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Leveraging Artificial Intelligence Algorithms for Retirement Income Optimization in Financial Planning

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***Abstract*—Responsibility for one's own financial future is required in people's financialized everyday lives. However, as a larger proportion of the population ages, more people are concerned about their financial stability due to factors such as fluctuating retirement and pension systems, uncertain government funding, and market and other crises. The present study addresses the urgent issue of low uptake of pension schemes by developing and testing high-performance predictive models based on data from FinAccess. To address the extreme imbalance among the classes, the more extensive AdaSyn resampling method was used. A sophisticated combination of 22 sociodemographic predictors was specified to train and optimize Multi-Layer Perceptron (MLP) and Decision Tree (DT) models systematically. The obtained results show outstanding predictive power, as the MLP model has an accuracy of 95.74%, precision of 96.26%, recall of 95.60%, F1-score of 95.76%, and a near-perfect AUC of 0.9968, while the DT model yielded closely competitive metrics of 95.25% accuracy, 95.65% precision, 95.03% recall, 95.26% F1-score, and a 0.9950 AUC. A comparative study proves that both of the proposed models are far much better than modern standards, such as RNN-LSTM, LightGBM, and Random Forest. The study develops a new analytical pipeline that offers practical, quantitative information of creating specific financial inclusion initiatives to enhance security in changing retirement environments.**

Keywords—Financial Literacy, Financial Risk Tolerance, Saving Behavior, Retirement Planning, Pension Uptake, FinAccess Data.

I. INTRODUCTION

In recent years, communities across the entire world have assumed additional responsibilities with regards to their financial well-being. This heightened self-sufficiency of consumers who do not make financial choices such as saving, investing and accumulating wealth on behalf of workers and retirees has been blemished by smoothing swings into the pension backdrop [1]. The financial health of people should be prioritized during the retirement. The accelerated development of financial market products, and the leverage of the private duty to enhance retirement financial well-being pose questions on whether individuals possess the financial knowledge and skills required to plan and ensure sufficient retirement protection in the new era. Retirees have to deal with opposing financial objectives and high financial risk [2]. There are a few financial issues that people worry about in their retirement, namely; a reliable income to meet lifestyle expenses (longevity), there is a risk of outliving the limited retirement savings (legacy) and people want to be sure they have the money when it is required (liquidity) [3]. It should develop and manage their portfolios to satisfy their needs to create the wealth as well as a reliable lifetime income [4].

Failure to make proper financial planning can bring about financial instability, missed opportunities and more exposure to economic volatility [5]. Conversely, proper financial planning motivates individuals and organisations to achieve their intended financial goals [6]. It assists individuals in tracking their finances, accumulating wealth and insuring against risks. The importance of effective and reliable financial planning mechanisms is increasingly being realised due to these implications. As new possibilities are introduced, and the features are enhanced, ML has become an indispensable tool in the sphere of financial planning [7][8]. The possibility of MLA and methods to radically alter the conventional financial planning processes has been enabled by the geometric growth of data and improvements in computational capabilities. ML can generate important predictions and insights using big data, automation, and sophisticated modelling methods. The algorithms can be trained on historical data, adapt to different market conditions, and identify more complex patterns that conventional methods might miss. ML has a number of benefits to the handling of big and heterogeneous financial data sets.

A. Problem statement and Motivation

In recent few years, individuals have increasingly been accountable concerning what they can do to ensure their own retirement, which is increasingly complex as pension security declines and financial choice becomes more detailed. The goals of lifetime income, longevity protection, and healthcare funding, and legacy planning are difficult to balance, and individuals with low financial literacy and tools are not easily offered an opportunity. This consequently subjects people to financial insecurity, missed opportunities and an increased economic risk due to poor planning.

This study addresses the growing problem of inadequate pension uptake by developing a machine-learning-driven predictive model to mitigate the rising burden of individual responsibility and the lack of planning assistance. The study attempt to create accurate and realistic models of retirement

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financial behavior by addressing real-life problems, such as extreme imbalance in classes and limited socioeconomic statistics, using approaches, such as AdaSyn and systematic hyperparameter tuning. The framework offers a scalable tool to enhance decision-making, policymaking, and retirement readiness.

