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A Study on Market analysis of investors

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ABSTRACT
The complexity and growth of financial markets and the increasing diversity of investors have presented a demand for market analysis based on data, with intelligent data-driven approaches to market analysis. Different conventional techniques of analysis are usually ineffective to include the nonlinearity between financial performance indicators and behavioural features of the performance of investors. This paper will address a machine-learning-based system to understand investor market behaviour and categorize investor performance by a structured set of 6000 investor records with demographic, financial, and behavioural data. The main characteristics are age, annual income, size of investment, its past return percentage, diversification of the given portfolio, type of investor and risk profile. Four controlled machine learning classifiers used include Logistic Regression, Decision Tree, random Forest and grade boosting which were implemented and tested to classify investor performance based on the high, moderate, and low return. The findings of the experiment indicate that Logistic Regression excelled the highest classification (99 percent) which was followed by Gradient Boosting (95.08 percent), Random Forest (94.17 percent) and Decision Tree (88.67 percent). That analysis also determined the high level of discrimination of the Logistic Regression and Gradient Boosting as they achieved close to perfect scores of nearly 1.00. The results indicate the efficiency of the combination of financial and behavioural characteristics towards predicting investor performance and prove the efficiency of ensemble and linear models as algorithms to deal with complex investor data. The suggested framework can give investors, financial analysts, and decision-makers a lot of insights because it allows classifying performance correctly and then makes informed investment decisions..

INTRODUCTION

The world has turned into a global village, technology has been developed fast, and all these factors have made financial markets very complicated and involved a large number of different categories of investors. The use of nonlinear and behavioural patterns that determine investor decision-making and performance requires traditional methods of investment analysis which are based mainly on descriptive statistics and econometric models. In the last few years, the access to massive financial data volumes and the development of computational intelligence have placed machine learning as a potent instrument of market research and modelling investor behaviour The performance of the investor does not just depend on the financial factors like income, size of investment and past returns, but also on the behavioral factors like risk taking ability, diversification of the portfolio and sentiments of the market. It is imperative to understand how these behavioural and financial factors interact in order to be able to make prophecies and decision-making in the market. Machine learning models provide the opportunity to process high-dimensional data and they reveal hidden patterns and give predictive insights more accurately than a traditional analytical tool.

This research aims to analyse the investor market behaviour by employing the supervised machine learning classification models. A regular investor database comprising demographic, financial and behavioural profiles is used to classify the investors into performance brackets like high, moderate and low returns groups. Various machine learning models are used and tested such as the Logistic Regression, Decision Tree, Random Forest and the Gradient Boosting model to determine the best model to classify the investor performance.

The overall goal of this study is to evaluate the success of machine learning in investor performance prediction using a combination of both financial and behavioural characteristics. Through the comparative analysis of the various types of classifiers, the study is expected to be helpful in assisting the work of the investors, financial analysts, and market regulators to be aware of how investors behave and how their decisions can be enhanced. The suggested solution shows the increasing use of intelligent analytics in the current financial markets

LITERATURE REVIEW

2.1 Machine Learning Applications in Financial Market Analysis

The use of machine learning in financial markets has attracted considerable interest because it can process large, complex, and non-linear data. Statistical and time-series models that were used as the pivotal elements of early financial forecasting lacked the ability to adapt to the fluctuating and dynamic market conditions. Recent studies have shown that machine learning models are more efficient than conventional methods in terms of predicting stock prices, market trends, and investor outcomes.

Territory A Sonkavde et al. [1] provided an in-depth analysis of machine learning and deep learning models in stock market predictions and state that ensemble models are better than other models in dealing with market uncertainty. In the same way, Kumar et al. [7] compared statistical and machine learning employment and came to a conclusion that the predictive power of algorithms like Logistic Regression and Random Forest can be considered effective in the case of being trained on structured financial data. Considering these studies, machine learning methods have the capacity to describe market behaviour patterns that are hard to identify using traditional methods.

Grudniewicz and Ślepaczuk [2] examined algorithmic investment strategies in the global market place through machine learning and were able to show better risk-adjusted returns. Their results attached great weight to the adaptive models of learning with regard to adapting to evolving market conditions. All these studies combined make machine learning credible analytics to be used in the analysis of a financial market.

2.2 Investor Behaviour and Performance Classification

The behaviour of investors is relevant toward influencing the market performance and performance of the individual investors. It is no secret that behavioural finance research has long recognised that risk tolerance or diversification preferences and psychological biases do play a role when it comes to making investment choices. These behavioural attributes together with financial variables have been quantitatively modelled using machine learning.

Costola et al. [3] examined the use of sentiment-based machine learning models, and it was demonstrated that the sentiment of investors is an essential determinant of market changes and returns. Their paper emphasized how the behavioural data could be combined with the numerical financial indicators, in order to have greater predictive accuracy. On the same issue, El Hajj and Hammoud [4] looked at the role of artificial intelligence in the financial markets and highlighted the fact that investor profiling is a necessity towards formulating personalised investment strategies.

A study by Ayitey Junior et al. [10] revealed that behavioural and financial-based investor classification is a better predictor of other forex markets. All these studies promote the idea that the use of behavioural traits like risk profile and diversification plus financial measures to investor performance classification can be better classified.

