Paper ID: 243

Predictive Models for Monetary Asset Price Evaluation: A Comparative Review

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Abstract— *This study focuses on analyzing and evaluating predictive techniques for asset price forecasting, centering attention on gold, real estate, and automobile markets. The paper explores numerous algorithms, techniques, methods and models utilized in foreseeing the values of these assets. A thorough appraisal is conducted that which present various procedures for forecasting the value of assets.*
This exploration compares the pros, cons, and performance metrics of the anticipating models applied in each discipline. Remarkable attention is granted to the forecasting ability of Convolutional Neural Networks (CNN), fuzzy rule-based systems, deep learning (DL) techniques, ensemble regression models, and other machine learning (ML) algorithms. Moreover, the tasks of data analysis, preprocessing and feature selection methods in boosting prediction accuracy is investigated.
The review paper calls attention to the implications along with applications of error-free asset value forecasting, together with knowledge-based decision making, risk mitigation in addition to investment strategies. Moreover, it examines the challenges and limitations along with future directions in the domain, highlighting the demand for robust, compliant and interpretable forecasting models.
By assessing and differentiating the approaches and outcomes of asset value prediction across contrasting fields, this review delivers important insights appropriate to researchers, professionals and decision-makers concerned in the dynamics and predictive potentials of these platforms.
Keywords— **Gold price prediction, Real estate price prediction, Automobile price prediction**

I. INTRODUCTION

Forecasting values of assets has been for a considerable time, a field of significant interest in finance, investments, economics and associated disciplines. Precise price prediction of properties is crucial for rational decision making, risk mitigation and increasing revenue on investments. In the most recent times, the emergence of modern computational approaches and machine learning algorithms has offered novel directions for developing forecasting techniques in predicting values of assets.
This study provides an overall evaluation and comparison of forecasting models for predicting asset prices, concentrating on 3 different merchandise: gold, real estate, and automobiles. Aforementioned merchandise was hand-picked because of their magnitude in the global economy and the presence of ample of studies in each discipline.

The aim of this review is to examine the algorithms, techniques, methods and models utilized in foretelling values of properties covering above domains. By assessing and comparing the prognostic models employed in every market, the aim is to recognize the strengths and weaknesses along with performance metrics corresponding to specified perspective. Besides, we discover the contribution of data analysis, feature selection and preprocessing approaches in strengthening the reliability of forecasts.

The review encircles a variety of researches which engross numerous predictive modeling techniques in particular ensemble regression models, fuzzy rule-based system, DL techniques, CNN and other ML algorithms. Every study presents understanding towards the forecasting capability and suitability of these techniques in forecasting market value of assets.
By carrying out this research, contribution is made to the awareness of asset price forecasting covering various fields. The intuition obtained through this exploration can assist researchers, professionals, and policymakers in assessing the functioning and reliability of forecasting models in each separate market. Furthermore, the study underlines the challenges, drawbacks, limitations and probable future paths for amplifying the accuracy and explicability of techniques used for predicting price of assets.

II. LITERATURE REVIEW

The visualization below depicts the summary of the existing researches conducted with regards to price prediction of different asset domains.