B. *Paper organisation*

Here is the outline for the rest of the paper: Section II presents a concise literature overview. Describes the methods used to compile this data in Section III. Computing experiments and their outcomes are detailed in Section IV. Section V provides a brief overview of the paper's main results and discusses their significance for guiding future study.

II. Literature Review

Despite the wealth of information available, most retirement planning models are infeasible because they rely on stochastic formulations or intricate simulations.

Sousa *et al.* (2025) propose an alternative mathematical model for retirement savings that uses modified geometric progressions. Instead of using the same assumptions as standard annuity models, the suggested technique adjusts contribution and withdrawal amounts for inflation. This opens the way to real-world financial behavior consistent simulations. The model can be applied in simulations in the government, individual financial planning programs, and pension fund policies. We create a case study that illustrates how a 25-year invested amount of R$ 767.67 produces a 30-year retirement income of R$ 3049.19 with purchasing power held at 3% per annum geometric annuity and an interest rate of 0.5% per month. The model allows future realizations in government and individual pension systems due to the provision of a realistic and practical instrument of personal retirement planning [9].

Das (2025) proposes a Quality Assurance (QA) automation approach to update these critical processes. We design and implement an automated test and processing framework that leverages behavior-driven development and state-of-the-art test automation tools to enable straight-through processing and comprehensive verification of loan and distribution transactions. The method was applied to real retirement system environments, with much shorter processing cycles and a near-elimination of processing errors. Results demonstrate that automation-driven modernization can deliver 50% faster processing, better regulatory compliance, and higher participant satisfaction. The research's conclusions have important ramifications for the advancement of financial technology [10].

Zhang *et al.* (2025) propose a new approach to predicting battery retirement states using the TabNet model and multidimensional retirement features. A total of 23,741 decommissioned vehicles were analysed, along with 720 electric vehicles that had been in operation for three years, providing static data. After preprocessing, a label was determined on the battery retirement condition. The decision-making dimensions of battery retirement were further advanced by developing a retirement-related feature-extraction methodology that incorporated the vehicle, health, and use dimensions. At last, a model to predict retirement status was created and trained using Bayesian optimization and TabNet. Experiment findings show that the suggested method can use real-world data to anticipate when batteries will be ready for retirement (F1score of 0.850, AUC of 0.977 on test-data) [11].

Liu and Zhang (2024) investigate how retirement affects the distribution of wealth amongst elder households and speculate on the role of Confucian culture as a moderator. The empirical results, which use data from the China Household Finance Survey, reveal that after retirement, older individuals save more and reduce risky assets. The Confucian cultural concepts support this tendency toward conservatism. Additionally, the research shows that household head health, urban-rural differences, and risk attitudes have different effects on allocation. Optimising the distribution of financial assets for older families and tackling the issues of ageing are both addressed in this study, which serves as a vital reference in this regard [12].

Bravo *et al.* (2023) used a Bayesian Model Ensemble method for stochastic mortality modelling to anticipate pension ages for 23 nations between 2000 and 2050 that are both actuarially and intergenerationally fair while addressing model risk. The results demonstrate that pension age rises are substantial and much higher than those enacted or implemented in most countries, in order to restore intergenerational parity and account for the effect of longevity advances on pay-as-you-go equilibrium. A new wave of pension adjustments could be on the way [13].

Harahap *et al.*, (2022) analysed data collected from 388 medium-scale enterprises in Indonesia's Bekasi Regency using PLS-SEM. The study showed that (a) investing habits and comfort level with financial risk play a mediating role in the connection between financial education and retirement preparation, (b) herding behavior might make financial literacy have a bigger effect on retirement planning, and (c) the correlation among financial literacy and retirement planning is unaffected by saving behavior while acting as a mediator. This study lends credence to the idea that herding behavior and financial risk tolerance are two ways in which financial literacy relates to retirement planning [14].