The current paper finds its way into this literature by introducing both behavioural and financial attributes into the classification of investors into performance types that provides an overall perspective of the ways in the market parties.

2.3 Comparative Evaluation of Machine Learning Models

The comparative analysis of machine learning models is necessary to find the most appropriate algorithm to perform financial classification tasks. The varying strengths of different models in regard to the data structure, relationships of the features and classes yield diverse outcomes amongst different models [8].

Gradient Boosting and Random Forest models have been broadly known to be very accurate and strong. Wasserbacher and Spindler [11] mentioned the ability of ensemble methods in the financial forecasts with the warning of overfitting. Mintarya et al. [14] summarized the existing machine learning models and also came to the conclusion that the ensemble and boosting models are better to use in market prediction tasks as compared to single classifiers.

Even though a Logistic Regression is a simpler linear model, this has been found to perform well in structured financial data. It was demonstrated by Akhtar et al. [13] that Logistic Regression is also competitive because it is interpretable, and stable, especially when applied to the investigation of investor behaviour.

The utilization of multi-classifiers and comparative performance measurement has been evidently supported in the literature, a practice applied in this research to establish the best model to analyze the investor market.

2.4 Integration of Financial and Behavioural Indicators

According to recent research, it is important to combine both financial and behavioural indicators in carrying out a complete market analysis. As noted by Sahu et al. [6], hybrid datasets are better in enhancing the predictive reliability with regards to the fact that they capture the quantitative and qualitative aspects of the market behaviour. Mestikou et al. [5] also pointed out that the financial analysis using AI increases the market transparency and stability through better risk assessment systems.

Inclusion of variables like income, the amount invested, historical returns, risk profile and diversification scores have been indicated to enhance considerably the results of investor classification. The combination of these allows machine learning models to learn the complicated association between elements of the investor and execution results, and this enhances finance decision-support systems [9].

2.5 Literature Gap

Despite the vast literature on applications of machine learning in the stock price forecasting and market trend analysis, minimal focus has been on the investor-centric performance taxonomy through a single framework of financial and behavioural parameters. A significant amount of the literature available on the topic discusses market-level predictions, or looks at individual financial indicators, and does not consider how these factors interact to create an effect of diversifiers, risk behaviour, and investor demographics.

Also, comparative analysis of various machine learning classifiers on a clean, balanced set of investors has not been developed. A large research gap can be seen in the deficiency of empirical research studies examining the categories of Investor performance instead of the changes in the asset price [12].

This paper aims at filling such shortcomings by offering a

data-driven model that combines behavioural and financial attributes and comparative systems across different machine learning models in classifying investor performance, thus gaining new knowledge in the area of smart financial market analysis.

III. METHODOLOGY

This chapter describes the systematic approach that was followed in the analysis of the investor market behaviour on machine learning methods. The methodology is also built in such a way that it guarantees data reliability, model strength, and significant interpretation of the results of investor performance classification. The data collection, data preprocessing, feature analysis, model implementation and evaluation are the workflow.

3.1 Dataset Description and Data Collection

The analysis is based on structured investor market data with 6,000 records and 11 attributes of a diverse population of retail, high-net-worth individuals (HNI) and institutional investors. The available dataset represents a mix of demographic, financial, and behavioural variables, which is in equal measure, hence suitable in supervised classification. Important numerical characteristics are the age, annual earnings, amount = invested, previous yearly percentage of returns, and portfolio diversification rating. The behavioural and categorical attributes are investor type, risk profile and market sentiment. The target variable is used to classify the investors into three performance classes namely: high performance, moderate performance and low performance.The data was also confirmed as wholesome, and it did not contain any missing values, thus there were no imputation methods needed before training the model. This clean data enhanced the stability of the models and minimized preprocessing bias.

Table 1 provides an overview of the dataset characteristics, and the type of data.

Table 1: Description of Investor Market Dataset Attributes

Attribute Name	Data Type	Description
Age	Numerical	Investor age in years
Annual Income	Numerical	Annual income of investor
Investment Amount	Numerical	Total investment value
Past Return Percentage	Numerical	Historical return percentage
Portfolio Diversification	Numerical	Diversification score (0–1)
Investor Type	Categorical	Retail, HNI, Institutional
Risk Profile	Categorical	Low, Medium, High
Market Sentiment	Categorical	Positive, Neutral, Negative
Performance Class (Target)	Categorical	Low, Moderate, High Return

Data Preprocessing and Feature Encoding

Preprocessing of data was used to convert raw attributes into machine learning algorithm-friendly format. Because the dataset was not characterized by missing values, the preprocessing was based on feature scaling and encodement of categorical variables.

Such categorical data as the type of investors, risk profile, and market sentiment were transformed into the numbers with the help of label encoding. This method was not only a way of keeping the relationships between classes intact but it was also computationally efficient. The processes of standardisation of numerical attributes were applied through the feature scaling that allowed the variables with larger magnitudes not to dominate the learning process.