Table 1. Structured Literature Review

Paper	Commodity	Model	Data considered	Accuracy	Important
(Hajek and Novotny, 2022), (Livieris, Pintelas and Pintelas, 2020)	Gold	Fuzzy Rule Based Prediction System	Prices of gold 2007 – 2017. COMEX Gold futures – daily prices - MarketWatch db. positive and negative news sentiment. news affect – one day ahead indexes from other financial and precious metal markets – five days ahead	MAE - (forecasting horizon equal to 4, 6, 9) - 0.0079, 0.0082, 0.0089.	Summarized previous studies. 1 & 5 days ahead predictions.
(Zeynep Hilal Kilimci, 2022)	Gold		Financial websites - July 2019 - July 2020. Simple Moving Average (SMA) - 20, 50, and 100 days. Opening and Closing prices. Highest, lowest dollar index (DXY) prices. 14 days Relative Strength Index (RSI). Upper, middle and lower values of the Bollinger Band (BB),	MAPE - 2.2036	
(Baser, Saini and Baser, 2023)	Gold	Gradient Boost Regression	SMA 10 days. Weighted Moving Average (WMA) 14 days. Momentum, Stochastics K%, Stochastic D%, Relative Strength Index (RSI). William's R%, Moving Average Convergence Divergence (MACD). Commodity Channel Index (CCI). Volume, high, low, open, close of gold commodity.	MAPE - 0.49, 1.20,0.49,0.36.	Lowest error and best capacity to fit, by the average values.
(Weng *et al.*, 2020)	Gold	Genetic Algorithm Regularization Online Extreme Learning Machine (GA-ROSELM).	Gold price data - public websites. Silver price of the previous day. Standard & poor - 500 indexes. The crude oil price, gold price - 3 days. Opening price of gold, silver, crude oil per day.		
(S and S, 2020)	Gold	CNN – RNN, LSTM model.	Dataset - World Gold Council - daily gold price rates - past 30 years - including yearly, quarterly, monthly, and daily gold price in INR, US dollar, EURO, RMB, HK dollar.	RMSE value obtained is 7.385. CNN – RNN - best suited.	LSTM model put forwarded outshines conventional practices - ARIMA, covariance matrix estimation, deep regression, SVR, CNN.

(Wagh *et al.*, 2022)	Gold	LSTM, Linear Regression, Random Forest model	Daily gold price values: 2010 - 2022. Monthly Gold Price values: 2015 - 2022. Six Months Gold Price values: 2010 - 2022. Yearly Gold Price values: 2010 - 2022.	LSTM Model - Best Results, great accuracy.	Totally Python based project source code.
(Manjula and Karthikeyan, 2019)	Gold	Random forest regression, Gradient boosting regression, Linear Regression	Stock market, crude oil price, rupee dollar exchange rate, inflation, interest rate. Monthly price data - Jan 2000 - Dec 2018. Nifty500 index values - (stock prices depiction). Consumer Price Index - (inflation depiction). Term deposit rate - above 1 year deposits - (interest rate depiction). Spot gold price in rupees per ounce - (gold price depiction).	Better prediction accuracies, - Random forest regression - entire period. - Gradient boosting regression - two periods taken separately.	Implemented using python.
(Makala and Li, 2021)	Gold	SVM(Poly), SVM(RBF) and Arima model.	Daily gold price data - World Gold Council - 1979 - 2019.	SVM preferrable over ARIMA. SVM, -RMSE - 0.028 -MAPE - 2.5 ARIMA, RMSE - 36.18 MAPE - 2897.	
(Dabreo *et al.*, 2021)	Real estate	XGBoost Regression, Random Forest regression algorithm, Decision tree	Per capita crime rate by town. Residential land zoned - lots over 25,000sq.ft. Non-retail business acres per town. Charles River dummy variable. Nitric oxides concentration. Average rooms count, Governing council, method of sale, general region, type of house, distance from CBD, number of rooms bathrooms, built year of the house, number of properties that exist in the suburb. Price in Australian dollars.	1 - XGBoost Regression 2 - Random Forest regression (closely followed) 3 - Decision tree 4 - Linear Regression	
(Ravikumar, 2017)	Real estate	Random forest, Gradient boosted tress.	Longitude, Latitude, Median age of housing, Ocean Proximity, Total Rooms, Households, Population, Median Income,	Gradient boosted trees are performing better.	
(Yu and Wu, 2016)	Real estate	Lasso, Ridge, SVM regression, Random Forest regression, Naive Bayes, logistic regression,	House features (79) - areas of the houses, types of the floors, and numbers of bathrooms. Sold prices of1460 houses.	PCA improves accuracy. Classification problem - SVC with linear kernel (with PCA preprocessing - 0.6740 accuracy	The goal was to implement a regression and a classification model that is able to accurately

