gini impurity where the probability assessment over asset identifications can be done.

$Gini = 1 - \sum P_i^2$ (2)

The equation 2 works on a special risk assessment with the probability checking of each training distinguishing data driven portfolio allocation decision. A training model will be pre-defined on specifying the probability with a threshold value.

Multiple decision tree with real estate, gold mutual funds, and stocks as the main branches, and risk categories (high risk stable low risk) as sub-branches, with importance given to the connections:

Decision Tree Layout Main Branch:

Types of Investments Sub-Branches:

- Real Estate (Stable Low Risk)
- Gold (Stable Low Risk)
- Mutual Funds (Stable Low Risk High Risk)
- Stocks (High Risk Stable)

Each type of investment will have sub-branches grouped by their risk level:

Real Estate: People often put this in the Stable or Low Risk group because it keeps its value over time and doesn't change much with the market.

Gold: Most see it as Stable or Low Risk. It helps protect against rising prices and market drops.

Mutual Funds: These can be a mix of Stable and High Risk. It depends on the funds you pick. Funds with stocks have more risk. Funds with bonds have less risk.

Stocks: High Risk, but some stocks are Stable (like blue-chip stocks). Weight age Over Connections:

Here a weight based on how risky each investment is

- Real Estate: Weight = 0.2 (low risk stable)
- Gold: Weight = 0.3 (low risk stable)
- Mutual Funds: Weight = 0.4 (mix of stable and high risk)
- Stocks: Weight = 0.5 (high risk)

So, the weight age could reflect the risk-reward ratio in each case. You can create this decision tree using a diagram or in a tool like Python (with libraries such as scikit-learn or graphviz) to visualize it.

e) Recommendation

On analyzing the classification from the ARIMA model and the Random Forest the recommendations over the investment and the risk factors will be recommended.

V. RESULTS AND DISCUSSION

The result and discussion show a comparative analysis of the identification where the ARIMA and Random Forest accuracy plot can be verified with some metric measures.

1. Accuracy

On analyzing the accuracy of the algorithm implementation Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) with R^2 score with regression analysis. Multiple Iteration value gives with error rate of ARIMA is comparatively high where else Random Forest surpasses ARIMA at a higher level.

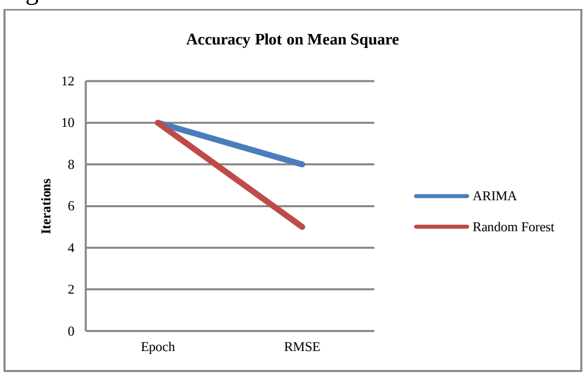

Fig 4 Error rate plot for the portfolio system

- Mean Absolute Error (MAE): Measures the average absolute differences between actual and predicted values.
- Mean Squared Error (MSE): Measures the squared average difference between actual and predicted values.
- Root Mean Squared Error (RMSE): Square root of MSE, useful for penalizing large errors.
- Mean Absolute Percentage Error (MAPE): Measures the percentage error in predictions.
- R² Score (Coefficient of Determination): Measures how well the model explains variance in data

Asset Class	Model	RMSE	MAPE	R^2
Gold	ARIMA	2.5	3.8	0.78
Gold	Random Forest	2.2	3.5	0.82
Mutual Fund	ARIMA	1.9	2.6	0.81
Mutual Fund	Random Forest	1.7	2.2	0.86
Real Estate	ARIMA	3.1	4.5	0.75
Real Estate	Random Forest	2.8	4.1	0.79
Stock	ARIMA	2.8	4.2	0.73
Stock	Random Forest	2.3	3.7	0.89

Table 2 represents on predicting the accuracy functions

The implementation can be maintained with the process of comparing the models where the portfolio functional system where a multiple variation analysis can be done.