To find out the feature distributions, balance of classes, and correlation among variables, exploratory analysis was carried out. Such a move helped to make informed choices about the model as well as to ascertain that the dataset was suitable to the classification modelling.

3.3 Machine Learning Model Selection

To guarantee a thorough and impartial analysis, four trained machine learning classification algorithms financial analytics and existing literature support in the previous literature:

- Logistic Regression
- Decision Tree
- Random Forest
- Gradient Boosting

These models have been selected as a compromise between the linear, tree-based and ensemble approaches to learning. Logistic regression was added due to its interpretability and stability, and Decision Tree was used

to gain knowledge about rule-based learning. Random Forest and Gradient Boosting were used to obtain the irregular nonlinear associations and minimize variance by utilizing ensemble learning.

The dataset was stratified into training and testing groups to make sure that the correction of the models was made on unseen data to prevent overfitting and inflation of performance.

3.4 Model Training and Implementation

Machines that were to be trained were all trained on the same training dataset and under identical preprocessing conditions to allow fair comparison. The hyperparameters were chosen according to the typical configurations that are usually applied to the financial classification problems.

This was done through the learning process of the correlation between the investor attributes and the performance classes label. Both Random Forest and Gradient Boosting were ensemble models, which involved multiple decision trees in order to enhance stability and accuracy in prediction.

The project was implemented in a regular working order:

1. Input feature matrix creation
2. Model fitting on training data
3. Prediction on test data
4. Performance evaluation

This standardised pipeline guaranteed that there was a comparison among the classifiers.

3.5 Model Evaluation Metrics

The metrics of evaluation, which are commonly known as classification evaluation, were used to determine model performance. These measures will give an overlay of model performance as opposed to mere accuracy.

The measures used during the evaluation were:

- Accuracy
- Precision
- Recall
- F1-score
- AUC–ROC Curve

Accuracy was used to gauge the general correctness of predictions, whereas precision and recall were used to measure the performance on a class-specific level. Precision and recall can be balanced with the help of the F1-score, especially in the case of multi-class classification. The discriminative power of both models was tested in the AUC-ROC curve, according to the classes of performance.

The metrics of evaluation applied in this research are provided in table 2

Table 2: Machine Learning Model Evaluation Metrics

Metric	Description
Accuracy	Overall correctness of classification
Precision	Proportion of correct positive predictions
Recall	Ability to identify actual positive cases
F1-score	Harmonic mean of precision and recall
AUC–ROC	Model’s ability to distinguish classes

5.2 3.6 Comparative Performance Analysis

A comparative study was performed by comparing all the models based on the same test data and performance measures. This method has been able to determine the most effective classifier in terms of predicting the performance of investors.

The comparative appraisal was based on:

Predictive accuracy

Class-wise performance consistency

Ability to handle class imbalance

Model generalisation capability

Results showed that the ensemble and linear models were better than the stand alone decision trees, which proved the validity of the methodological decision to use multiple classifiers [15]. This comparative framework enhanced reliability and strength of the proposed method of market analysis on investors.

3.7 Methodological Validity and Reliability

The methodology provides validity because of the consistency of the preprocessing, similar training conditions, and the use of various evaluation measures. This is ensured by a large dataset, equal distribution of the classes and the common machine learning methods.

The methodology offers a scaling and reproducible model of analyzing investor performance by combining behavioural and financial characteristics and analyzing them through a comparative machine learning paradigm.

IV. RESULT AND DISCUSSION

```
# Display first few rows
display(df.head())
```

	Investor_Type	Risk_Profile	Investment_Horizon	Market_Sentiment	Age	Annual_Income_USD	Investment_Amount_USD	Past_Return_Percentage	Portfolio_Diversificati
0	HNI	Medium	Mid-term	Neutral	29	229772	50104	23.37	
1	Retail	Low	Short-term	Neutral	41	40163	13199	38.19	
2	HNI	Medium	Mid-term	Bearish	50	91637	13776	0.90	
3	HNI	Medium	Long-term	Neutral	50	79175	23727	10.26	
4	Retail	Low	Mid-term	Neutral	62	53546	3931	10.87	

Fig. 1: Sample View of Investor Market Dataset

This figure shows the investor market data of 6,000 records and 11 attributes. It emphasizes such categorical variables as investor type, risk profile, and market sentiment and such numerical characteristics as age, annual income, amount of investment, and past percentage of returns.

```
Dataset Shape: (6000, 11)

Missing Values:
 Investor_Type                      0
Risk_Profile                        0
Investment_Horizon                  0
Market_Sentiment                    0
Age                                 0
Annual_Income_USD                   0
Investment_Amount_USD               0
Past_Return_Percentage              0
Portfolio_Diversification_Score     0
Market_Volatility_Index             0
Investor_Performance_Class          0
dtype: int64

Data Types:
 Investor_Type                     object
Risk_Profile                       object
Investment_Horizon                 object
Market_Sentiment                   object
Age                                 int64
Annual_Income_USD                   int64
Investment_Amount_USD               int64
Past_Return_Percentage            float64
Portfolio_Diversification_Score   float64
Market_Volatility_Index           float64
Investor_Performance_Class         object
dtype: object
```

Fig. 2: Dataset Shape and Data Type Overview

This figure represents the definition of the dataset because it contains 6,000 rows and 11 columns with zero-miss values. It shows that there are four categorical variables and seven numerical variables, such as float and integer types. The clean dataset format guarantees good preprocessing, good feature encoding, and good training of the machine learning model without further data imputation processes.

