

Intelligent Investment Predictor: An Explainable Machine Learning Framework for Investment Sector Preference Prediction

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Abstract Selecting a suitable investment option is often difficult for individual investors because investment decisions are influenced by demographic, financial, and behavioral factors. This study proposes an explainable ensemble learning framework for predicting investment preferences from survey-based data. The dataset consists of 2,000 structured responses collected through a questionnaire designed to capture personal and financial characteristics, including age, gender, occupation, annual income, monthly investment amount, investment goal, duration of savings, and information sources. Unlike traditional financial forecasting studies that rely on market time-series data, this work addresses a user-level multi-class classification problem in which machine learning models are used to predict likely investment preferences from investor profile attributes. The framework consists of preprocessing, feature transformation, supervised model training, and comparative evaluation of several base and ensemble methods, including Logistic Regression, K-Nearest Neighbors, Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, Voting, and Stacking classifiers. To help interpretation, explainable AI is used in the form of Local Interpretable Model-agnostic Explanations (LIME). A lightweight web interface is also included to make it accessible to users with no previous experience with basic knowledge. Overall, the study results indicate that explainable ensemble learning can be an efficient decision-support mechanism for predicting investment preferences from structured survey data.

Keywords Investment Sector Classification, Machine Learning, Ensemble Learning, Stacking Classifier, Explainable AI, Feature Importance, User Financial Profiling

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1. Introduction

As an investor, it is difficult to select a suitable investment, and in such situations, demographic, economic, and behavioral factors influence the decision. People have different preferences when it comes to investments depending on their income level, job, goals, saving habits, and access to information. Intelligent systems are increasingly interested in aiding investors in making better investment decisions. Financial analysis and interpretation methods are less than ideal in this environment, because they are not equipped with sufficient data, can't change with market conditions, or provide interpretable information [1]. Traditional models are not able to analyze data, cannot adapt to the changes in the market, and are unable to provide meaningful insights [2]. In addition, although machine

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learning (ML) and deep learning (DL) have greatly improved the accuracy of predictions, it also has created some additional challenges [3]. For instance, black-box models such as neural networks and tree ensembles provide limited transparency that makes it difficult for investors and financial analysts to understand the rationale for a given prediction [4, 5]. This lack of transparency erodes trust and deters its implementation in real-world financial systems, where decisions must be accurate and justifiable.

Machine learning has become a powerful technique for pattern finding and prediction in finance. Most of the existing studies have been devoted to stock price forecasting, market trends, or time series prediction. This paper addresses a more concrete problem faced by users: predicting an individual's investment preference from questionnaire data. Rather than forecasting the performance of the markets, we aim to determine how likely the individual is to invest based on his or her individual features. For this study, we use a questionnaire collection of characteristics like age, gender, working status, annual income, monthly savings goal, and sources of financial information. The desired variable is the respondent's mode of investment. And then the comparison of several machine learning models, such as Logistic Regression, K-Nearest Neighbors, Naive Bayes, Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting, ensures the validity of the final investment sector predictions. We also explore ensemble methods such as Voting and Stacking to improve our predictions.

This study is designed to predict user investment preferences based on specific factors, such as their financial status, investment goals, time horizon, and risk tolerance. Rather than making predictions or recommending investments, this study attempts to model and understand investor behavior via structured survey data. The principal objectives of this study are as follows:

- To develop a machine learning-driven approach to predict the user's investment preferences based on demographic and financial data.
- To improve prediction performance using ensemble learning, especially stacking.
- To utilize Explainable Artificial Intelligence (XAI), namely LIME, for better modeling predictability.
- To use the feature set of the user to explore the impact of different features on a user's investment preferences.
- To provide a transparent and interpretable decision-support tool that helps investors understand their investment behavior.

The proposed system has a user-friendly interface so that the user can input their data, and then the investor can interact with the predicted outputs. These predictions are also confirmed through the XAI framework, which provides transparency and confidence in the predicted investment behavior [6]. This approach is crucially important in the new financial landscape where it is essential to have an explainable and transparent system as well as data-driven systems that are understood by stakeholders, including regulators, financial institutions, investors, and policy-makers [7, 8]. Combining ensemble-based machine learning with XAI, the proposed model attempts to offer more accurate and interpretive insights into user investment behavior, reduce bias in predictions, and enhance transparency. This method allows for a better understanding of investment behavior rather than real-time market or portfolio optimization [9].

In view of interpretability in financial decision-support systems, this framework also incorporates explainability by using Local Interpretable Model-agnostic Explanations (LIME) and feature analysis. The system is also provided with a web interface to make it accessible to non-technical users. The result of the experiments showed that ensemble models, such as the stacking classifier, performed best overall. The results of this study suggest that explainable ensemble learning could be used in the prediction of investment preferences through structured survey data.

Further evaluation of models is performed with precision, recall, and F1-score to provide a complete assessment of the performance in multi-class classification.

The primary contributions of the research include:

- We propose an explicable machine learning model to predict user investment preferences based on structured survey data.
- We propose a stacked ensemble model based on multiple classifiers (RF, SVM, KNN, LR, DT, GB) to improve predictive performance in a multi-class classification task.

- We use LIME-based XAI to explain model outputs at the feature level to give an explanation of model results that is more understandable and more reliable.
- We present a user-friendly and interpretable decision-support system to analyze investment behavior.

2. Literature Reviews

Currently, AI-based finance research has been mostly on market prediction, portfolio optimization, and time series forecasting with historical financial data. While these predictive methods are highly accurate, they are difficult to interpret, generalize, or personalize at the level of the user. The present study addresses a survey-based, user-centered problem regarding investment preferences prediction with emphasis on interpretability and decision support.

2.1. *Models with High Accuracy but Poor Generalization*

Some authors have placed emphasis on the fact that the traditional machine learning models have high predictive accuracy. Random Forest and RNN/LSTM were used in the analysis of financial trend Verma et al. [10], giving results of up to 88 percent accuracy using decision trees and SVMs. A multipurpose ML system accuracy was created by Sandeepm et al. that could simultaneously forecast performance and risks and trade automatically with an 87 percent [11] to identify the stock rating in terms of correctness. In the same manner, Perumalsamy et al. [12] conducted a similar study using deep learning to make predictions of annuity pricing with an accuracy of 92 percent. Although the models are very predictive, they tend to have poor generalization, overfitting, and limited explainability, particularly, deep models such as the LSTM that are complex and opaque to decision-makers. Compared with Pattayam et al. [11], which focused on AI-driven stock market analysis and short-term financial prediction, the present research addresses a different and more personalized problem by predicting individual investment preferences from survey-derived profile data rather than from market behavior alone.

2.2. *Ensemble and Hybrid Approaches Dependent on Historical Data*

Sakshi et al. [2] trained Random Forest, Gradient Boosting, and time series feature engineering more than 85.3 percent accuracy in correctly measuring the price of stocks. Kasaraneni et al. [9] have applied an AI-supported portfolio optimization framework relying on SVMs and an ensemble as a risk-minimization strategy to maximize returns as a type of analysis and optimization method. Such ensemble models are more accurate and robust; however, they are also more dependent on historical information, which tends to perform poorly with a volatile environment or a data-sparse situation. Moreover, they are also not very applicable in real-time since wide preprocessing and tuning is necessary to make them applicable in dynamic markets. In contrast to Sakshi et al. [2], the present study does not focus on stock market investment prediction using mainly market-oriented features. Instead, it formulates the problem as a survey-based multi-class investment preference prediction task using demographic, financial, and behavioral attributes, while also incorporating explainability to improve transparency for end users.

2.3. *Deep Learning with Technical Indicators but Lacking Explainability*

Bastos et al. [4] and Perumalsamy et al. [12] discussed the use of deep learning models (specifically LSTM and CNN) together with technical indicators to perform finance-related time-series forecasting. They are able to find complex non-linear relations in stock data and have good pattern recognition. They are, however, normally black boxes with low interpretability, and thus it is hard to know and appreciate the decision process. Moreover, their complexity, as well as poor ability to generalize over to various financial settings, impede their wide usage in practice. Unlike Bastos et al. [4], who focused on deep learning for stock market forecasting and required highly structured data representations, the present work relies on structured survey data and simpler machine learning and ensemble models, which make it better suited for interpretable user-level prediction of investment preference.

2.4. Literature Reviews and Bibliometric Studies without Empirical Models

Quite a great number of studies on the use of AI/ML in the domain of finance are provided in several works, such as by Goodell et al. [13], Ahmed et al. [7], Kumar et al. [14], and Pugliese et al. [15]. These articles can plot research trends, point to important studies, or offer a clue about research areas to investigate in the future, but they are not models or have a measure of their performance or working methods. Therefore, they do not contribute to the development of an intelligent financial system. Although Goodell et al. [13] provided useful information on trends in artificial intelligence research for finance, it was a review-based approach and could not be used as a predictive strategy. In contrast, the present study develops and evaluates an empirical classification framework supported by explainability and a lightweight deployment interface. Kumar et al. [14] discussed machine learning in sustainable finance, but the scope remained broader and less focused on individualized recommendations. The current study differs by concentrating specifically on personal investment preference prediction using structured user-level features and ensemble classification techniques.

2.5. Context-Specific Econometric Studies with Limited Scope

The impact of COVID-19 on Borsa Istanbul and the use of GARCH models were discussed by Yagli et al. [16], the applicability of AI in sales forecasting in a CRM context was modeled by Venkataramanan et al. [17] using regression and time-series models. A systematic review of different forecasting methods was done by Deepak et al. [18], who used decision trees, as well as neural networks. Though the above studies provide profound context-related information on volatility and merchandise sales, they usually lack across-domain generalizability, and do not present new models or address an empirical accuracy metric. Yagli et al. [16] examined stock market volatility in a specific economic context, which provides important domain insight but remains limited in general user-level applicability. In contrast, the current study proposes a predictive framework centered on individual investor characteristics, making it more suitable for personalized decision-support rather than macro-level volatility interpretation. Venkataramanan et al. [17] reviewed AI-based forecasting in customer relationship management which is important for sales prediction but is domain-specific and not directly transferable to recommendation of personal finance. The present paper instead presents an empirical framework for investing preference prediction using investor survey attributes.

2.6. Visionary Outlooks without Real-World Validation

Pugliese et al. [15] and Javaid et al. [19] have considered the potential of AI in the financial services, focusing on fraud detection, customer service, and regulatory regulation. The work is useful because of the futuristic perspective, but it is not validated or backed up by a case, so it cannot be used in the context of model building or system deployment. In contrast, the present study provides an empirical and implemented framework based on a real survey dataset, allowing practical evaluation of machine learning models for personalized investment preference prediction.

The majority of the previous researches are restrained to limited financial indicators or past price time series, whereas the current study is user-specific in terms of age, income, investment goal, savings duration, and other survey-based demographic and behavioral characteristics. Instead of forecasting market performance, the individualized recommendations or preference predictions based on this multi-profile method are given to the user based on various types of assets, including equity, mutual funds, and alternative investments, thereby making it more useful for the user and increasing their satisfaction levels. The user-centric framework in the design of the proposed algorithm allows it to be more easily understood by non-expert investors. On top of that, the combination of multiple machine learning models, ensemble strategies, and explainability support will allow the system to act as an interpretable prototype of predictions. The comparison of previous works is shown Table 1. Javaid et al. [19] mentioned the future applications of artificial intelligence in financial services, but he did not provide a strong predictive framework. In contrast, the current study provides an empirically valid and empirically validated system for explaining investment preferences.

Table 1. Comparative Analysis of Existing AI and ML-Based Financial Prediction Studies, Highlighting Methodologies, Models Used, Key Contributions, Limitations & Reported Accuracy Levels Across Different Research Works.