A. *Research Gap*

Available literature on retirement planning falls under mathematical modelling, financial behavior study, pension system automation, and machine learning in related fields, but there is a clear gap in the literature of proposed practical, data-driven predictive systems that are specifically focused on enhancing the decision to take pensions. Earlier research dwells upon theoretical financial model, automated process frameworks, cultural and behavioral predictors, or retirement-related forecasting in other areas (e.g. battery retirement), but does not touch upon the long-standing problem of correctly distinguishing those who are likely to miss out on joining a pension scheme. Additionally, the lack of socioeconomic information, extreme class disparity and a lack of scalable ML-based tools used in decision-supports hamper real-world application. Such a gap underscores the need to develop sophisticated, powerful predictive models that can handle imbalanced datasets and behavioral patterns, and provide individual, policy-relevant interventions to enhance retirement preparation.

III. Methodology

The study utilized FinAccess data that is processed includes cleaning of the data, encoding of the categorical variables and Z-score normalization. AdaSyn technique was

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employed to remove large class imbalance and resampling was done after which a 70:30 train-test split was performed. Multi-Layer Perceptron (MLP) and Decision Tree were used as the architectures to develop models, and their performance has been compared based on conventional measures such as acc, prec, rec, F1score, and AUC-ROC, derived from the confusion matrix. Fig. 1 shows the implementation workflow.

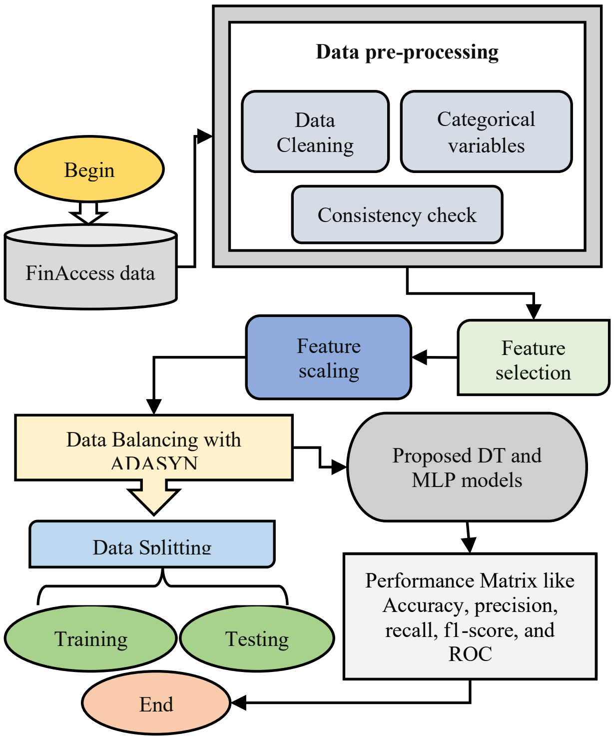

Fig. 1. Propose Flowchart for Retirement Income Optimization

The detail steps of the implementation system explained in next steps.

A. *Data Gathering*

This study made use of 2019 Kenya FinAccess data that is typical of the country as a whole. It was possible to interview one individual from each family for a total of 8669 people in 820 clusters. The information gathered included mobile money and pension uptake, as well as sociodemographic traits and the availability and use of financial services.

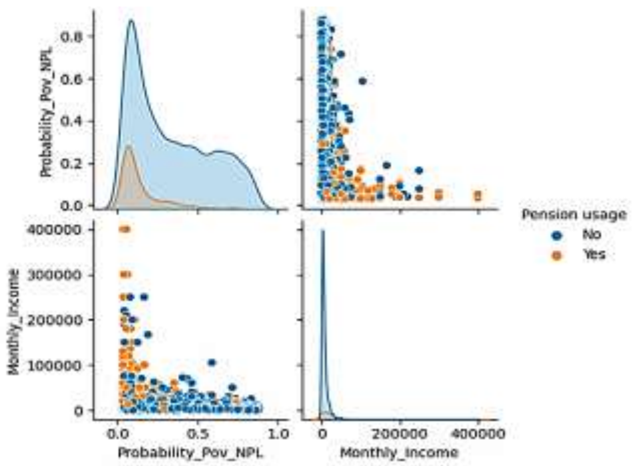

Fig. 2. Pair Plot for Socioeconomic variables

Fig. 2 investigates the correlation between the use of pensions and two socioeconomic factors monthly income and poverty vulnerability (Probability_Pov_NPL). It exposes different distributions of pension users and non-user whereby, using kernel density estimates (KDEs), the results indicated that pension users are more likely to have higher income and less vulnerable to poverty. The scatterplots also reveal clustering behavior, which indicates that the decision to take pension is also connected with financial stability. This graph helps to see the nature of the relationship between income and perceived risk of poverty and pension participation and it provides the insights on how the targeting may be used to enhance the coverage of the pension participation.