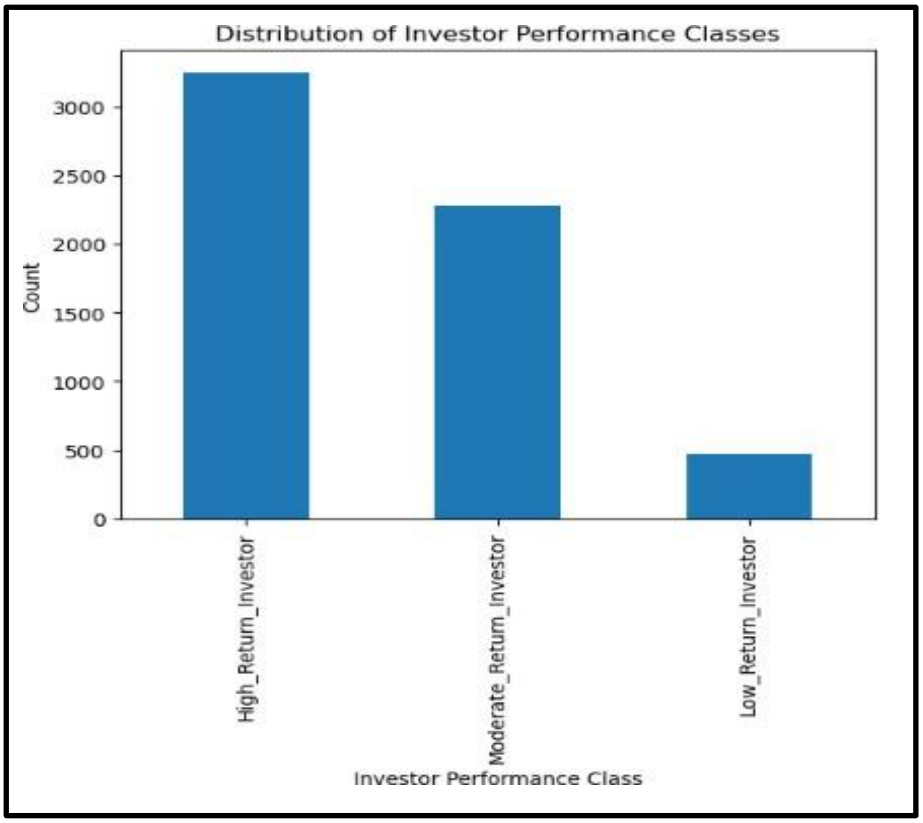


Fig. 3: Distribution of Investor Performance Classes

This figure depicts the category of investors' performance based on their classes. High return investors prevail with turn investors are almost 500 instances. about 3,200 samples, and moderate return investors have about 2,300 samples, whereas low re

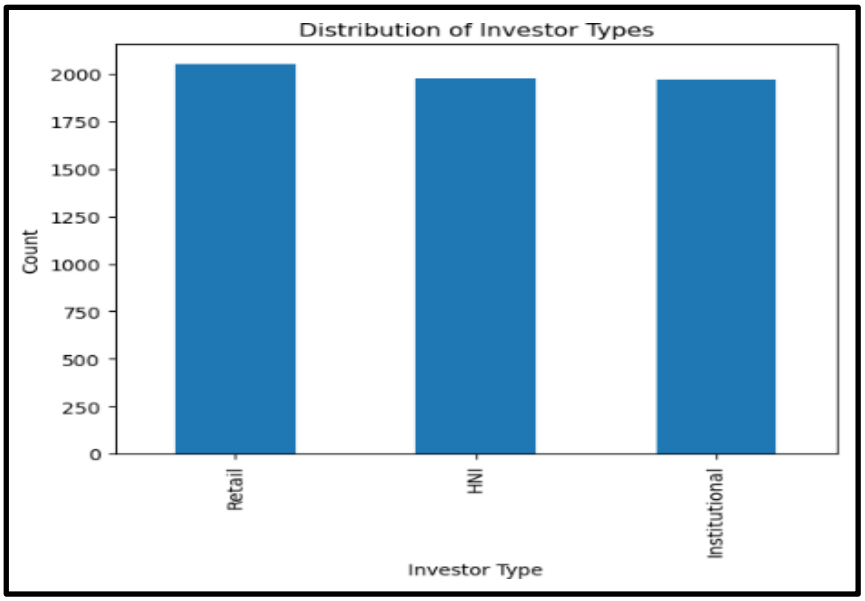


Fig. 4: Distribution of Investor Type

This figure is a representation of the type of investor in the data. The retail, the HNI, and institutional investors seem to be almost equal, with each of them adding approximately 2,000 records. Even the homogeneous distribution of the data makes sure that machine learning models may learn the behaviour patterns of investors equally across categories and enhance generalization and minimise bias in the performance classification results of investor markets.