		SVM, Random Forest.		can be raised to 0.6913. Regression problem - SVR with gaussian kernel (RMSE - 0.5271).	estimate the price of the house.
(Pai and Wang, 2020)	Real estate	Classification and Regression Tree (CART), Backpropagation neural networks (BPNN), General Regression Neural Networks (GRNN) Least Squares Support Vector Regression (LSSVR),	City, Town, Prices per square meter, Purpose of land use, Transaction floors, Longitude, Materials of buildings, Number of living rooms, Types of parking space	LSSVR performs best.	Parameters for ML models were selected using Genetic Algorithms
(Gupta *et al.*, 2022)	Automobile	Elastic net, Random Forest regression, SVR, Linear regression, Decision tree,	Make, fuel type, cylinders, price, aspiration, symbolling, wheelbase, number of doors, engine-location	Random forest regression model performed best. R2 - 0.93 MAE - 1390.9 RMSE - 2139.7	
(Selvaratnam *et al.*, 2021)	Automobile	Stepwise selection regression LASSO	Drive wheels, city mpg, engine size, stroke, number of doors, make, aspiration, body style, width	Training data accuracy - 92% Testing data accuracy - 87%.	

III. METHODOLOGY

Based on the research area of the Final Year Individual Research Project, the research question "What could be the machine learning techniques and methodologies employed in predicting gold prices, automobile prices and real estate prices?" was arisen. Thereby a comprehensive literature search was carried out using various databases and sources utilizing Systematic Literature Review (Gunathilake and Neligwa, 2013).

With order to assist writers with improving the disclosing of not only systematic reviews but also meta-analyses, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach was used. PRISMA is supported by evidence. PRISMA is basically interested with disclosing reviews that evaluate the results of initiatives, further it assists as a base for documenting systematic reviews.

Maneuvering the abovementioned keywords, references for gold price prediction, real estate price prediction and automobile price prediction was gathered. Including studies that focus on machine learning techniques for price prediction, published in peer-reviewed journals or conferences from 2019 to 2023, excluded the papers published prior to 2019. Data extraction was done focusing on information about the machine learning algorithms, features used, data preprocessing techniques, evaluation metrics, and performance results. Extracted data were then appraised and entered into a tabular structure. Further, Requirement Gathering questionnaire was conducted identify the best solution that could be implemented in order to answer the research question.

IV. RESULTS AND DISCUSSION

Summary of the Requirement Gathering is shown below along with the findings.

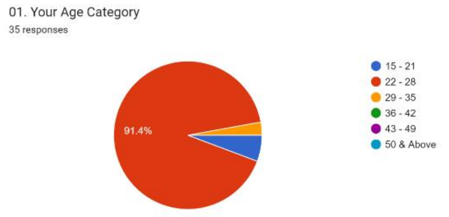

Figure1. Age categories of respondents

Fig 1. assists in identifying the needs and preferences of the target audience including factors such as investment goals, risk tolerance, investment experience, and investment timeframe.

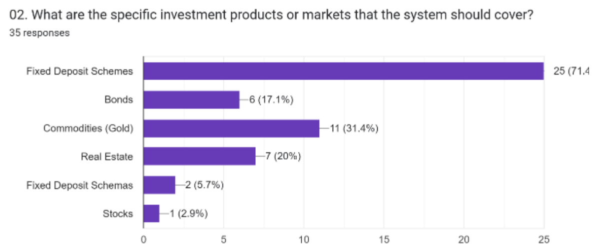

Figure 2. Specific investment products or markets the system should cover

Fig 2. covers the asset classes and investment products that the proposed system should cover.

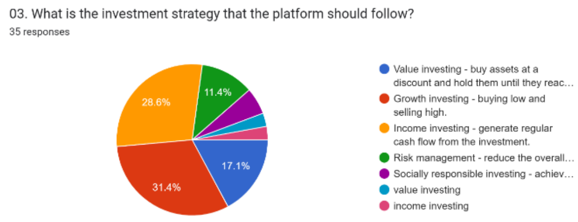

Figure 3. Investment strategies that the system should allow

Fig 3. query helps in determining the investment styles and specific markets that the intended platform should provide.