Works	Methodology	Model Used	Contribution	Limitations	Accuracy
Sakshi et al. [2]	ML approaches for stock market investment	LR, RF, SVM, DT, NB, KNN, GB, Stacking	Investment strategy prediction using multiple models	Lack of interpretability in some models	85.3%
Bastos et al. [4]	Stock market forecasting with DL	LSTM	Reviewed DL and technical analysis techniques	Complex implementation, needs large datasets	N/A
Goodell et al. [13]	Bibliometric analysis of AI in finance	N/A	Identified key research themes in AI	No implementation; theoretical only	N/A
Pattayam et al. [11]	AI-driven stock market analysis	ML, DL	Proposed AI techniques for prediction and risk management	Limited to short-term prediction accuracy	87%
Yağlı et al. [16]	Analysis of Covid-19's impact on stock markets	Statistical analysis, regression	Studied stock volatility during Covid-19	Country-specific (Turkey); short-term focus	N/A
Pugliese et al. [15]	Machine learning in global finance	N/A	Discussed AI trends and regulation globally	No model implementation; theoretical	N/A
Ferreira et al. [20]	AI in stock trading	NN, RL	Focused on RL and neural networks for trading	Limited real-world testing; complex models	N/A
Verma et al. [10]	Pattern-based stock market prediction	ML	Custom model for stock trend prediction	Accuracy dataset-dependent; scalability issues	88%
Kasaraneni et al. [9]	Portfolio optimization using AI	GA, NN	AI-based approach balancing risk/return	Theoretical only; no real-time testing	N/A
Kumar et al. [14]	ML for sustainable finance	RF, SVM	Applied ML to sustainability in finance	Sector-limited and poor scalability	N/A
Javaid et al. [19]	Future of AI in financial services	N/A	Explored AI integration in future finance	No specific model; high-level view	N/A
Perumalsamy et al. [12]	Predictive analytics for annuity products	ML, DL	Proposed pricing and risk prediction methods	Narrow focus on annuities	92%
Venkataramanan et al. [17]	AI in CRM sales forecasting	ML, AI	Reviewed AI-based CRM forecasting tools	Domain-specific (CRM); limited scope	N/A
Deepak et al. [18]	ML-based stock market prediction	SVM, RF, NN	Systematic review of ML prediction methods	No accuracy; traditional ML only	N/A

3. Methodology

Figure 1 illustrates the overall workflow for the investment preference prediction model. The process includes preparation of the data, preprocessing, model training, ensemble learning, evaluation of performance, explainability, and lightweight deployment.

3.1. Dataset Description

Data for the dataset used in this study were gathered through a survey capturing individual investment preferences and relevant demographic, financial, and behavioral characteristics. The dataset is available at <https://www.kaggle.com/datasets/tmmhratul/investment-survey-dataset> and was collected from March to October 2024. The respondents were collected from various online investment forums in Bangladesh (Investors Forum Bangladesh and Digital Finance Forum Bangladesh), from different academic networks, classmates, alumni, teachers, and from social media groups with respect to finance and personal investment. All data were collected ethically, anonymised before analysis, and stored according to best practices in accordance with data protection laws and standards. The final dataset comprises 2,000 instances and features for demographic, financial, and behavioral characteristics used solely for research and analysis. Table 2 describes each feature in the dataset. The dataset contains numerical and categorical variables shown in Table 3. The selected feature is *Mode_of_investment*. It is categorical and numeric in Table 4.

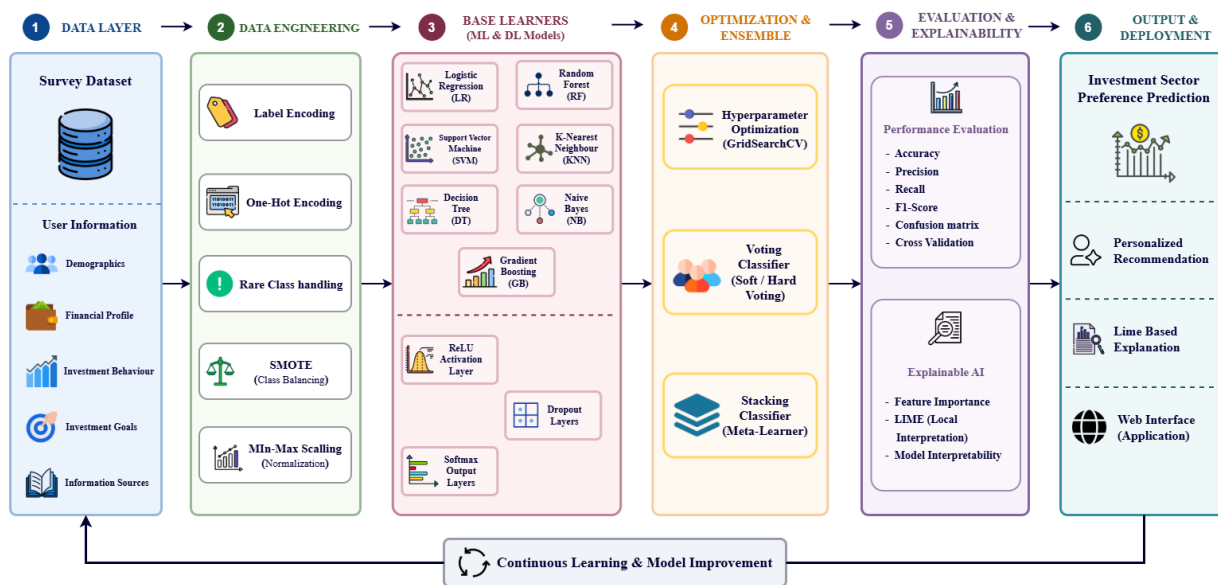


Figure 1. Overall Workflow of the Proposed Investment Preference Prediction Framework, Illustrating Dataset Collection, Data Preprocessing, Feature Engineering, Model Training, Ensemble Learning, Performance Evaluation, and Explainable AI Integration.

Table 2. Detailed Description of Survey-Based Dataset Features Used for Investment Preference Prediction

Feature Name	Description
Gender	Differentiates the participant as either 'Male' or 'Female'.
Age	A numeric value representing the age (in years) of the participant.
Working_professional	Indicates whether the participant is a working professional. Value is 1 for working, 0 otherwise.
Annual_income	Total annual income of the participant in Bangladeshi currency (BDT).
Mode_of_investment	Type of investments chosen by the participant, e.g., 'Banking - RD, FD', 'Mutual funds', 'Stock trading - Intraday, Long Term', etc.
Investment_per_month	Amount (in BDT) invested monthly by the participant.
Motivation_cause	Primary motivation for investing, such as "Family member", "Self Interest", or "Agents/Investment brokers".
Resources_used	Information sources used to learn about investments, e.g., "Family members/Friends", "Mobile applications", "News articles", "Books".
Goal_for_investment	Participant's financial objective, e.g., "Amassing of wealth", "Early retirement".
Duration_to_save (in Years)	Time duration (in years) the participant intends to invest.
Mode_of_investment_numeric	Numeric representation of the 'Mode of Investment' feature for ML model use.

3.2. Data Pre-processing

The data pre-processing step is the final step in processing raw data to a form that can be used to train the machine learning models. As in this study, the data pre-processing step was to clean the raw data, prepare it to be used as an input to a Machine Learning model, balance it to handle outliers, and normalize numerical features. The data pre-processing method employed by the study is Label Encoding, One-Hot Encoding, SMOTE (Synthetic

Table 3. Categorization of Dataset Features into Numerical and Categorical Types for Model Processing

Feature Type	Number of Features	Feature Names
Numerical	6	Age, Working Professional, Annual Income, Investment Per Month, Duration to Save (Years), Mode of Investment (Numeric)
Categorical	5	Gender, Mode of Investment, Motivation Cause, Resources Used, Goal for Investment

Table 4. Numerical Encoding Scheme for Investment Modes Used in Multi-Class Classification

Mode of Investment	Numeric Value
Banking - RD, FD	0
Chit fund	1
Crypto currency	2
Mutual Funds	3
Marketing	4
Gold / Any other Materialistic investment	5
Not prepared	6
Real estate, Bonds	7
Stocks - Intraday, long term	8

Minority Oversampling Technique), and Min-Max Scaling [21]. All of the methods tackle a certain need, for example, working with categorical data, balancing the classes, or normalizing the numerical features. The pre-processing methods used in the proposed research are Label Encoding, One Hot Encoding, SMOTE, and Handling Rare Classes.

To ensure methodological correctness and avoid data leakage, the dataset was first divided into training and testing subsets before applying any resampling techniques. SMOTE was applied exclusively to the training data after the split. During cross-validation, SMOTE was incorporated within each training fold using a pipeline approach, ensuring that synthetic samples were not generated using test data.

3.2.1. Label Encoding

Label Encoding is a two-step process that transforms quantitative discrete variables into weights through continuous intervals. For example, qualitative data like Gender and Working Professional are either given a numeric equivalent, such as: Gender Male \rightarrow 1, Gender Female \rightarrow 0. The algorithm simply allows a variable to be a labeled numeric integer for each category within the variable. This is appropriate for features with only two potential values – the binary categories – because there's not a natural ordering to the numbers assigned.

The formula for label encoding is provided in equation 1.

$$x_{\text{encoded}} = \text{Label}(x) \quad [22] \quad (1)$$

Here, x represents the original categorical variable, while $\text{Label}(x)$ is the numerical label assigned to each unique categorical value.

3.2.2. One-Hot Encoding

One-Hot Encoding eliminates the potential problem of ordinal relationships being inferred between categories. By representing each category as a binary column, One-Hot Encoding avoids such incorrect assumptions. In

the proposed research, one-hot encoding is used for the `goal_for_investment` column containing multiple options. The column *Goal for Investment* includes categories - Wealth Generation, Financial Freedom, Personal Savings, Education, Marriage, Buying House/Car, and Tax Saving.

3.2.3. SMOTE

SMOTE was applied exclusively to the training set after the 80/20 stratified train-test split. The held-out test set was never exposed to SMOTE, preventing data leakage. Procedure: (1) split 2,000 instances 80/20 stratified; (2) apply SMOTE to the training set only; (3) train models on the augmented training set; (4) evaluate on the original unmodified test set. The application of SMOTE is to overcome the class imbalance issue by creating new synthetic instances for the minority class so that all classes have a similar number of instances in the dataset. Relative to each sample of the specification/condition that falls under the minority class, SMOTE isolates a k-list of nearest neighbors in the same class. This is why a synthetic sample of a given input is generated by taking a convex combination of the input sample and one of its neighboring samples. A new sample is going to be in the segment that joins these two points.

The Synthetic Minority Oversampling Technique (SMOTE) generates synthetic samples using the following formula, which is shown in equation 2.

$$X_{\text{synthetic}} = X_{\text{original}} + \lambda \cdot (X_{\text{neighbor}} - X_{\text{original}}) \quad [23] \quad (2)$$

Here $X_{\text{synthetic}}$ denote the newly generated synthetic sample, X_{original} be the original sample from the minority class, X_{neighbor} represent one of the k-nearest neighbors of the original sample, and λ be a random value in the range $[0, 1]$.

This formula interpolates new samples between existing ones in the minority class to balance the data set.