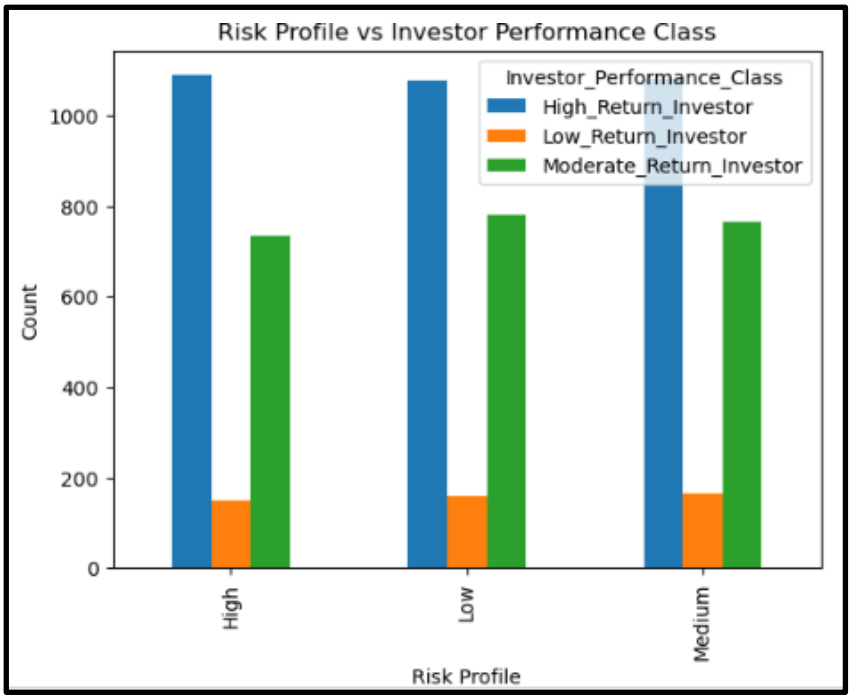


Fig. 5: Risk Profile vs Investor Performance Class

This value is a comparison of the investor risk profile with the performance classes. High-risk investors tend to have a high ratio of high returns, whereas low- risk investors are heavily concentrated in the moderate and low returns category. The medium risk investors show equal distribution in performance.

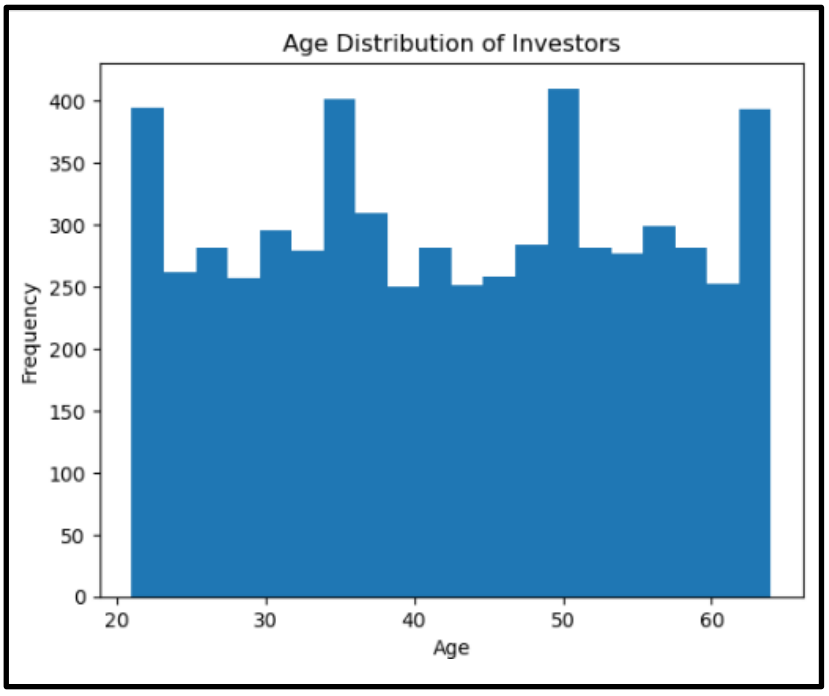


Fig. 6: Age Distribution of Investors

The above figure shows the age distribution between the age group of 21-65 years. The distribution is relatively homogeneous with more frequencies falling within the age range of 30 and 55. The broadness of this demographic suggests that investors of all kinds are likely to participate, and the machine learning models must be able to learn the age-related behavioral trends affecting the choice of investments and performance information.