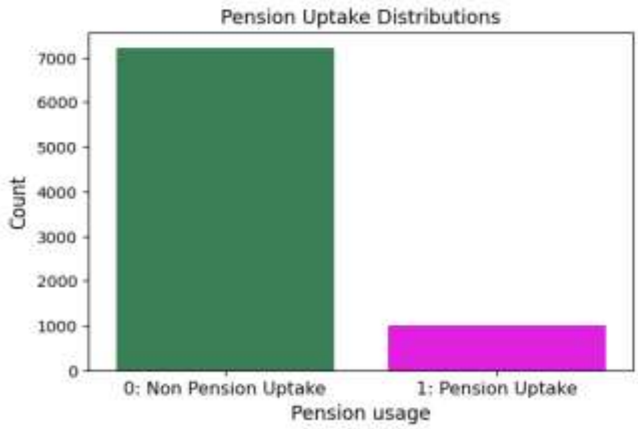

Fig. 3. Count plot for Class Distribution

The distribution of the classes of respondents who have taken pension is provided in Fig. 3. The x-axis groups people in two categories; 0: Non Pension Uptake and 1: Pension Uptake, and the y-axis shows the number of people in each group. As can be seen in the chart, the ratio of the classes is quite significant, with more than 7000 people in the non-uptake group (marked with a dark green bar) and slightly more than 1000 in the uptake group (marked with a bright pink). This difference indicates the low uptake of pension schemes among the population surveyed on the topic and the need to develop specific financial inclusion measures.

B. *Data Pre-processing*

Pre-processing aims to prepare the dataset for subsequent processing. Pre-processing involved cleaning, encoding, Zscore normalization, and data balancing. These steps are listed in below:

- **Data cleaning:** Removal of irrelevant, redundant, or non-sociodemographic variables to keep only meaningful predictors.
- **Categorical variables:** These are those attributes such as gender, occupation, residence type, or level of education. There being a need of numerical input in machine learning models, categories were converted to numeric codes.
- **Consistency check:** After encoding, the dataset was reviewed to ensure no unintended ordinal relationships were introduced (e.g., treating “occupation codes” as ranked values).

C. *Feature Selection*

The feature selection was conducted so as to make sure that only the most pertinent sociodemographic variables were to be kept to predict the uptake of the pension. There were over

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a thousand variables in the original dataset, but only thirty of them were related to sociodemographic. Non-sociodemographic, redundant, and irrelevant variables were eliminated and a set of 22 features was refined in the after preprocessing. The goal in making this decision was to keep the model as efficient and easy to understand as possible by avoiding variables that were already there and adding new ones that contributed significantly to the prediction process.

Fig. 4. Feature Importnace Score

The feature significance that was taken from the RFC is shown in Fig. 4. The following characteristics were ranked in order of significance: NHIFusage, Monthly Income, bank usage, Poverty Vulnerability, helping others, Education Level, Household Size, age group, Internet access, source of financial advice, Financial Health, Wealth Quintile, ownership of the place of residence, Marital Status, savings in the previous 12 months, gender, whether one met personal goals, type of residence (rural or urban), VulnerabilityIndex, setting aside money for a specific purpose, social network device used, mobile ownership, and Crypto currency Adoption.

D. Feature Scaling

Normalising the distribution of variable values is referred to as feature scaling. Normalization involves dividing the variable by the data's StandardDeviation or subtracting the mean from the variable in order to eliminate the mean and make the distribution of the values consistent. The data was normalized by calculating the Z-score, which is the difference between the StandardDeviation (s) and the average ($\bar{x}$), as displayed in Equation (1).

$$Z_i = \frac{x_i - \bar{x}}{s} \quad (1)$$

Where Z_i is i-th Zscore, and x_i is i-th variable value. This study calculates Z-scores using the scale() function that is supplied in the R package.