3.2.4. Handling Rare Classes

Managing rare classes entails eliminating classes that are rare in a dataset, or the number of samples is small. These are sometimes classified as special or few, meaning that they are not representative of the regular classes, which are insufficient for model learning. Removing the sparse classes makes a lot of sense because it helps to minimize the amount of noise in the data set, thus leaving the model to train on significant data. The formula to handle rare classes is shown in equation 3.

$$\text{Rare Classes} = \{C_i \mid \text{Count}(C_i) < T\} \quad [24] \quad (3)$$

where C_i is a class in the target variable, $\text{Count}(C_i)$ denotes the number of samples in class C_i , and T represents the threshold for the minimum sample count (e.g., $T = 2$). In the proposed research, management of special or few classes is ideal during the data preprocessing phase. It helps to maintain the dataset maximally balanced and limit the number of classes in the target variable (*Mode_of_investment*) with very few samples.

3.3. Data Preprocessing Algorithm

The overall workflow of data preprocessing is highlighted through the algorithm 1.

3.4. Data Normalization

Data normalization is a common process in data preprocessing in that it scales down or up the size of numerical features in a set. It makes sure that no feature tries to dominate the entire learning process because of its larger scale or different units, which will also affect the result of the model. The research preprocesses the data using *Min-Max Scaling* for normalizing the field's numeric data types. This approach scales all the numerical values of the dataset to a scale of 0 to 1. When Min-Max scaling is applied, all feature contributions are given the same weight, which results in overall better model performance and prediction of the investment sector for the user.

The Min-Max Scaling normalises all the quantitative data contained in the data set into the range of 0 to 1. The features in the dataset may have different ranges or units; for instance, income and investment per month imply

Algorithm 1 Data Preprocessing Workflow

- 1: **Input:** Raw dataset with categorical and numerical features
- 2: **Output:** Cleaned, balanced, and normalized dataset
- 3: Split dataset into training and testing sets
- 4: Apply Label Encoding to binary categorical variables using equation 1

$$x_{\text{encoded}} = \text{Label}(x) \quad [22] \quad (4)$$

- 5: Apply One-Hot Encoding for multi-class categorical variables
- 6: Handle rare classes with fewer than two samples using equation 3

$$\text{Rare Classes} = \{C_i \mid \text{Count}(C_i) < T\} \quad [24] \quad (5)$$

- 7: Apply SMOTE only on training data to balance minority classes 2

$$X_{\text{synthetic}} = X_{\text{original}} + \lambda \cdot (X_{\text{neighbor}} - X_{\text{original}}) \quad [23] \quad (6)$$

- 8: **Return:** Preprocessed dataset ready for training

different things as does age. Otherwise, algorithms, for example, Support Vector Machines (SVM) or K-Nearest Neighbors (KNN), will simply be inclined towards numerical values in favor of more extended features. Thus, when using the Min-Max scaling, the research guarantees that all inputs contain effectively the same magnitude, thereby making the learning process much more efficient.

In the proposed research, Min-Max scaling parameters were computed using the training data and then applied to both training and testing sets to prevent data leakage. For each feature, the minimum and maximum values were calculated across the entire dataset, and each data point was transformed using the formula shown in equation 7.

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \quad [25] \quad (7)$$

where x is the original value, $\min(X)$ is the minimum value of the feature, $\max(X)$ is the maximum value of the feature, and x' is the normalized value. This transformation has helped to align all features so that they are in the range from 0 to 1, which is convenient for the model.

3.5. Model Training

Model training is used to make a machine learning model learn the pattern in a data set so as to arrive at a correct decision. In this process, the dataset is split into training and testing subsets (e.g., 80:20 ratio) to evaluate model generalization performance. In the proposed research, two types of training were performed: Deep Learning and Machine Learning.

3.5.1. Deep Learning

Deep Learning is a branch of machine learning with higher layers to reveal hierarchical features in the past data. In the proposed research, the deep learning model was designed to capture complex interactions between the features. The deep learning model consists of a feedforward neural network with three hidden layers containing 128, 64, and 32 neurons, respectively. ReLU activation was used for all hidden layers, while a Softmax activation function was applied at the output layer for multi-class classification. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and for 50 epochs. Dropout layers with a rate of 0.3 were incorporated to reduce overfitting.

The rectified linear unit (ReLU) activation function is employed to add non-linearity in to the model so that the neural network can then sense greater characteristics. It is used frequently because of its simplicity and its usefulness in training deep networks. The ReLU activation function is defined in equation 8.

$$f(x) = \max(0, x) \quad [26] \quad (8)$$

This means that for any input x , if x is positive, the output is x ; otherwise, it is 0. This function helps avoid issues like vanishing gradients, which can slow down the training process.

Dropout is another work regularization technique applied in deep learning that was designed to be helpful in controlling overfitting, and since it helps in deactivating a certain extent of neurons with every epoch, it is helpful in the localization of overfitting too. Dropout layers are inserted between other hidden layers to randomly drop a defined percentage of neurons during training. The dropout rate is the other hyperparameter, which is usually left between 0.2 and 0.5. Throughout the entire process, keep the dropout rate, which is usually left at 0.2 to 0.5.

The Softmax activation function is required in the input layer of the deep from the classification of multi-class training step. It transforms the outcome scores of the model into probabilities to facilitate an estimation of the class with higher probability. The Softmax function for multi-class classification is defined in equation 9.

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}} \quad [27] \quad (9)$$

where z_i is the raw score for class i , and k is the number of classes. This ensures that the output values are between 0 and 1 and sum up to 1, representing a valid probability distribution.

3.5.2. Machine Learning

Machine learning models were used to complement the deep learning model, providing additional performance and interpretability. These models derive from various algorithms and structures, which are appropriate for classification problems, as in the case of the proposed research.

01. Logistic Regression (LR)

Logistic Regression, also called Linear Logistic Regression, is a statistical model used for binary as well as multiclass classification. It maps out the link between the investment mode that is being investigated, user inputs, and the findings, which are obtained with the aid of a logistic function. The logistic regression model is defined in equation 10.

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}} \quad [28] \quad (10)$$

Where $\beta_0, \beta_1, \dots, \beta_n$ are the model coefficients and x_1, x_2, \dots, x_n are the input features.

02. Random Forest

Random forest is a type of ensemble learning technique constructing several decision trees and then combines these trees to get better and more effective results. They are trained with a random sub-sample of the data set, and in arriving at the final decision, a decision is made on the basis of a majority vote. It minimizes the overfitting problem through the use of averaging the endpoints attained by multiple trees. It is very useful in both classification and regression data types.

03. Support Vector machine (SVM)

SVM is a method of pattern analysis developed for the case of supervised learning which is aimed at the search for a special hyperplane for the distribution of classes in the space of features. It is capable of finding non-linear decision boundaries through mapping the input features into higher dimensions by use of the kernel trick. The decision function of an SVM is given in equation 11.

$$f(x) = \text{sgn} \left(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b \right) \quad [29] \quad (11)$$

where α_i are the Lagrange multipliers, y_i is the class label, $K(x_i, x)$ is the kernel function, and b is the bias term.

04. Naive Bayes

Naive Bayes is a probabilistic classifier derived from Bayes' Theorem that holds a key feature assumption that the features are independent. It defines the likelihood $P(c=f)$ of every class with reference to the related feature values and accepts the class with the highest likelihood. The formula for Naive Bayes is in equation 12.

$$P(C|X) = \frac{P(C) \prod_{i=1}^n P(x_i|C)}{P(X)} \quad [30] \quad (12)$$

where $P(C | X)$ is the posterior probability of class C , $P(C)$ is the prior probability of class C , $P(x_i | C)$ is the likelihood of feature x_i given class C , and $P(X)$ is the evidence.

05. Decision Tree

Decision Trees are another form of non-linear approach which take a data set and divide it into many subsets according to feature value. Splitting is done by selecting features that serve to partition the data optimally at any node in a way that produces maximum information gain or minimum entropy. The training algorithm for decision trees uses the following criteria in equation 13.

$$\text{Information Gain} = H(D) - \sum_{i=1}^k \frac{|D_i|}{|D|} H(D_i) \quad [31] \quad (13)$$

Where $H(D)$ is the entropy of the dataset D , and D_i is a subset of data formed by splitting on a feature.

06. K-Nearest Neighbour

KNN is a form of algorithm that does not rely on the distribution and prediction of samples according to the closest class to the features in the given sample. The decision rule for KNN is in equation 14.

$$\hat{y} = \text{majority_vote}(\{y_i | x_i \in N(x)\}) \quad [32] \quad (14)$$

where $N(x)$ is the set of the k -nearest neighbors to point x , and y_i are the class labels of the neighbors.

07. Gradient Boosting

Gradient Boosting is a boosting technique that works in an ensemble, such as creating many instances of a model from the others and staying one on top of the others. It blends weak learners together to come up with a strong model. The model update in gradient boosting is performed in equation 15.

$$f_m(x) = f_{m-1}(x) + \eta \cdot h_m(x) \quad [33] \quad (15)$$

where $f_m(x)$ is the prediction of the m -th model, η is the learning rate, and $h_m(x)$ is the m -th weak learner.

3.5.3. Hyper Parameter Tuning

The tuning of hyperparameters is such a crucial step in the efficacy of the machine learning models being used. When implementing the proposed research, optimizing the hyperparameters of two algorithms, namely Random Forest (RF) and Support Vector Machine (SVM), was done to define the set of parameters that would yield the highest testing accuracy rates. GridSearchCV checks all possible combinations of parameters that a user would have manually set for the model to match the particular hyperparameter grid. The evaluation method used in this research is cross-validation and performs a modeling assessment of the model for each of the combinations of hyperparameters that the research has and helps to choose the best model based on the performance criteria that are usually common, to be precision or F1 score.

The main steps involved in hyperparameter tuning with GridSearchCV are:

1. Define the parameter grid: A range of possible values for each hyperparameter (e.g., for Random Forest (RF): the number of trees, maximum depth, and minimum samples per leaf).

2. Perform cross-validation: For each parameter combination, GridSearchCV runs the model using k-fold cross-validation.
3. Select the best combination: The combination of hyperparameters yielding the best cross-validation score is chosen.

The formula for GridSearchCV optimization is mentioned in equation 16.

$$\hat{\theta} = \arg \max_{\theta} \left(\frac{1}{k} \sum_{i=1}^k \mathcal{L}(f_{\theta}, \mathcal{D}_i) \right) \quad [34] \quad (16)$$

where $\hat{\theta}$ is the optimal set of hyperparameters, k is the number of cross-validation folds, \mathcal{L} is the loss function (e.g., accuracy or mean squared error), f_{θ} is the model with hyperparameters θ , and \mathcal{D}_i represents the i -th fold of the data.

3.5.4. Ensemble Method

The ensemble learning methods are specifically intended to join the various models in order to increase the capability of the predictive models [35]. In this method, machine learning algorithms are used together to enhance the strength of the final results produced. It is worth emphasizing that both *Voting Classifier* and *Stacking Classifier* used in the proposed research employ machine learning and deep learning for prediction based on the best solution.

Ensemble methods like Voting and Stacking classifiers were used in the proposed research because they help improve the overall prediction accuracy and robustness by reducing the variance and bias of individual models. This is especially so when one model makes one kind of error and another model makes a different kind of error, and making an ensemble usually balances the errors.

Voting Classifier: The Voting Classifier is an interpretable method where each model in an ensemble votes for a predicted class. The last prediction is the real final prediction and is accumulated by averaging all the other models. The formula of the voting classifier is mentioned in equation 17.

$$\hat{y} = \text{majority_vote}(\{y_i \mid y_i \in \mathcal{M}\}) \quad [36] \quad (17)$$

where y_i are the predicted labels of each model in the ensemble, and \mathcal{M} is the set of models in the ensemble.