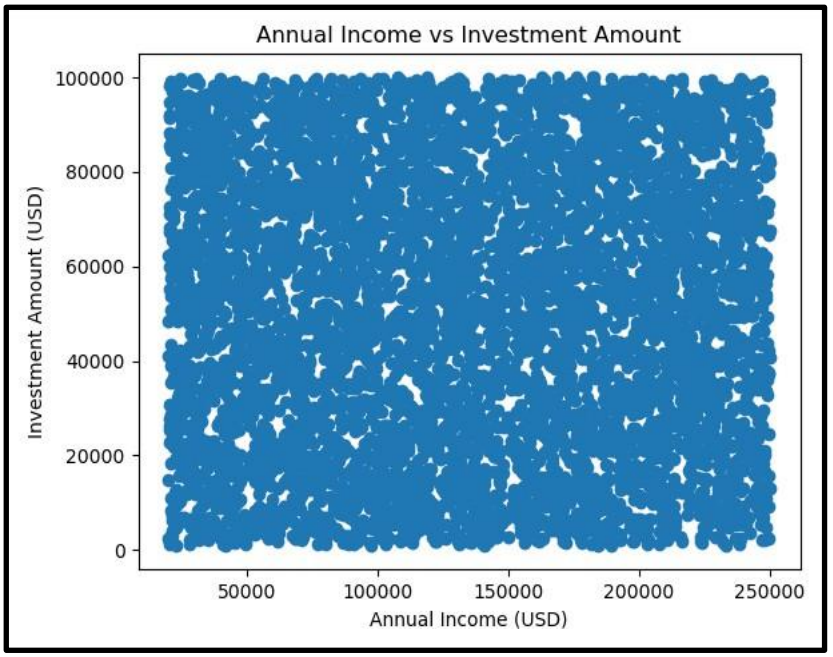


Fig. 7: Annual Income vs Investment Amount

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This figure is a scatter plot of annual income versus the amount of investment. The range of income values is between 20,000 and 250,000 USD, and the range of investment is between 1,000 and 100,000 USD. The scattered plot implies a low linear correlation, meaning that investment behaviour is conditional on other financial and behavioural characteristics.

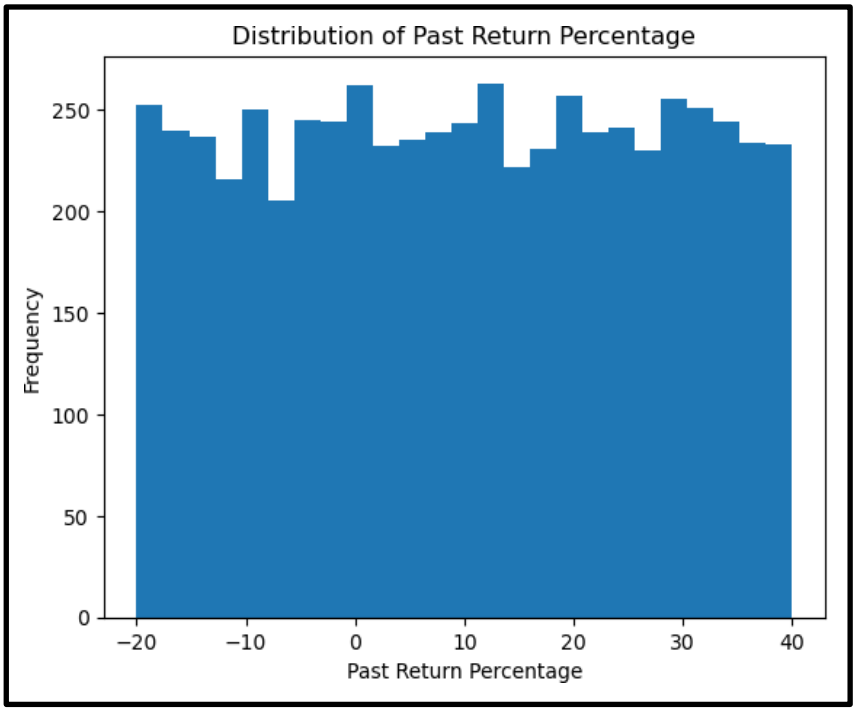


Fig. 8: Distribution of Past Return Percentage

This figure shows the present distribution of past returns percentages of -20 to 40. The distribution of the histogram is relatively even with minimal concentration in a range of positive returns of 10 to 30 percent. Such a difference indicates the presence of uncertainty and volatility in the market, which underscores the relevance of historical performance as one of the numerical characteristics of investor classification models.