E. Handling Class Imbalance

An example of class imbalance is a much larger training dataset for one class than for another. This research used resampling to address this issue. AdaSyn creates data samples for complicated or difficult-to-learn minority-class samples. The original data's decision boundary is improved by creating synthetic samples based on the distribution of the minority class density. In addition to balancing the dataset (see Figure 5), the artificial data points produced by AdaSyn also lessen the original dataset's learning bias.

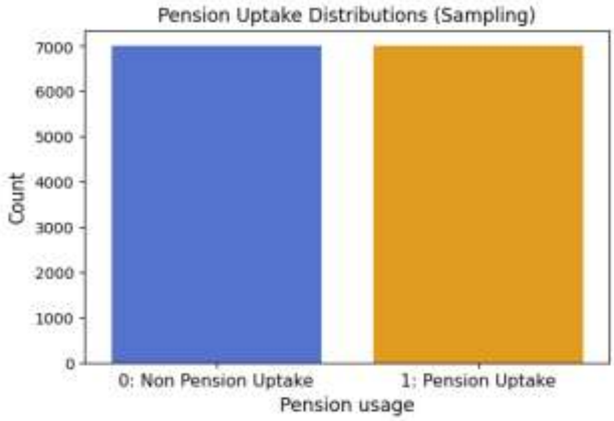

Fig. 5. Distribution of Pension Uptake After Sampling

Fig. 5 shows that, after sampling, the number of those who chose to take a pension and those who did not is evenly distributed. The non-uptake category (0) and the uptake category (1) have almost the same number, approximately over 7000, each. This indicates that the sampling technique was effective at maintaining class parity, which is important for unbiased training and testing of models in predictive analyses.

F. Train-Test Splits

Data was partitioned so that neither the model's validation nor its testing used the training data. There was a 70:30 split between the training and test sets, with 70% used for training and 30% for validation and testing.

G. Baseline Architectures (models)

This section provides an overview of the metamodel's primary designs, which include MLP and Decision Tree.

1) Propose Multilayer Perception (MLP)

An MLP is a kind of ANN that consists of an InputLayer, a HiddenLayer (or layers), and an OutputLayer [15][16]. Despite the apparent simplicity of MLP with only three layers, we have optimized the model for prediction by experimenting with different parameter values and layer counts. A function may be used to depict a simple multilayered perceptron model with one hidden layer, as shown in Equation 2:

$$f(x) = g(b^{(2)} + W^{(2)}\left(s\left(b^{(1)} + W^{(1)}x\right)\right)) \quad (2)$$

Here, $b^{(1)}$ and $b^{(2)}$ are the BiasVectors, $W^{(1)}$ and $W^{(2)}$ are the WeightMatrices, and g and s are the activationfunctions. Fig. 6 shows that our system's input layer occurs before the dense hidden layer, which is the final output layer.

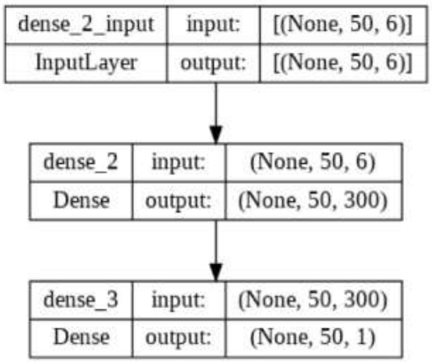

Fig. 6. Architecture of MLP Model

The design of the structure is such that it stages the transformation of the input features to increasingly higher abstraction levels meaning that the model can be trained to learn non-linear relationships. This is a fast, fully connected structure that efficiently extracts and classifies features, which also contributes to the model's strong predictive performance.