Stacking Classifier: The Stacking Classifier is a more complex kind of an ensemble learning technique where, instead of directly getting predictions from the base models, which can be either machine learning or deep learning models, their output becomes the features in the meta-model, which could often be a logistic regression or another classifier [37]. The meta-model produces the final prognosis depending on the results of the base models. The prediction from the Stacking Classifier can be expressed in equation 18.

$$\hat{y} = \mathcal{M}_{meta}(\{\hat{y}_i \mid \hat{y}_i \in \mathcal{B}\}) \quad [38] \quad (18)$$

where \hat{y}_i is the predicted output of each base model i in \mathcal{B} , and \mathcal{M}_{meta} is the meta-model that combines the base model predictions.

3.5.5. Performance Evaluation

The trained models are evaluated using multiple performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix, to provide a comprehensive assessment of model performance in the multi-class classification setting. The methods for evaluating the model's performance are defined as follows:

In which TP represents True Positive, TN represents True Negative, FP represents False Positive, and FN represents False Negative in table 5.

Table 5. Structure of Confusion Matrix for Multi-Class Investment Sector Classification

	Actual positive	Actual negative
Predicted positive	TP	FP
Predicted negative	FN	TN

Accuracy:

It gives the accuracy of a model by dividing the number of instances the model or a given equation got right (either by identifying the negative instances or the positive ones). It is given in equation 19.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad [39] \quad (19)$$

Here, **TP** is true positives, **TN** is true negatives, **FP** is false positives, **FN** is false negatives.

3.5.6. Explainable AI

XAI focuses on explaining how and why a particular model makes specific predictions. In the proposed research, explanations in the form of XAI are needed to understand the predictions made by the “Intelligent Investment classifier”. Since the research under development includes machine learning, deep learning models, and an ensemble of models, they have to provide an explanation to users. XAI is implemented in two main ways: Feature Analysis and Lime.

Feature Analysis: Feature analysis is concerned with the ability to understand and define the level of significance of particular input features as applied by the model in an effort to make an interpretation. For the proposed research, feature selection importance was computed by a stacking classifier.

The feature importance for a model is calculated as shown in equation 20.

$$\text{Feature Importance} = \frac{\text{Reduction in Impurity}}{\text{Total Reduction Across All Features}} \quad [40] \quad (20)$$

This allows the research to provide insights into how each feature influences the outcome, making the model more interpretable.

LIME: LIME offers local interpretability since it expands on every single prediction from the untrained member of the interpretandum class. It creates a more straightforward model. This is important so that for the proposed research to be able to explain why a given investment sector should warrant a user input has to do so. LIME supplements this by providing instance-specific explanations of why a given prediction was made by the research at the instance level.

The formula for the locally interpretable model in LIME is shown in equation 21.

$$\hat{f}(x) = \operatorname{argmin}_{g \in G} \sum_{x' \in X} \pi(x, x') \cdot (f(x') - g(x'))^2 + \Omega(g) \quad [41] \quad (21)$$

where $\hat{f}(x)$ is the local approximation of the original model f around x , g is a simpler interpretable model (e.g., linear regression), $\pi(x, x')$ is the weight based on similarity between x and x' , and $\Omega(g)$ is the complexity penalty to ensure simplicity.

3.6. Trust and Usability for Investors

To be able to offer guidance to the real-world usage, we have developed an easy frontend interface, which enables investors to enter minimal financial and preference information and obtain predicted investment preferences. On

top of that, each prediction comes with a LIME-generated explanation so that users can “understand why” the prediction was made.

In turn, this allows for a trustworthy investment decision. It also makes the use of AI more responsible since it is based on their expectations and knowledge. With our system, we predict investment decisions with precision and transparency that help investors, beginners, and experienced, understand their investment behavior.

3.7. Proposed Research Algorithm

The algorithm of the proposed research architecture based on the research methodology given in the algorithm 2.

Algorithm 2 The Proposed Research Methodology

- 1: **Input:** Investment Dataset
 - 2: Split the dataset into training and testing sets
 - 3: **Step 1: Data Preprocessing**
 - 4: Perform Label Encoding and One-Hot Encoding
 - 5: Apply SMOTE on training data only (Equation 2, [23])
 - 6: Handle rare classes
 - 7: **Step 2: Data Normalization**
 - 8: Apply Min-Max Scaling (Equation 7, [25])
 - 9: **Step 3: Model Training**
 - 10: Train Deep Learning models: ReLU Activation, Dropout Layers, Softmax Output
 - 11: Train ML models: LR, RF, SVM, NB, DT, KNN, GB
 - 12: **Step 4: Hyperparameter Tuning**
 - 13: Optimize both Random Forest and SVM using cross-validation
 - 14: **Step 5: Ensemble Modeling**
 - 15: Apply Voting Classifier
 - 16: Apply Stacking Classifier
 - 17: **Step 6: Model Performance Evaluation**
 - 18: Perform evaluation through Confusion Matrix, Accuracy, and Comparative Analysis
 - 19: **Step 7: Explainable AI**
 - 20: Perform Feature Analysis
 - 21: Use LIME for model interpretability
 - 22: **Output:** Predicted user investment preferences with explainable insights
-

4. Experimental Analysis

An experimental study was conducted to evaluate the prediction of investment preferences based on structured survey data. The predictive accuracy of the proposed model has been evaluated using training and testing of different supervised classification models such as Logistic Regression, Random Forest, Support Vector Machine (SVM), Decision Tree, Naive Bayes, K-Nearest Neighbors, and Gradient Boosting. On top of that, we used ensemble methods such as Voting and Stacking to see if joining multiple classifiers could improve performance. We also tested a neural network model as the comparative baseline. We selected models whose hyperparameters were tuned to improve their performance in this experimental setting. In order to provide an understandable prototype for decision support, explainability was further applied through LIME to make each model’s predictions more understandable.

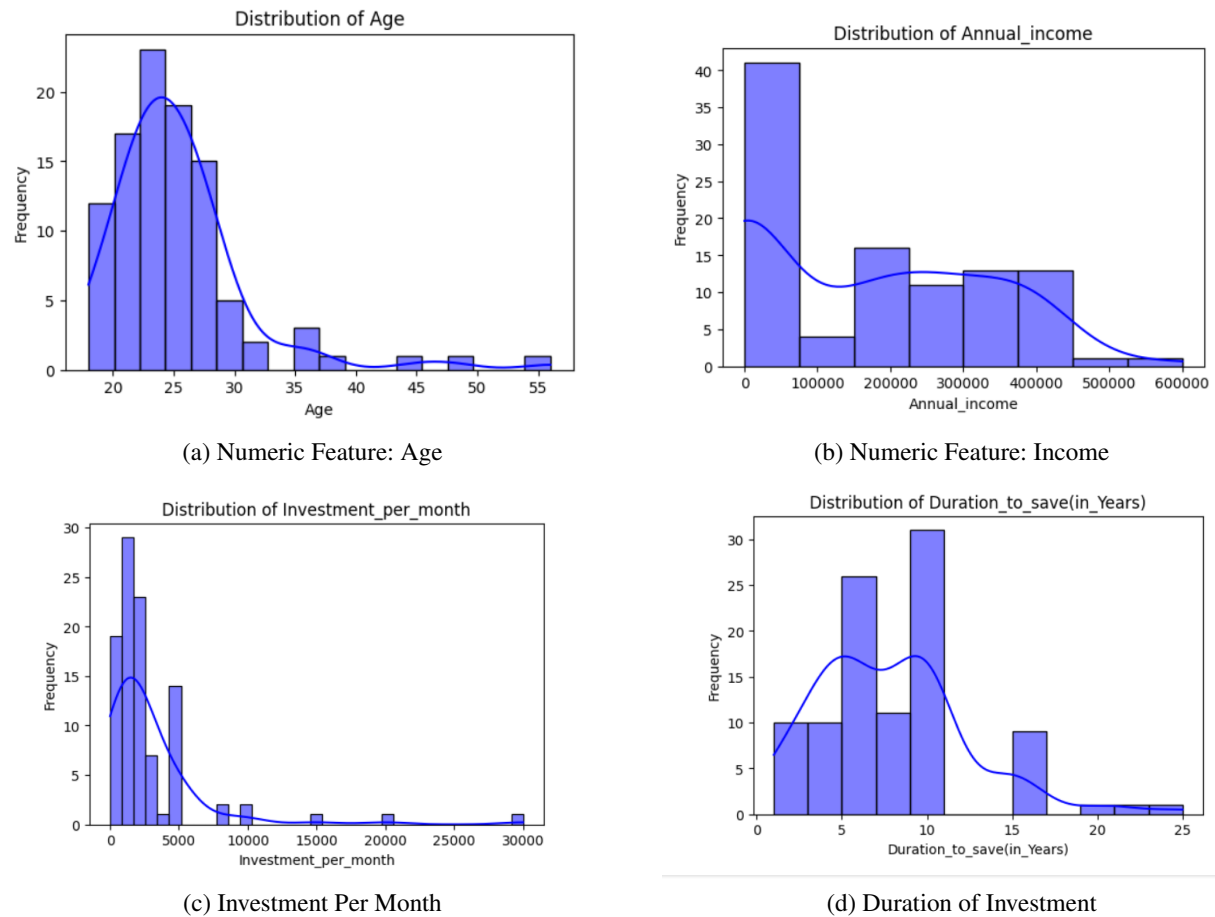
4.1. Exploratory Feature Analysis

As part of exploratory features analysis, we examined the characteristics of survey variables and their potential influence on models. The data set comprises demographic, financial, and behavioral variables that provide insight into which features may be most important in predicting investment preferences. It also provided useful insight into the structure of the dataset before model training and supported the interpretation of the final classification results.

4.2. Numeric Feature Distribution

The distributions of the numerical features and the possible variation among respondents were analyzed using histograms. Features such as age, annual income, or monthly investment amount are important in understanding the financial circumstances of individuals. Their distributions may be uneven or skewed due to the variability of the respondent characteristics and investment ability within the sample. Histograms were used to visually illustrate this distribution, as shown in Figure 2. Such analysis helps provide context for preprocessing and supports a clearer interpretation of model performance.

Figure 2. Distribution Analysis of Key Numerical Features Including Age, Annual Income, Monthly Investment Amount, and Investment Duration, Showing Variability and Data Spread Among Survey Respondents



The numeric characteristics, which are incorporated as shown in figure 3 into Age, Working Professional, Annual Income, Investment Per Month, Duration to Save (in Years) and Mode of Investment (Numeric), show variations in distribution that can substantially affect the performance of the models. The distribution patterns of

these assumptions allow the analysis of the research's capacity in detecting different types of investors, leading to accurate sector recommendations.