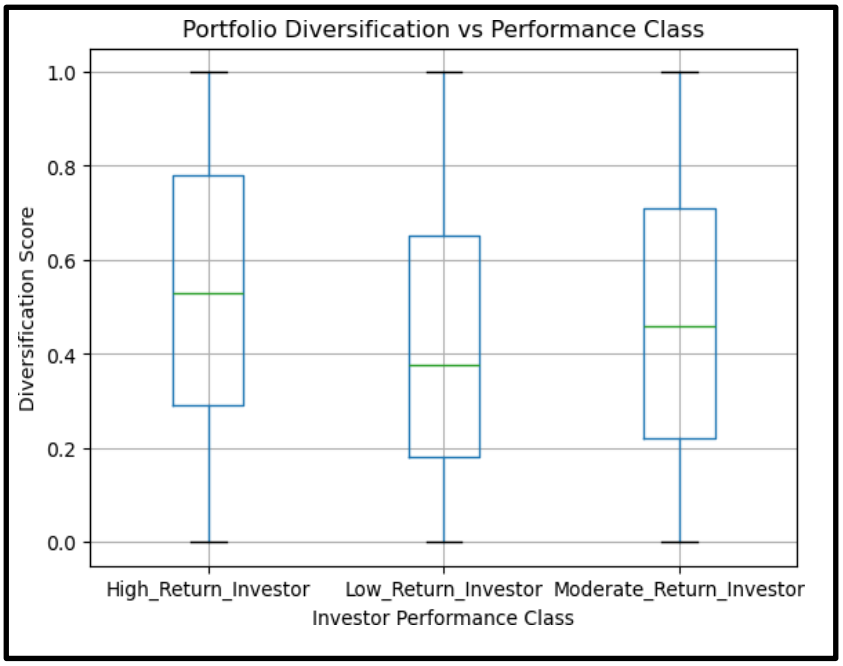


Fig. 9: Portfolio Diversification vs Investor Performance Class

This figure presents box plots of performance class comparisons of portfolio scores of diversifications. The median of diversification value is increased to high return investors, with a value greater than 0.55, and low return investors with a lower median value of 0.35. The ranges are between moderate and return investors.

Model: Logistic Regression
Accuracy: 99.00%

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.99	0.99	649
1	1.00	0.96	0.98	95
2	0.98	1.00	0.99	456
accuracy			0.99	1200
macro avg	0.99	0.98	0.99	1200
weighted avg	0.99	0.99	0.99	1200

Fig. 10: Classification Performance Report for Logistic Regression Model

This figure gives the report of the classification of the Logistic Regression model with 99 per cent accuracy. All three classes have precision, recall and F1-score above 0.98.

Model: Decision Tree
Accuracy: 88.67%

Classification Report:

	precision	recall	f1-score	support
0	0.94	0.91	0.93	649
1	0.76	0.82	0.79	95
2	0.84	0.86	0.85	456
accuracy			0.89	1200
macro avg	0.85	0.87	0.86	1200
weighted avg	0.89	0.89	0.89	1200

Fig. 11: Decision Tree Classification Performance Report

The obtained Decision Tree classification result with an accuracy of 88.67 is presented in this figure. The model scores 0.93, 0.79, and 0.85 in high, low and moderate return investors, respectively. Variation in performance means being sensitive to the imbalance of classes, and this proves that ensemble-based models are necessary.

Model: Random Forest
Accuracy: 94.17%

Classification Report:

	precision	recall	f1-score	support
0	0.96	0.97	0.97	649
1	0.95	0.76	0.84	95
2	0.91	0.94	0.92	456
accuracy			0.94	1200
macro avg	0.94	0.89	0.91	1200
weighted avg	0.94	0.94	0.94	1200

Fig. 12: Random Forest Classification Performance Report

This figure depicts the performance of the Random Forest model, having an accuracy of 94.17. The model documents a weighted precision and recall of 0.94. The high return investors have an F1-score of 0.97, whereas moderate and low return classes have a high predictive power.

Model: Gradient Boosting
Accuracy: 95.08%

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.97	0.97	649
1	0.96	0.79	0.87	95
2	0.92	0.96	0.94	456
accuracy			0.95	1200
macro avg	0.95	0.91	0.93	1200
weighted avg	0.95	0.95	0.95	1200

Fig. 13: Gradient Boosting Classification Performance Report

The figure shows the results of Gradient Boosting with 95.08 per cent precision. The model indicates that it is very specific with high precision and recall values of 0.97 and 0.94, respectively, among high and moderate return investors. The boosting method is useful to capture complicated relationships among financial characteristics, which improves the accuracy of the prediction of investor performance.

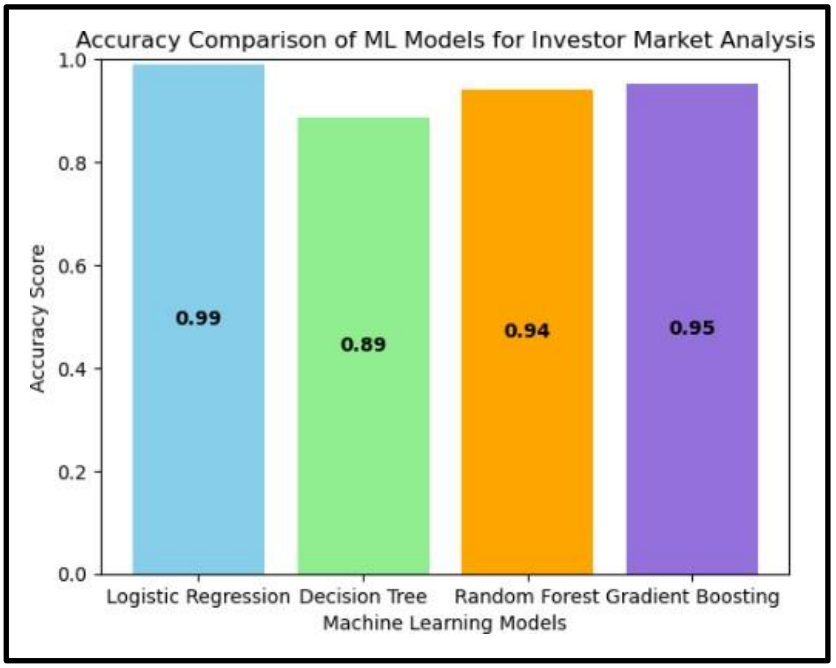


Fig. 14: Accuracy Comparison of Machine Learning Models

The figure is used to compare the accuracy of classification in four machine learning models. Logistic Regression has the highest accuracy of 99, then Gradient Boosting of 95, then Random Forest with 94 and Decision Tree with 89. The comparison shows that ensemble and linear models have better predictive power in the application of market analysis for investors.