2) Propose Decision Tree (DT)

Decision trees are hierarchical structures that use a battery of feature tests to make predictions [17][18]. The decision tree (DT), input attributes (X), and target variable (Y) must all be defined. The decision tree repeatedly partitions the dataset based on feature tests to optimize class separation or minimize impurity. Equation (3) shows the prediction made by the decision tree:

$$DT(X) = \sum_{i=1}^{L} y_i . l(X \in R_i) \quad (3)$$

In this case, L is the number of nodes that make up the decision tree's leaf, y_i is the class-based label assigned to the i-th LeafNode, and R_i is the region or set of cases that the i-th LeafNode was assigned based on the feature tests. $l(X \in R_i)$ is a function that indicates if the input instance X is in the area Ri by returning 1 if it is and 0 otherwise. The decision tree gives the appropriate class label, y_i to the LeafNode where the instance is located after traversing from the root to a LeafNode depending on the feature tests.

H. Model Building with hyperparameter Tunning

During model development, we systematically tuned the hyperparameters of the MLP and Decision Tree models to improve their performance. In the case of MLP, the number of hidden layers, the number of neurons, the activation functions, the batch size, the learning rate, and the optimization functions were tuned to maximize learning capacity and generalization. Likewise, the Decision Tree model, the main parameters such as maximum depth (5-20), minimum samples split (2-10), minimum samples leaf (1-4), and criterion (gini, entropy) were optimized in order to reduce overfitting and maximize class separation. This systematic exploration of hyperparameters allowed each model to run with its most effective hyperparameter values, ensuring high, robust, and generalizable classification.

I. Evaluation Parameters

Metrics are used to assess ML models. Accuracy, precision, recall, and f1 scores are computed using a confusion matrix. The training subset provided the metrics used for this analysis. True positives are instances in which real positive instances were correctly classified as positive. Negative occurrences that are misinterpreted as positive are called false positives. True negatives are situations that were projected to be negative. When favorable outcomes are mistakenly seen as bad, this is called a false negative.

The percentage of accurate predictions relative to all predictions in the test set is called accuracy. Equation (4) is used to compute the accuracy.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

Precision measures how well a model predicts a given class action relative to all model predictions for that class in the training dataset. Equation 5 is used to determine precision:

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

The recall measures the percentage of genuine class activities in the test dataset. Equation (6) allows one to determine recall, which is also called sensitivity.

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

The F1-score is the weighted average of recall and precision, as shown in equation (7). Thus, the F1-score is a more useful statistic for an assessment than the accuracy meter.

$$F1 - score = 2 * \frac{(precision*recall}{(precision+recall)} \quad (7)$$

ROC curve (AUC), which is defined as the integral of the FPR multiplied by the TPR, is a measure of the accuracy of a test. Equation (8) is used to determine AUC.

$$AUC = \int_0^1 TPRd(FPR) \quad (8)$$

The TPR is calculated as the ratio of true positives (TP) to the sum of false negatives (FN) and true positives (TP). The false positive rate (FP) is the ratio of false positives to the total of false positives and true negatives (FP + TN). An alternative name for FPR is 1-Specifcity.

IV. Results And Discussion

The experiments in this study were conducted on a laptop with an IntelCore i7-8550U 1.80 GHz CPU, 8 GB of RAM, and an NVIDIA GeForceMX150 with 2 GB of RAM. The apps were built using the sklearn package in Python 3.6. As shown in Table I, both the MLP and Decision Tree models deliver strong financial planning predictions, with the accuracy, precision, recall, and F1 Scores of both models exceeding 95%. The MLP is a little bit better than the Decision Tree in all the evaluation measures, which show that it is more consistent in falsely labeling positive and negative classes. On the whole, the both models can offer good and sound classification capability, although the MLP has a slight performance edge.

TABLE I. Experiment Performance of the Propose Models for Financial Planning

Measures	MLP	DT
Accuracy	95.74	95.25
Precision	96.26	95.65
Recall	95.60	95.03
F1 Score	95.76	95.26

Fig. 7. Plot MLP Model Confusion Matrix

Fig. 7 shows the MLP model's confusion matrix, which shows a high degree of categorisation, particularly in the Non-

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Pension class with 7,521 accurate predictions and 41 misclassifications. The model is also effective on the Pension class and it identifies 1,058 correct cases, but with 49 false negatives. On the whole, MLP proves to be very accurate and reliable in discriminating between two classes, with very low error rates and balanced class distributions.