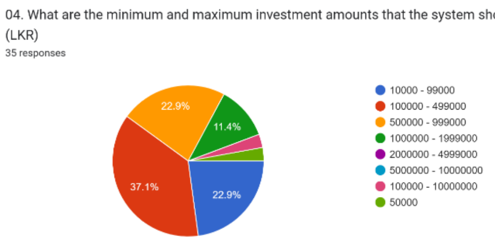

Figure 4. Range of the investment amounts the platform should provide

Intended platform should consider the Fig 4. when determining the minimum and maximum amounts of investment products.

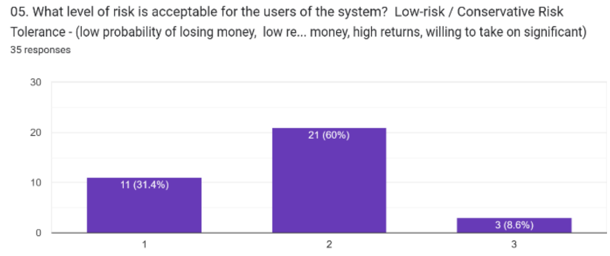

Figure 5. Accepted level of risk

The risk tolerance and risk appetite possessed by the investors out of Low, Medium and High risk levels are denoted by Fig 5.

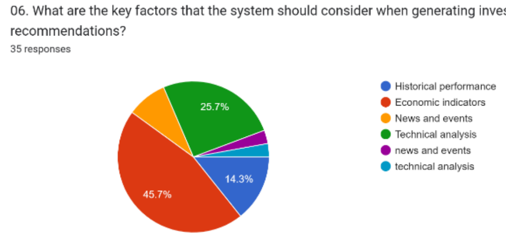

Figure 2. Factors to be considered

Fig 6. denotes the factors to be considered when generating investment recommendations.

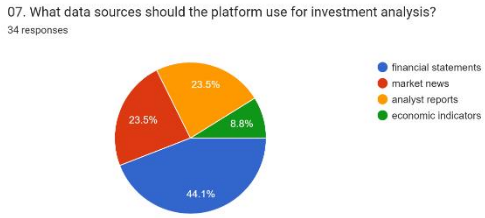

Figure 7. Platforms for investment analysis

Fig 7. ensures that your automated investment recommendation system is using accurate and relevant data to generate investment recommendations that are tailored to the user's financial situation and investment objectives.

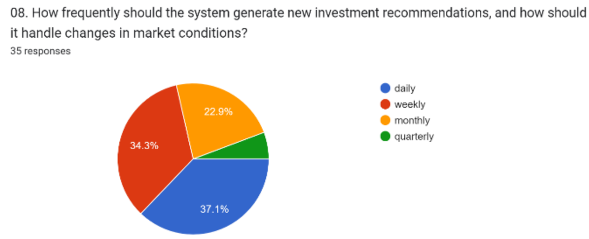

Figure 8. Frequency that the investment recommendations should be generated

How often the investment recommendation updates should be generated in the proposed system can be verified by Fig 8.

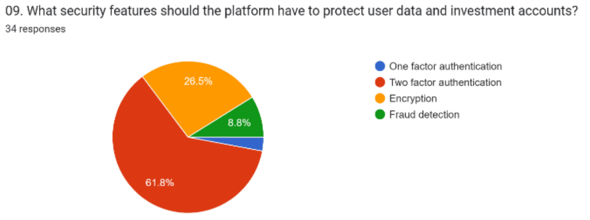

Figure 93. Security features to be provided

Figure 9. ensures that user data and investment accounts are protected against unauthorized access and potential threats.

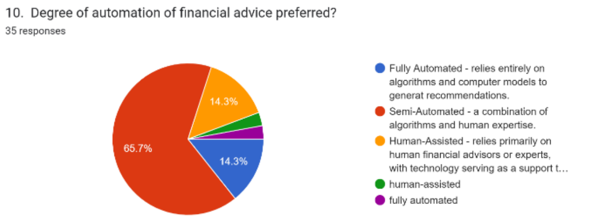

Figure 10. Degree of automation

Appropriate balance between human expertise and technology in generating investment advice can be obtained by Fig 10.

Findings of the above requirement gathering is as follows,

Table 2. Summary of Requirement Gathering Phase.