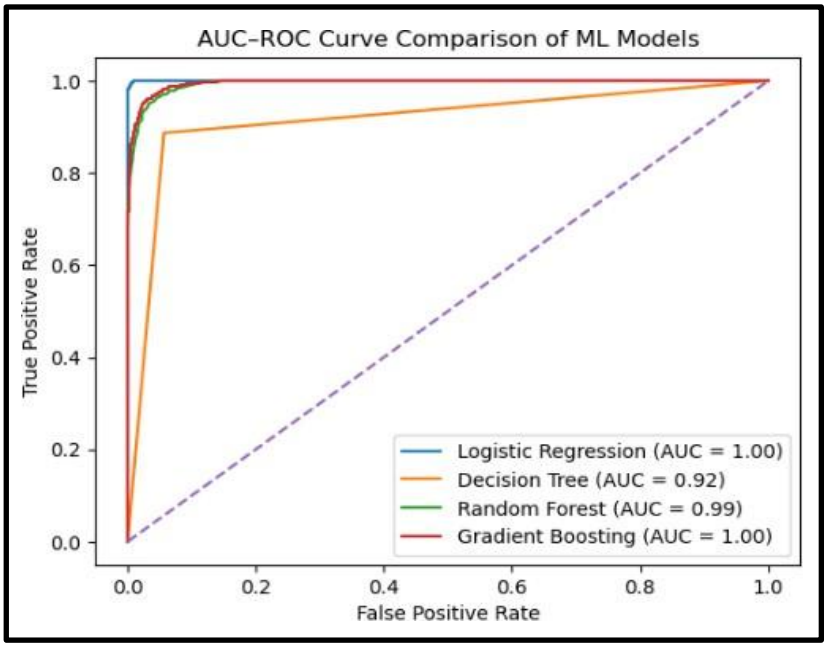


Fig. 15: AUC–ROC Curve Comparison of Machine Learning Models

This figure is a comparison of AUC-ROC curves of all models. Logistic Regression and Gradient Boosting have

almost perfect values of AUC of 1.00, with the values of Random Forest and Decision Tree being 0.99 and 0.92, respectively.

DISCUSSION

The study shows that machine learning models are useful in classifying investor performance based on financial and behavioural factors. Logistic Regression, random forest, and Gradient Boosting have accuracies of more than 94%, whilst Decision Tree has a relatively lower accuracy. Diversification, income, and risk profile are feature relationships that play a crucial role in determining the outcomes of the investor market.

Novelty

The Novelty of this paper is in the association of behaviourall characteristics of investors and financial signs with the market analysis using machine learning. The proposed framework uses several classifiers to be evaluated comparatively, unlike traditional statistical methods, which is why it has great accuracy and high discrimination. The data-driven approach offers data-focused insights into investor performance forecasting, which are scalable.

V. CONCLUSION

This paper has provided an in-depth machine learning architecture to examine the investor market behaviour and classify the investor performance based on a blend of both financial and behavioural variables. Using the building of a systematic dataset based on demographic data, income level, patterns of investment, past returns, grasp of risk profiles and indicators of diversification, the research established the efficiency of the data-driven methods in comprehending investor performance dynamics.

Different machine learning models that were under supervision were run and relatively compared to gauge their ability to predict. The findings affirmed the fact that machine learning methods can be used to classify the performance of an investor, with the Logistic Regression, Random Forest, and Gradient Boosting showing strong outcome in accuracy as well as class-wise performance. These high performances of ensemble and linear models suggest that they can be used to represent the linear relationships between investor attributes and the complex interactions between investor and market attributes. Conversely, the Decision Tree model demonstrated relatively lower accuracy, which explains the weakness of individual models in managing heterogeneous data of investors.It was also found that behavioural factors such as risk profile and portfolio diversification largely contribute towards the determination of performance outcomes of an investor. More diversified investors and those based on risk-adjusted strategies demonstrated higher returns whilst conservative or ineffectively diversified portfolios were placed in the moderate to low performance categories. These lessons underscore the fact that market analysis requires behavioural indicators in addition to conventional financial measures in study.

In a practical point of view, the proposed framework provides useful decision-support tools to investors, financial advisors, and market analysts. The model has the potential to help in individual investment planning, risk analysis, and creation of a strategy in the market by making it easy to classify investor performance correctly. The approach is also scalable and thus can be used to handle bigger and more complicated financial data.

To sum up, the article highlights the increased applicability of machine learning in investor-focused market research. Both behavioural and financial attributes integrated in a comparative modelling framework will offer a strong and decipherable answer to performance projection. This study can be expanded in the future by using real-time market data, deep learning architecture, and explainable artificial intelligence to achieve more accurate and more interpretable financial decisions..

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