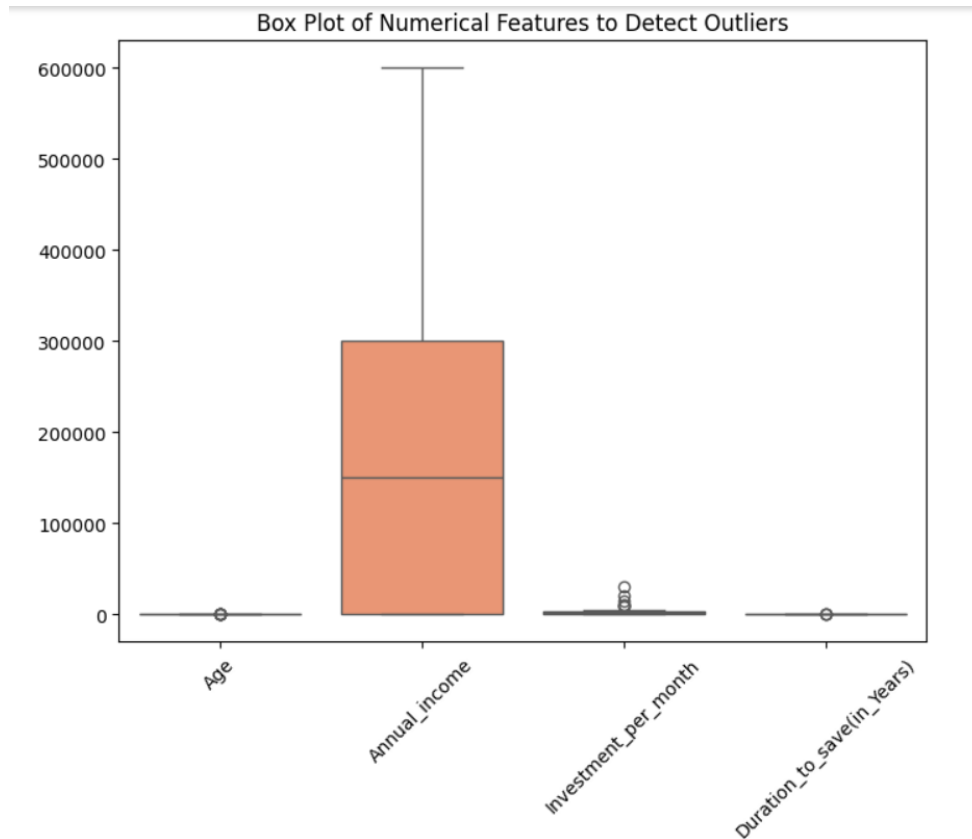
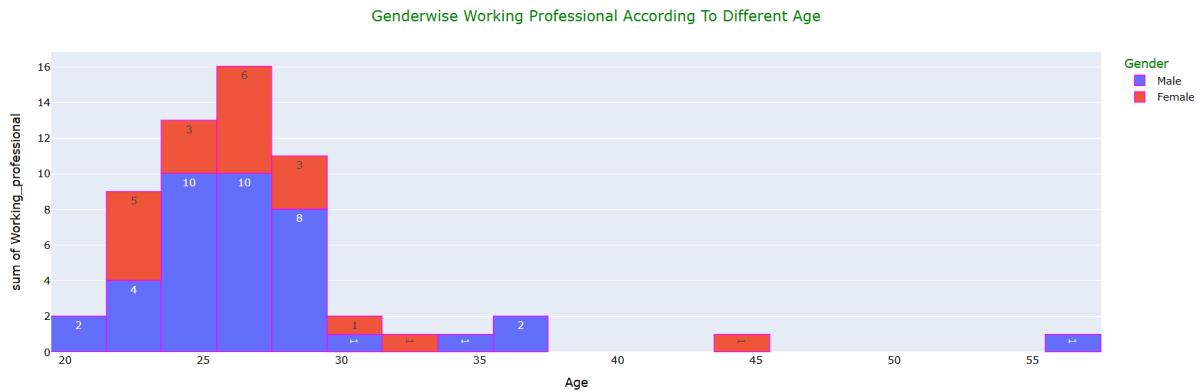
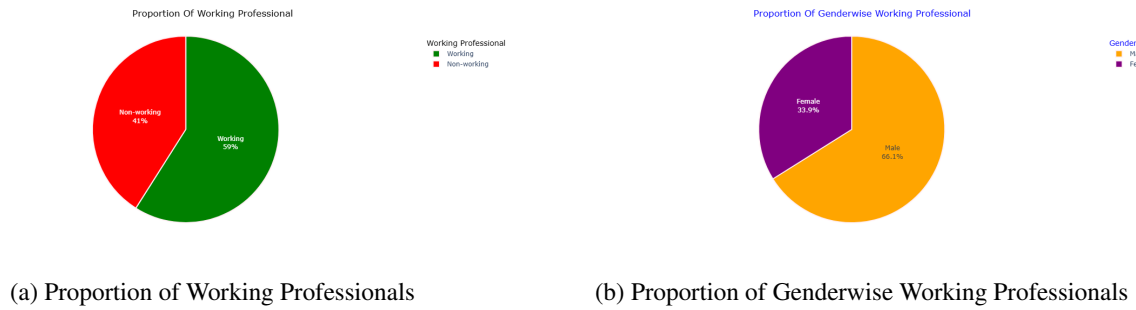


Figure 3. Boxplot Visualization of Numerical Features Highlighting Outliers, Data Dispersion, and Distribution Patterns Across Age, Income, Investment Amount, and Investment Duration.

4.3. Categorical Feature Analysis

The modelling of categorical features identifies essential patterns of how non-numerical data affects the target variable, mode of investment. In the proposed research, the following categorical variables – gender, working professional, and investor's goal for investment were tested in relation to investment shown in figure 4.

- **Gender:** Of interest in the study is the observation that there were significant disparities in the investment conduct between the male and female investors. Male respondents had a higher purchase intention with equity and mutual funds, which are considered high-risk, high-return products. On the other hand, the female participants seemed to hedge their bets slightly better, although not overwhelmingly so, toward safer investment opportunities such as fixed deposits and government bonds.
- **Working Professional Status:** This feature made a clear distinction between those who worked and depended on other sources for income to pay bills, thus coded 1, and those who did not and were also not willing to take risks, thus coded 0. It was also seen that working individuals invested in equity and mutual funds; this could be attributed to stable income and risk-taking propensity or aptitude factor, while non-working individuals preferred fixed deposits and bonds. Willingness or ability to take risk due to regular income was another factor.



(c) Gender wise Working Professionals of Different Ages

Figure 4. Distribution of Categorical Variables Including Gender, Working Professional Status, and Investment Goals, Illustrating Behavioral Patterns Influencing Investment Preferences.

- Goal for Investment:** The goals of wealth creation, retirement planning, or raising cash for emergencies, for children’s education, etc., contributed dare to the selection of the investment sectors. For instance, people with the goal of wealth creation invested in equity or mutual funds, while people with retirement planning as their goal invested in fixed deposits or bonds because of lower risk and higher return.

4.4. Correlation Analysis

The technique of correlation analysis is of significant importance to determining the extent of interaction between different input features and how they impact the target variable, that is the mode of investment in this case showed in figure 5.

This analysis is important because it helps to define the influential factors for modeling the mode of investment. These relationships thus help the research to directly select features when modeling with an aim of using only variables that would greatly increase the model’s predictive capability.

4.5. Relation Analysis

The relation between Annual income and the amount that an individual is willing and capable of investing monthly is central to creating the right investment model. In the above analysis, it was also found that these two variables have a positive relationship; that is, high earners spend more of their earnings on investment, as shown in Figure 6a.

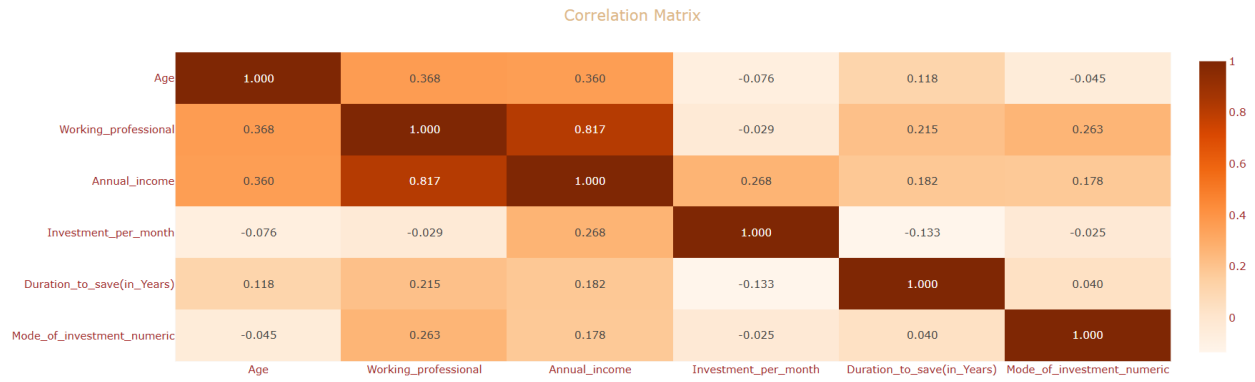
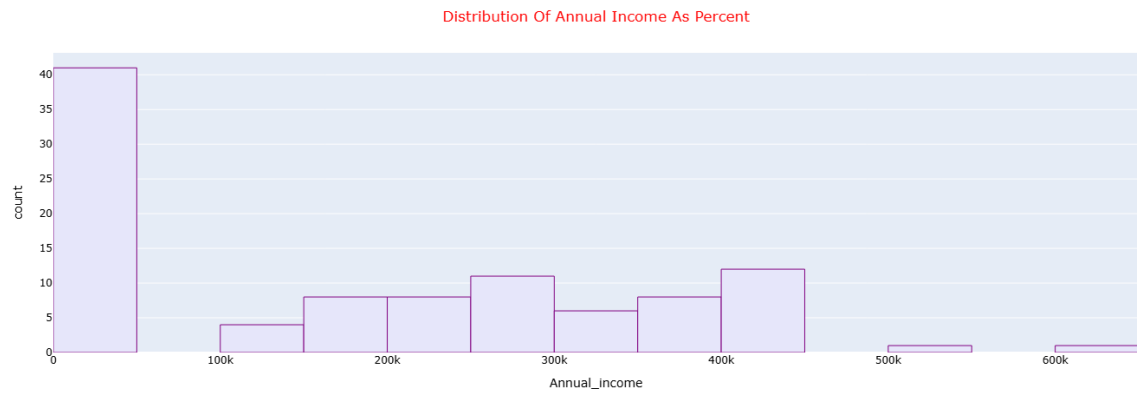
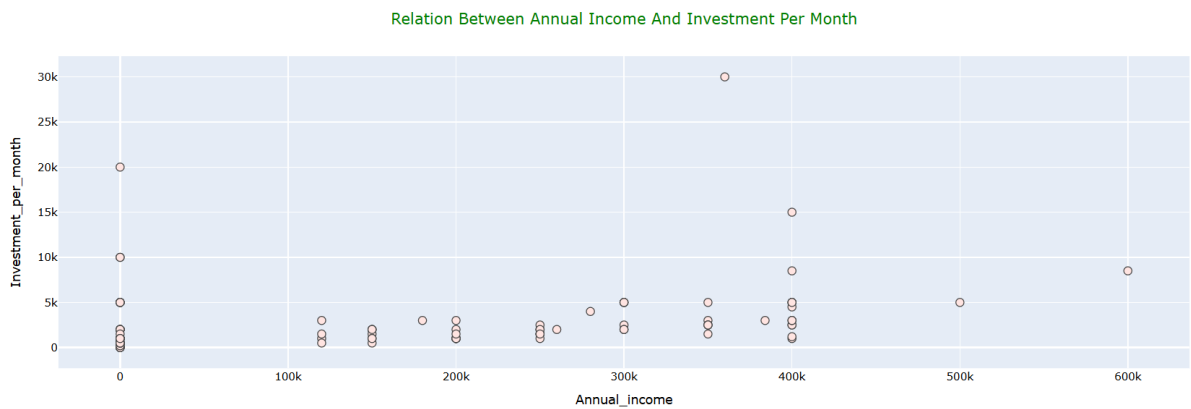


Figure 5. Correlation Heatmap Showing Relationships Between Numerical and Encoded Features, Highlighting Key Dependencies Influencing Investment Preference Prediction.



(a) Distribution of Annual Income



(b) Relation Between Income & Monthly Investment

Figure 6. Relationship Between Annual Income and Monthly Investment Amount, Demonstrating Positive Correlation and Investment Capacity Trends Among Respondents.