No	Question	Requirement specified	Finding
01	Age Category	Identify the needs and preferences of the target audience.	15-21 years old people are more likely to welcome the system
02	What are the specific investment products or markets that the system should cover?	Identify the specific investment products that the system should cover.	Fixed deposit schemes the most preferred by the users
03	What is the investment strategy that the platform should follow?	Identify the specific investment styles that the system should cover.	People tend to invest as Growth & Income investing
04	What are the minimum and maximum investment amounts that the system should consider? (LKR)	Identify the investment options that the system should consider based on the minimum and maximum investment amounts.	Most people tend to invest in 100000 to 100000000
05	What level of risk is acceptable for the users of the system?	Identify the investment options that the system should consider based on the risk tolerance and risk appetite of the users.	Medium Risk Tolerance is the most acceptable
06	What are the key factors that the system should consider when generating investment recommendations?	Ensure that your automated investment recommendation system provides accurate and suitable investment advice to users based on their investment objectives, risk profiles, and preferences.	People think that economic indicators are the most important factor the system should consider when generating investment recommendations
07	What data sources should the platform use for investment analysis?	Ensure that your automated investment recommendation system uses accurate and relevant data to generate investment recommendations that are tailored to the user's financial situation and investment objectives.	Most people think that financial statements should be the data source the platform should use
08	How frequently should the system generate new investment recommendations, and how should it handle changes in market conditions?	Ensure that your automated investment recommendation system is providing timely and relevant investment recommendations that are tailored to the user's financial situation and investment objectives.	Among the people who responded the questionnaire, most people think that system should be updated daily.
09	What security features should the platform have to protect user data and investment accounts?	Ensure that user data and investment accounts are protected against unauthorized access and potential threats.	Most people think that system should provide 2 factor authentications
10	Degree of automation of financial advice preferred?	Determine the appropriate balance between human expertise and technology in generating investment advice.	People are most likely to welcome a semi-automated system

V. CONCLUSION

Traversing various 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 for gold price prediction, real estate price prediction and for automobile price prediction, numerous valuable discoveries have brought to light.

For predicting gold prices, the reviewed research illustrated the productivity of various ML approaches. Fuzzy rule-based prediction (Hajek and Novotny, 2022) leverages news affect to forecast gold prices, while a CNN-LSTM model (Livieris, Pintelas and Pintelas, 2020) combines CNN and LSTM networks for time-series forecasting. Ensemble regression-based techniques (Zeynep Hilal Kilimci, 2022) and tree-based prediction techniques (Baser, Saini and Baser, 2023) provide supplemental vision towards gold price prediction. Moreover, researchers have explored the use of online extreme learning machine algorithms (Weng *et al.*, 2020), DL techniques (S and S, 2020), ensemble-based ML techniques (Manjula and Karthikeyan, 2019), and hybrid models comprising ARIMA and SVM (Makala and Li, 2021).

Concerning prediction of real estate prices, the chosen studies demonstrate the diversified range of ML methods used in this domain. Research on forecasting house prices recruiting ML (Liyanarachchi, Wijethunga and Madushanka, 2021) is of great advantage. The researches spotlight the importance of utilizing real transaction data (Ravikumar, 2017), ensemble-based approaches (Dabreo *et al.*, 2021), and regression models (Yu and Wu, 2016) to predict real estate prices precisely. Moreover, feature selection techniques (Pai and Wang, 2020) and exploratory data analysis (Selvaratnam *et al.*, 2021) have been recruited to enhance the performance and interpretability of ML models in this domain.

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

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.

In conclusion, the reviewed studies have highlighted the effectiveness and potential of ML techniques in predicting gold prices and real estate prices. These findings contribute to the growing body of knowledge in the field of price prediction and provide valuable insights for future research and practical applications.

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ACKNOWLEDGMENT

I would like to convey my utmost appreciation to the Individual Research Project module coordinators Dr. LP Kalansooriya, Ms. WMKS Ilmini and Mrs. GAI Uwanthika for their valuable support and guidance throughout this course. Their expertise, dedication, and passion for teaching have played a crucial role in shaping my understanding of the subject matter. I am truly grateful for their efforts in creating a stimulating and enriching learning environment that has contributed to my personal and academic growth.

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