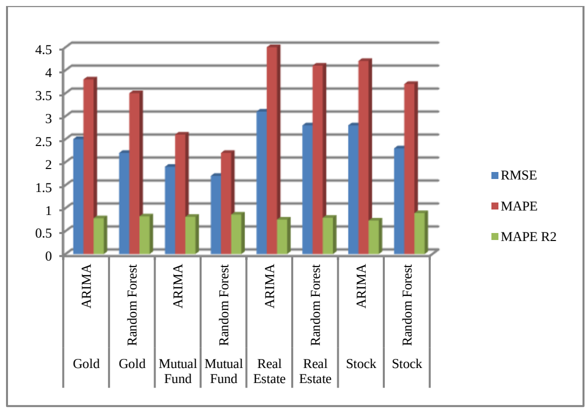

Fig 5 Comparison graph and analysis

Time Prediction

The time prediction can be done with execution of the system where the complete analysis can be done. The classification timing of each model can be processed with a attribute based execution rate.

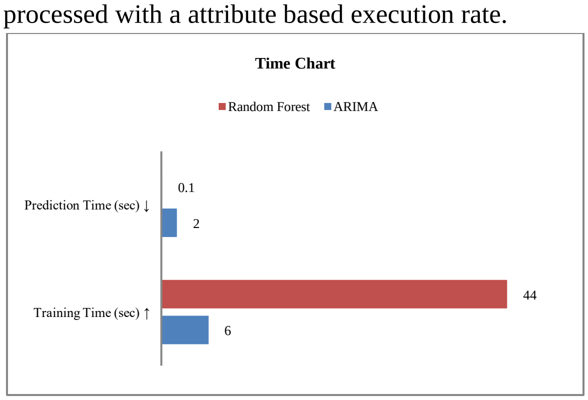

Fig 6 Time chart for the classification models

On comparative analysis the results show a that a long-term analysis and short-term analysis where random forest gives the best classification for the risk assessment with lower rate of error.

VI. CONCLUSION AND FUTURE ENHANCEMENT

A well-diversified portfolio comprised of stocks, mutual funds, real estate, and gold can effectively balance risk and return. ARIMA can be helpful in making time-series forecast analyses by dependence on the historical data required to predict stock, mutual fund, and gold price movements. However, ARIMA assumes linear relationships, which might be a drawback where markets are highly volatile. The machine learning approach, Random Forest, performs better on non-linear relationships and multiple influencing factors, which makes it better suited for the determination of general risk-reward balance in diversification. Smart recommendation approach provided with an efficient risk factors assessment and investment planning.

In future enhancement, combining both models, investors can make use of ARIMA for short-term trend forecast and Random Forest for robust risk assessment and decision-making that leads to a more informed investment strategy.

VII. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our guide, Dr N. Krishnaraj , for his invaluable guidance, continuous support, and encouragement throughout the course of this research. His expertise and insightful feedback have been instrumental in shaping the direction and outcomes of this project.

REFERENCES

[1] Li, Liang, Jia Wang, and Xuetao Li. "Efficiency analysis of machine learning intelligent investment based on K-means algorithm." Ieee Access 8 (2020): 147463-147470.

[2] Murugan, P., K. S. Suresh, and U. Parthiban. "The Future of Risk Management in Finance: An Algorithmic Approach to Portfolio Optimization." 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT). IEEE, 2024.

[3] Zhang, Xiaoqiang, and Ying Chen. "An artificial intelligence application in portfolio management." International Conference on Transformations and Innovations in Management (ICTIM 2017). Atlantis Press, 2017.

[4] Putha, Sudharshan. "AI-Driven Wealth Management Solutions in Banking: Enhancing Portfolio Optimization and Client Advisory Services." Australian Journal of Machine Learning Research & Applications 2.2 (2022): 417-455.

[5] Hejazi, Seyed Amir, and Kenneth R. Jackson. "A neural network approach to efficient valuation of large portfolios of variable annuities." Insurance: Mathematics and Economics 70 (2016): 169-181.

[6] Sebastian, Ashy, and VeertaTantia. "Deep Learning for Stock Price Prediction and Portfolio Optimization." International Journal of Advanced Computer Science & Applications 15.9 (2024).

[7] Hu, Xiao, et al. "Interactive preference analysis: A reinforcement learning framework." European Journal of Operational Research 319.3 (2024): 983-998.

[8] Beketov, Mikhail, Kevin Lehmann, and Manuel Wittke. "Robo Advisors: quantitative methods inside the robots." Journal of Asset Management 19.6 (2018): 363-370.

[9] Putha, Sudharshan. "AI-Driven Wealth Management Solutions in Banking: Enhancing Portfolio Optimization and Client Advisory Services." Australian Journal of Machine Learning Research & Applications 2.2 (2022): 417-455.

[10] Bartram, Söhnke M., Jürgen Branke, and Mehrshad Motahari. Artificial intelligence in asset management. CFA Institute Research Foundation, 2020