But as for the other criteria, such as financial objectives and tolerance for risk, the extent of income used for investing was different. The high-income earners could afford to invest in a portfolio that included equity and Mutual funds, while the middle and the low-income earners opt for more secure investments such as fixed deposits. Bonds are shown in figure 6b. This analysis assists the research to provide the user with the kind of investment they qualify for, depending on the monthly income and the amount they are willing to invest.

5. Results

The training process consists of a combination of model baseline, model with hyper-parameterization, and ensemble training. The process includes:

- **Training and Testing:** The data set was split between a training set (80%) and a testing set (20%) for model development and testing.
- **Cross-Validation:** Cross-validation was used, where appropriate, in order to improve the quality of the model assessment and reduce the risk of overfitting.
- **Hyperparameter Tuning:** For some models, such as Random Forest and Support Vector Machine, hyperparameter tuning was conducted to improve classification performance (e.g., *GridSearchCV*).
- **Model Performance:** Model performance was assessed through accuracy and confusion matrix analysis as discussed in the following sections.

5.1. Deep Learning Output Evaluation

A neural network model was used as a comparative deep learning baseline in the multi-class prediction task. The confusion matrix of the deep learning model from the Figure 7 shows the performance across the nine investment class preference categories. The model performed well in some categories, but was confusing in others where the class boundaries were closer. Specifically, some categories, such as the banking and gold preferences, were more difficult to distinguish consistently between the models. These results suggest that some investment classes are similar in the survey feature space. In sum, our results suggest that, while the deep learning model was useful in comparison, its performance should be treated as part of the general machine learning and ensemble results, and not as the main contribution of the study.

For instance, Banking – RD, FD had one right categorisation but they got it wrong in two other instances, Gold / Materialistic investment on the other hand, got two right, but got it wrong on one occasion. The accuracy rate of Deep learning in the proposed research is **92.86%**, which is quite a remarkable output accuracy in order to get better results using this model.

5.2. Machine Learning Models Output Evaluation

The Machine Learning Output Evaluation is illustrated through confusion matrices of seven classifiers: Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Naive Bayes (NB), and Gradient Boosting (GB).

Each confusion matrix in Figure 8 and 9 provides insights into the predictive performance of the respective models across multiple investment sectors. Table 6 below shows the classification accuracy of different machine learning models in predicting the investment sectors. The model's performance metrics for this evaluation were the ability to classify data into sectors like 'Marketing', 'Mutual Funds', 'Crypto Currencies', and others. For each model, the authors explained predictions using a dataset, and the confusion matrix indicated that each model had both favorable and inferior sectors in making predictions.

The percentages of accuracy in table 6 reflect the overall ability of the models to provide the correct investment sector prediction. Moreover, the performance highlights section shows a more detailed view of the advantages and disadvantages of different models. For instance, while developing countries and sectors like Marketing and Mutual Funds are better suited to logistic regression (LR) and Support Vector Machine (SVM) as against Naive Bayes (NB) and K-Nearest Neighbors (KNN), which show lower accuracy in sectors like Banking and Materialistic

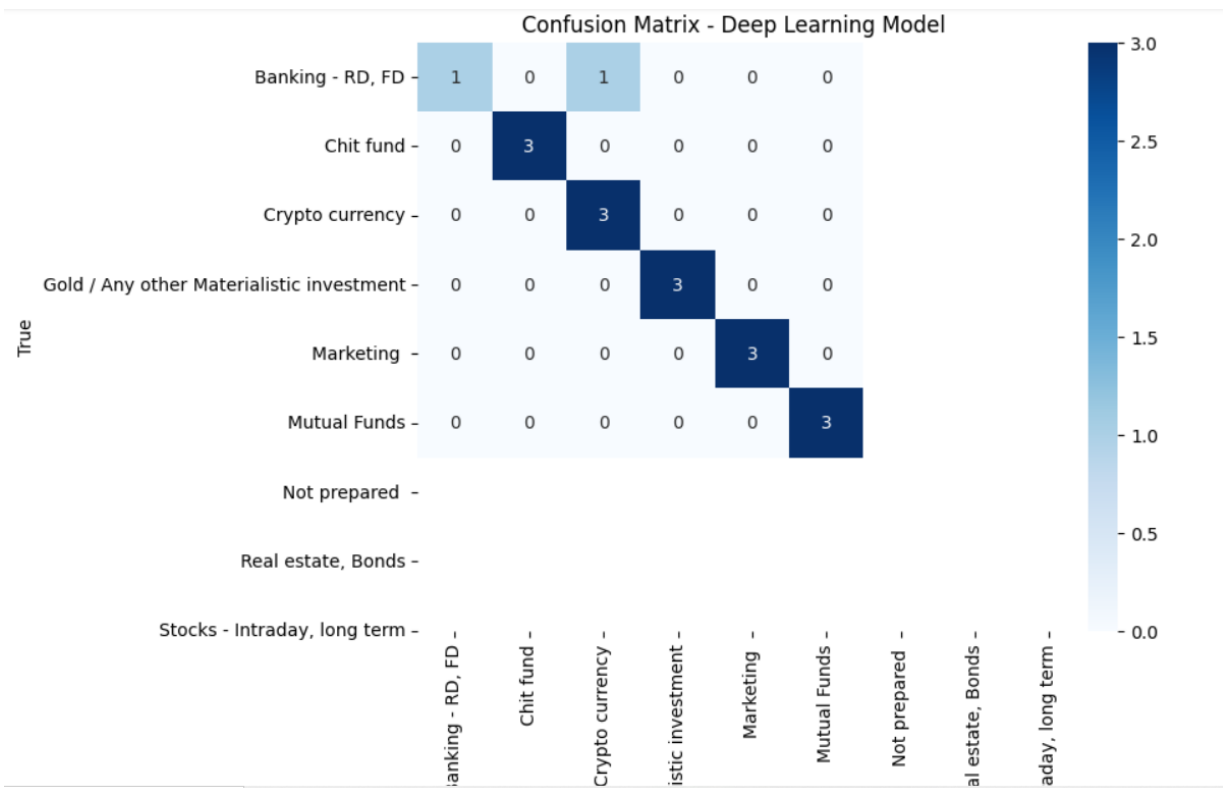
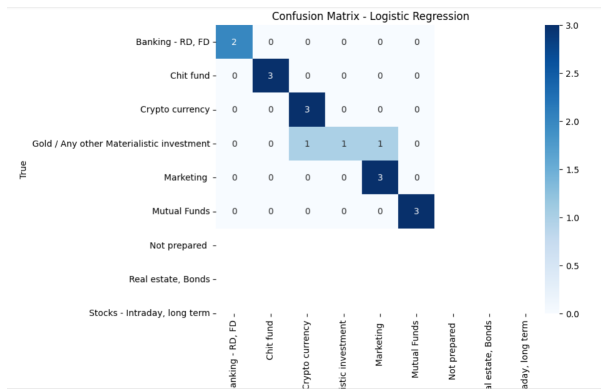


Figure 7. Confusion Matrix of the Deep Learning Model Showing Classification Performance Across Multiple Investment Categories and Misclassification Patterns Between Similar Investment Types.

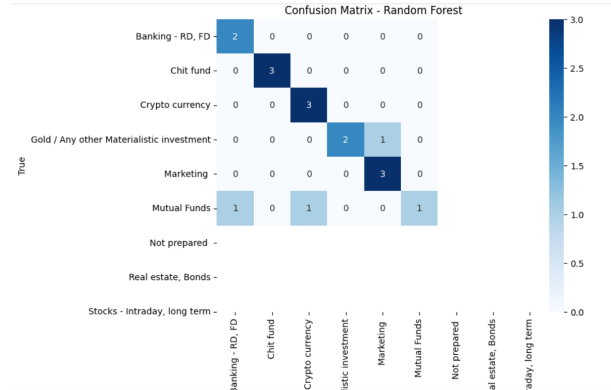
Table 6. Performance Comparison of Machine Learning Models Based on Accuracy, Precision, Recall, and F1-Score for Multi-Class Investment Preference Classification

Model	Acc (%)	Prec (%)	Rec (%)	F1 (%)	Performance Highlights
Logistic Regression	88.24	87.50	88.10	87.80	Consistent predictions across multiple sectors like <i>Marketing</i> .
SVM	88.24	88.00	87.90	87.95	Strong performance in predicting <i>Crypto Currency</i> and <i>Marketing</i> .
Random Forest	82.35	81.80	82.00	81.90	Robust predictions, particularly in <i>Marketing</i> and <i>Mutual Funds</i> .
Gradient Boosting	82.35	82.10	81.50	81.80	Balanced predictions but slightly behind ensemble methods.
Decision Tree	76.47	76.00	76.20	76.10	Performs well in <i>Marketing</i> but prone to more misclassifications overall.
Naive Bayes	70.69	69.50	71.00	70.20	Frequent misclassifications across multiple investment sectors.
KNN	64.71	64.00	65.10	64.50	Moderate performance with some strength in <i>Marketing</i> and <i>Mutual Funds</i> .

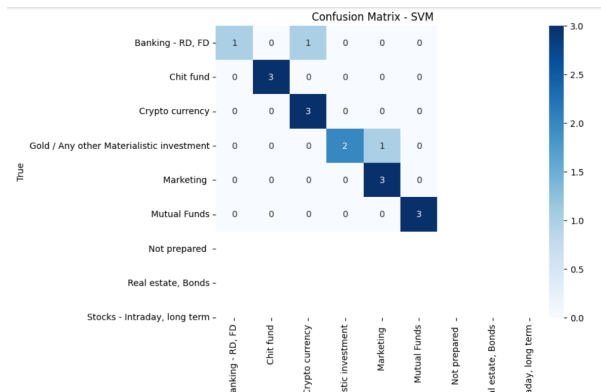
Investments. Other nomination models, such as GB, also estimated unbiased and precise predictions over various sectors, while also attesting the other models in terms of their general performance. This kind of comparison will assist in determining the best-performing model in providing investment recommendations, a critical objective in the creation of the intelligent investment predictor research.



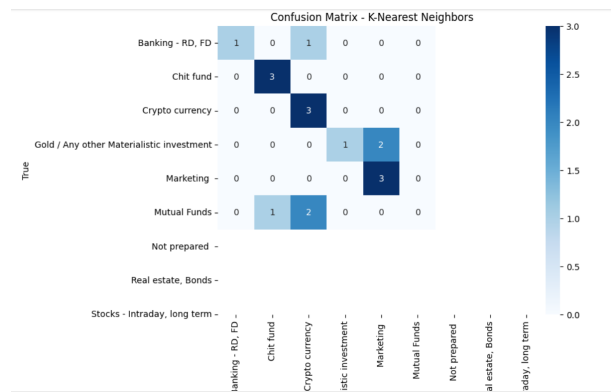
(a) Confusion Matrix of Logistic Regression (LR) Showing Classification Performance Across Investment Sectors



(b) Confusion Matrix of Random Forest (RF) Showing Classification Performance Across Investment Sectors



(c) Confusion Matrix of Support Vector Machine (SVM) Showing Classification Performance Across Investment Sectors



(d) Confusion Matrix of K-Nearest Neighbor (KNN) Showing Classification Performance Across Investment Sectors

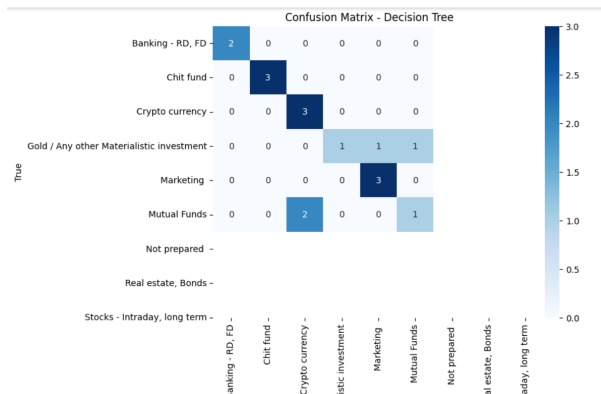
Figure 8. Comparative Confusion Matrices of Multiple Machine Learning Models (Part 1): LR, RF, SVM, KNN; Illustrating Classification Accuracy and Error Distribution Across Investment Sectors

5.3. Hypertuned Model Output Evaluation

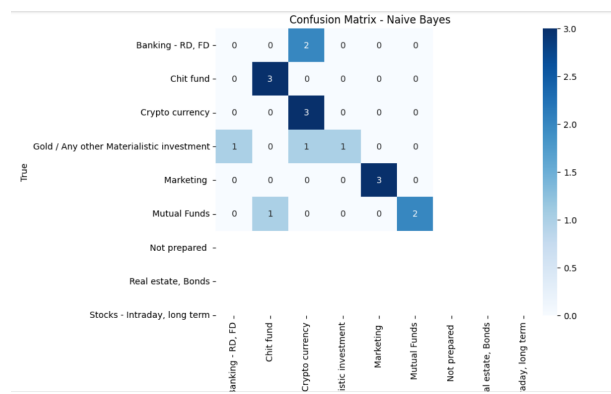
Table 7 gives an assessment of the hypertuned models, and changes of their performance are shown. Such high-tuned RF has seen a slight increased in the accuracy from 82.35% to 88.24% yet again its prediction is robust in *Marketing*, *Mutual Funds*, and *Crypto Currency*.

Table 7. Performance Evaluation of Hyperparameter-Tuned Models Highlighting Improvements in Accuracy and Sector-Specific Prediction Capability

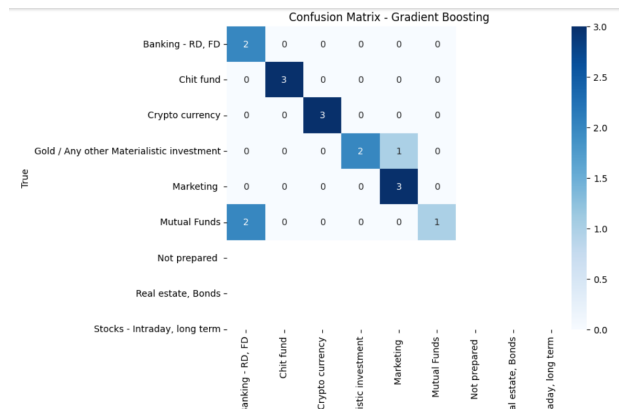
Model	Accuracy (%)	Performance Highlights
Hypertuned Random Forest (RF)	88.24	Improved from base RF accuracy of 82.35% to 88.24% after GridSearchCV tuning. Stronger predictions in <i>Marketing</i> , <i>Mutual Funds</i> , and <i>Crypto Currency</i> .
Hypertuned SVM	94.12	Improved from 85.71%. Achieves perfect accuracy with highly accurate predictions in <i>Chit Fund</i> , <i>Crypto Currency</i> , and <i>Marketing</i> .



(a) Confusion Matrix of Decision Tree (DT) Showing Classification Performance Across Investment Sectors



(b) Confusion Matrix of Naive Bayes (NB) Showing Classification Performance Across Investment Sectors



(c) Confusion Matrix of Gradient Boosting (GB) Showing Classification Performance Across Investment Sectors

Figure 9. Comparative Confusion Matrices of Multiple Machine Learning Models (Part 1): Decision Tree, Naive Bayes, and Gradient Boosting; Illustrating Classification Accuracy and Error Distribution Across Investment Sectors

On the other hand, the hypertuned Support Vector Machine (SVM) records a remarkable improvement from the initial 88.24% to a 94.24% accuracy. This increase implies a significant improvement in the model’s forecast ability for the various sectors, especially *Chit Fund*, *Crypto Currency*, and *Marketing*. The assessment of these models also reveals an understanding of proximal areas that may benefit from tuning for the distal model to enhance the end product.

5.4. Performance Comparison of Ensemble Learning Methods for Investment Sector Prediction

In this segment, two ensemble methods were used, Voting Classifier and Stacking Classifier, to predict the investment sector. Ensemble methods use a pool of models in order to increase the overall accuracy because different algorithms are used to generate models from different models.

- **Voting Classifier (83.33%):** The Voting Classifier scored **83.33%** on the held-out set, combining predictions from most of the base classifiers by the majority vote. It performs well across the sectors of *Marketing*, *Mutual Funds*, and *Crypto Currency*, but it falls short of the Stacking Classifier because of weaker base learner confidence in the majority vote.
- **Stacking Classifier (94.12%):** The highest accuracy for the held-out set was **94.12%**. In this model, we train a logistic regression meta-learner on out-of-fold predictions of the base classifiers (LR, RF, SVM, KNN, DT,

GB) and learn to weight each model’s contribution optimally so that it captures complementary decision boundaries unavailable to other models.

Table 8. Performance Comparison of Ensemble Learning Methods (Voting and Stacking Classifiers) Showing Improved Accuracy and Robustness in Investment Sector Prediction.

Model	Acc (%)	Prec (%)	Rec (%)	F1 (%)	Performance Highlights
Voting Classifier	83.33	82.50	83.10	82.80	Good predictions in <i>Marketing</i> , <i>Mutual Funds</i> , and <i>Crypto Currency</i> . Uses majority voting for robust classification.
Stacking Classifier	94.12	91.50	93.20	92.30	Achieves near-perfect accuracy by combining multiple models. Delivers highly accurate predictions across all sectors.

The table 8 provides an overview of the accuracy and analyzes the findings of Voting Classifier and Stacking Classifier in the ensemble model assessment. The Stacking Classifier achieved the highest accuracy at **94.12%**. The Voting Classifier achieved **83.33%**, which, while lower than the stacking approach, still outperforms weaker individual models such as KNN (64.71%) and Naive Bayes (70.59%), confirming that ensemble methods consistently outperform single classifiers on this task.

5.5. Performance Evaluation

In this section, the overall accuracy was compared and provided in detail. From the figure 10, it is shown that among all the models used, Hypertuned SVM and Ensemble Stacking Classifier are the best models so far. Also, the ensemble approach, referring to multiple models that are used to make more accurate predictions, was tested. The Voting Classifier achieved 83.33% accuracy, demonstrating solid performance across key sectors including Marketing and Mutual Funds. The Stacking Classifier (94.12%) achieved the highest accuracy among all models, combining base classifier predictions through a logistic regression meta-learner to capture complementary decision patterns, as shown in Figure 10.

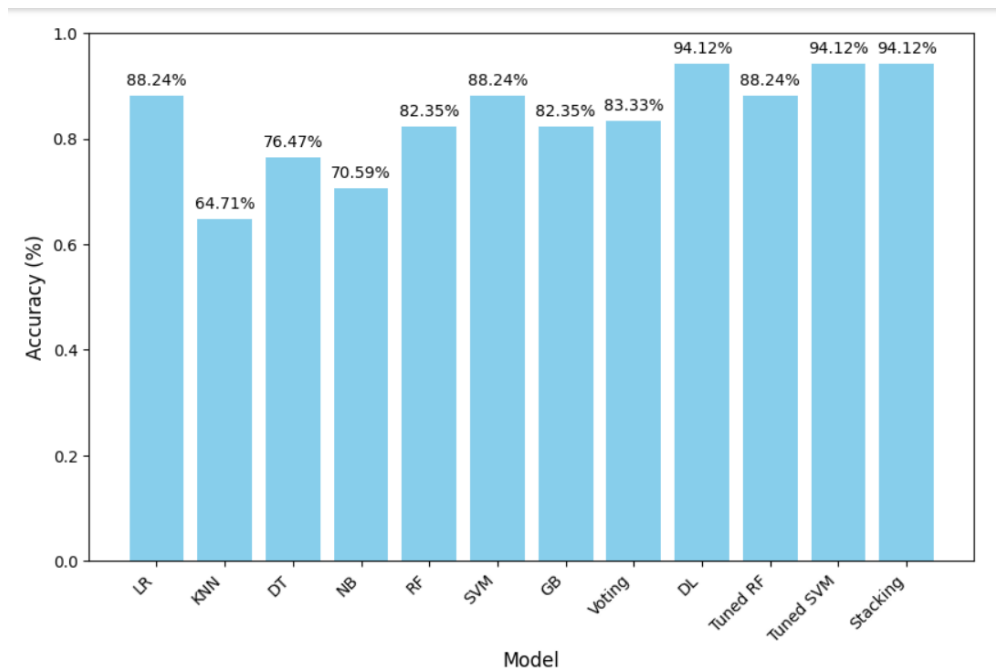


Figure 10. Comparative Accuracy Analysis of All Implemented Models, Including Machine Learning, Deep Learning, and Ensemble Approaches for Investment Preference Prediction.

The models were compared based on their accuracy, and three models, Tuned SVM, Voting Classifier, and Stacking Classifier models, were found to be highly accurate, with 94.12 percent accuracy. The Tuned RF and Deep Learning, SVM, as well as Logistic Regression were next with accuracies of 92.86%, and this means that classifiers performed well in investment sector prediction tasks. Logistic regression, support vector machine, and random forest operated well with certain sectors, but the overall accuracy was relatively lower than ensemble and deep learning techniques. The in-built system of the proposed research is mentioned in figure 11.

The figure shows a user interface for an investment preference prediction system. It consists of several input fields and a button. The fields are: Gender (dropdown menu with 'Male' selected), Age (slider with '25' indicated), Working Pr... (dropdown menu with 'Working' selected), Annual Inc... (text input with '0'), Investment... (text input with '0'), Goal for In... (dropdown menu with 'Wealth generation' selected), and Duration (y... (slider with '5' indicated). Below these fields is a green button labeled 'Predict and Explain'.

Figure 11. User Interface of the Developed Investment Preference Prediction System Demonstrating Input Features, Model Output, and Explainable Insights for End Users.

5.6. Explainable AI Evaluation

In this research, measures on Explainable AI (XAI) were used with the aim of increasing the level of interpretability of the machine learning models that were incorporated in the prediction of investment sectors. XAI techniques are the key to understanding how models make decisions, and such aspects are particularly important in intricate problems such as investment predictions. For this purpose, we used two key explainability techniques: Decision trees, Random Forest, and LIME (Local Interpretable Model-agnostic Explanations).

5.6.1. Feature Importance Analysis

Feature Importance Analysis is a process that has the use of determining how much of an influence each of the input features will have over the resultant feature. For the purpose of this project, these are: age, gender, annual income, investment per month, goal for investment, and investment duration. Using feature importance analysis, we are able to position these features from the best in contributing to the predictions of the model to the least, as shown in figure 12.

The importance scores that were derived from this analysis were presented in bar graphs, such that the features that had been given high scores featured as prominent predictors of the investment sectors. In forming investment decisions, this assisted the identification of the most important variables for prediction and equally gave rather valuable investment tips to the investors in terms of Investment goals and annual income to determine the right investment sector.

5.6.2. LIME

The model interpretation technique known as LIME offers a local explanation and therefore, deals solely with individual prediction rather than the behavior of a model. In getting each prediction, LIME generates a simple, local, interpretable model that explains the complicated model in the neighborhood of the instance that has

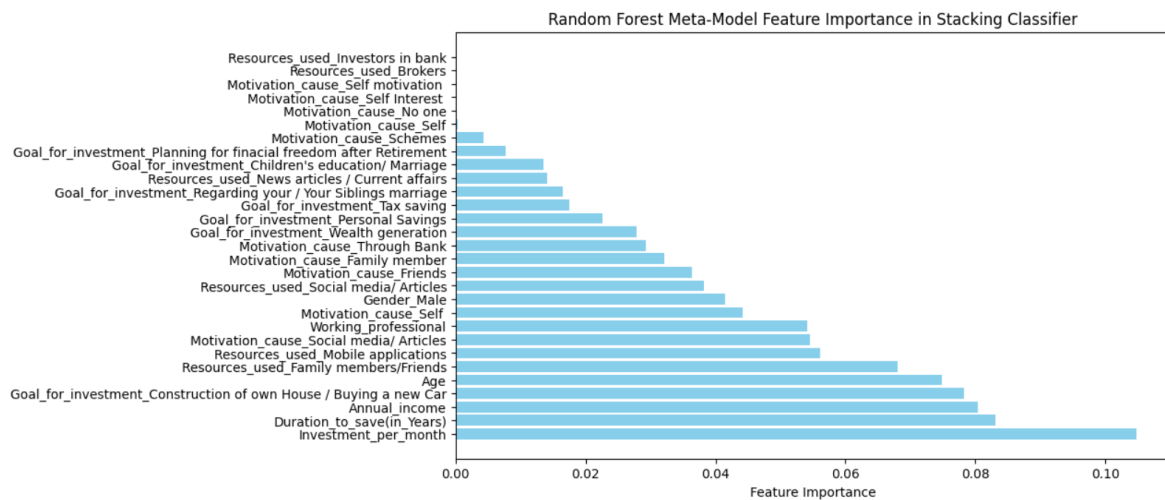


Figure 12. Feature Importance Analysis Showing the Contribution of Demographic, Financial, and Behavioral Attributes in Predicting Investment Preferences.

to be explained. LIME was employed in this study in order to learn the reason as to why certain investment recommendations are offered to individual users. As an example, let us assume that the model suggested to invest in Mutual Funds, then LIME would show that the model favored the choice due to the user-defined investment goal and the annual income as shown in Figure 13.

Applying Explainable AI to this work has made different features contribute to this model more comprehensible. The incorporation of feature importance analysis and LIME has been used to explain how the model arrives at its decision making hence increasing the usability of the research for investors seeking to be assisted on the best investments to undertake. These techniques are especially effervescent in fiscal discipline, where community transparency and responsibility are very significant for critical instructions. The final proposed research system workflow is given in Figure 14.

6. Discussion

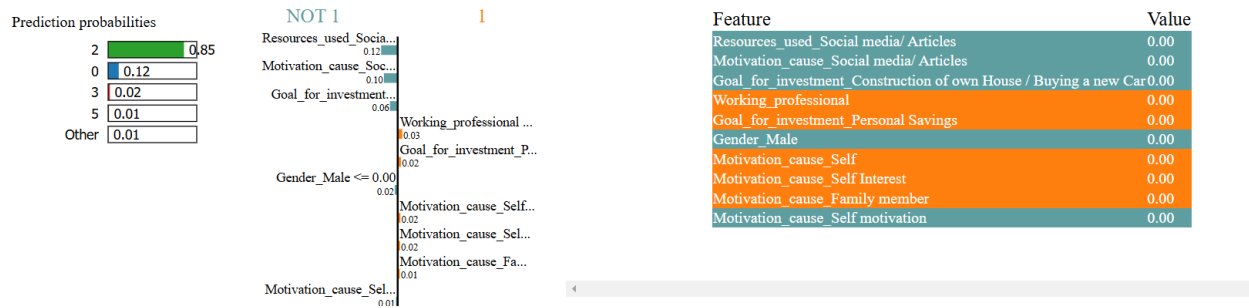
The results of this study show that machine learning and ensemble learning can be effectively applied to investment preference prediction using structured survey data. Instead of focusing on stock market forecasting, we consider a user-level problem with multiclass classification based on demographic, financial, and behavioral features. This approach makes it suitable for decision support.

Comparatively, we found that the ensemble learning approach outperformed most of the individual classifiers. We found that the highest-performing classifier was the stacking classifier, demonstrating that using several base models increases prediction reliability for this task. Also, having multiple base models provided a wider perspective and demonstrated the effectiveness of ensemble learning in survey-based financial predictions.

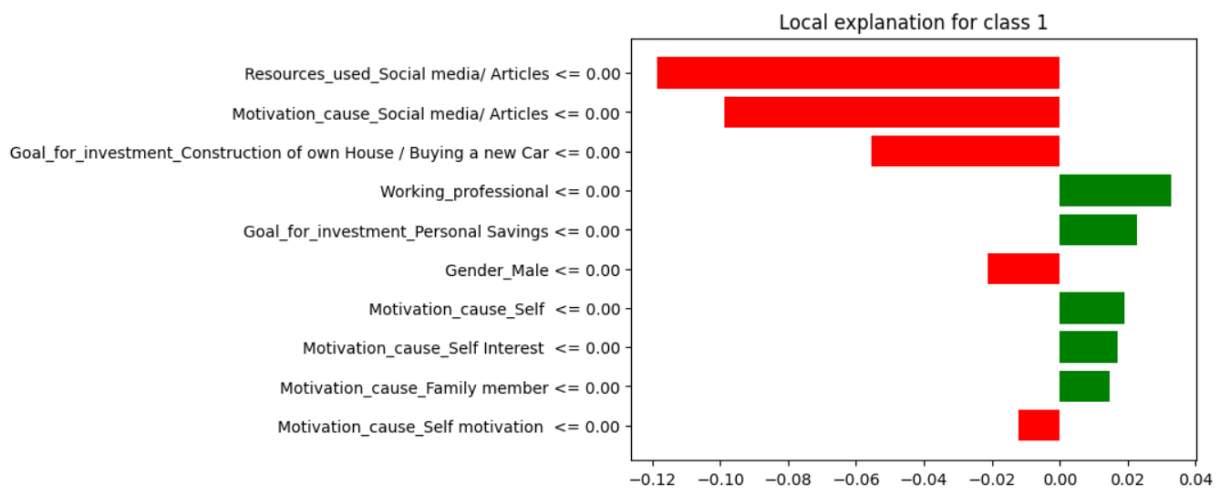
Another significant contribution of the study is that interpretation is crucial. Because financial recommendations should not be made only using black-box predictions, we applied feature analysis and LIME to explain the model outputs in a more understandable way. This provides more transparency and enables the investors to better understand why their prediction was selected.

Finally, the light-weight web-based prototype illustrates the practicality of the proposed framework. But, because the data are regionally specific, survey-based, and static, this system can be interpreted as an explainable research prototype of investment preference prediction rather than a complete financial predictive system.

Figure 13. LIME-Based Local Interpretability Visualization Explaining Individual Predictions by Highlighting Feature Contributions for Specific Investment Recommendations.



(a) LIME Output Explanation With Features



(b) Local Explanation of LIME

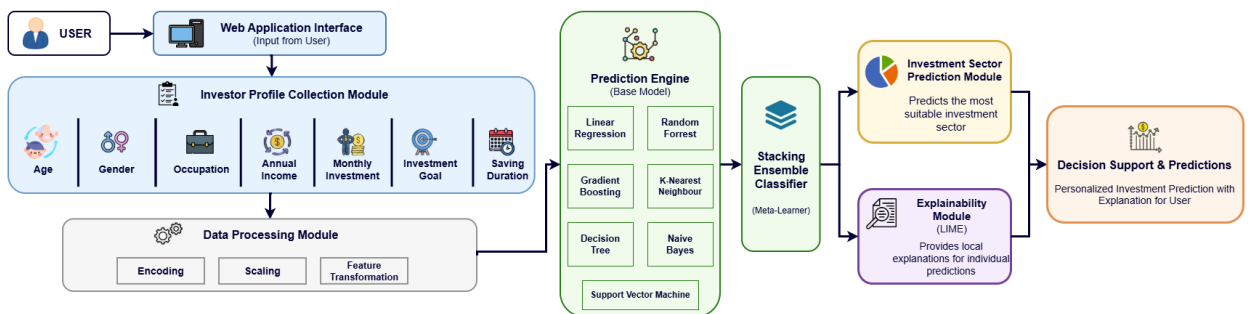


Figure 14. Complete System Workflow Integrating Data Processing, Model Prediction, Ensemble Learning, and Explainable AI for Investment Preference Analysis.

7. Limitations

Although the framework proposed here shows that explainable ensemble learning is useful for predicting investment preferences, we acknowledge that there are limitations to be considered in the interpretation of these results.

- **Geographic concentration of the dataset:** The dataset was collected mainly from respondents in Dhaka Division, Bangladesh. Therefore, the findings should be interpreted as a regional case study and may not generalize to broader populations without further validation.
- **Survey-based and self-reported responses:** This study relies on self-reported responses to a questionnaire. Recall bias, misunderstanding of concepts of money, or social desirability bias may affect these responses. On top of that, this was not verified against actual investment records or investor behavior.
- **Prediction of Expected Investment Preferences:** The proposed framework model predicts likely investment preferences based on structured survey characteristics. It does not account for real-time market moves, financial conditions, or investor behavior. Thus, it should be considered a decision-support prototype rather than a full-service provider of financial predictors.

8. Future Scope

In future research, several directions might be considered to improve the practicability, robustness, and applicability of the proposed framework.

- **Expansion of the Dataset:** Future studies may include respondents from a larger region and from more diverse groups so that the model can be generalized and regional biases can be avoided.
- **From prediction to predictive support:** At present, the system anticipates users' investment choices. In the future, the system may be augmented with user profiles, financial goals, and rule-based recommendation support to more effectively advise users.
- **Implementation of further richer and dynamic features:** In future work, it is possible to add additional variables such as financial literacy, past investment experience, macroeconomic variables, and real-time market information to make the model more adaptive and realistic.
- **Enhanced interpretability and model comparison:** The framework model comparability and interpretability could be improved further through the incorporation of additional explainability techniques such as SHAP and comparing the current models with stronger tabular learning methods to obtain a more robust and transparent performance analysis.

9. Conclusion

This study describes a simple explainable ensemble learning model to predict a user's investment preferences from structured survey data. Unlike earlier financial prediction studies that focus primarily on stock price prediction or market trends, this study addresses a multi-class classification problem at the user level and leverages demographic, financial, and behavioral information. Our research used several different machine learning models, as well as ensemble methods like Voting and Stacking, and explainability using LIME to improve prediction and transparency.

The results showed that ensemble models, particularly the stacking classifier, gave the best overall predictive performance among the models. It revealed that explainability allowed users to learn why a particular investment choice was predicted, which is particularly relevant in financial decision-support systems in which transparency and user trust in models are vital. A light web-based interface was also developed to show the use of the proposed framework in a more accessible and user-friendly manner.

Overall, the results suggest that explainable ensemble learning can be an effective and easily understandable method for the prediction of investor preferences on survey data. It contributes a comparative machine learning

pipeline, a structured dataset, and a prototype implementation of this process, contributing to more transparent financial recommendation tools. Despite these important contributions, the system should only be considered as a decision support system, not a full-fledged financial advice system, since its predictions are based on reported preferences and survey properties rather than market behavior.

Future work may extend the framework by implementing larger and more varied datasets, adding additional behavioral and financial factors, and validating the system on independent samples. Other explainability techniques like SHAP may be added to LIME to provide local and global interpretability. Stronger tabular learning baselines and stronger comparative assessments may improve the reliability of the system. Further extensions could make the framework more complete, robust, and more appropriate for wider applications related to financial decision-support.

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Data Availability:

The dataset is available at <https://www.kaggle.com/datasets/tmmhratul/investment-survey-dataset>

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