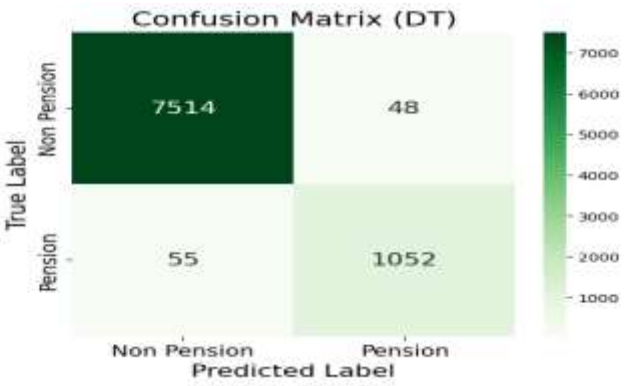

Fig. 8. Plot DT Model Confusion Matrix

Fig. 8 shows the usage of this confusion matrix to evaluate the Decision Tree classifier's performance in predicting pension uptake. The model has high classification accuracy, with an ability to classify non-pension and the number of pension cases correctly 7514 and 1052, respectively. The misclassifiations are limited as there were 48 non-pension cases that were misclassified as pension and 55 pension cases misclassified as non-pension. These findings suggest the DT model distinguishes between the two classes with equal precision and recall amongst categories.

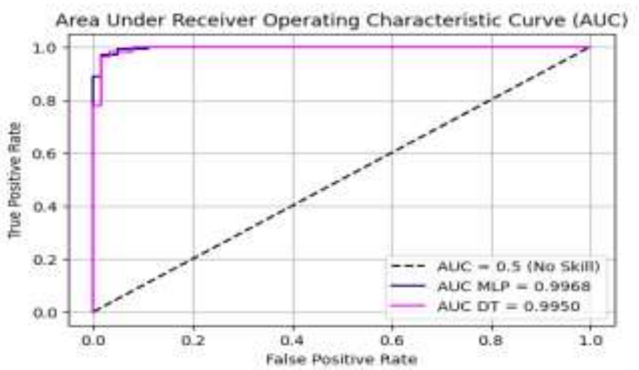

Fig. 9. Plot ROC Curve of Both MLP and DT Model

The ROC curve in Fig. 9 demonstrates the high discriminative power of both the MLP and DT models, with AUC scores of 0.9968 and 0.9950, respectively. They have a steep curve towards the top-left side which means that they have very high true-positive at low false-positive rates. The MLP model performs slightly better than the DT model, and both outperform the no-skill classifier (AUC = 0.5), indicating strong ability to differentiate the Pension and Non-Pension classes.

A. *Comparison and Discussion*

Table II shows that the suggested models outperform any known models, including RNN-LSTM, LightGBM, and RF, according to acc, prec, rec, and F1score. Although the current models are in the 86 -89 percent range of performance, the MLP is more than 95 percent in all metrics, which means a significant increase in both predictive strength and consistency. This indicates the performance of the proposed model architecture and tuning strategy in providing better and stable financial planning predictions than the previous methods.

TABLE II. COMPARATIVE ANALYSIS BETWEEN PROPOSED AND EXISTING MODEL PERFORMANCE

Models	Accuracy	Precision	Recall	F1 Score
RNN-LSTM [19]	88	89	87	88
Light GBM [20]	89.17	9256	8516	88.70
RF [21]	86.67	-	75	85.7
MLP	**95.74**	**96.26**	**95.60**	**95.76**
DT	**95.25**	**95.65**	**95.03**	**95.26**

B. *Advanatges and Contributions*

The main benefits of this study are that it has highly accurate and reliable predictive models (over 95% in all measures), and records near-perfect scores in AUC, which creates a very trustworthy tool to be used in the analysis. One methodological strength is that a serious imbalance of classes effectively can be overcome with the help of the AdaSyn algorithm which also guarantees that the model can learn with the help of critically important minority of the pension adopters. Moreover, the whole full-fledged pipeline, having gone through sophisticated preprocessing, to hyperparameter tuning, was demonstrated to work on some basic consumer hardware, demonstrating that this high-performance analytical method is feasible and available in practice. Finally, the work provides an improved and more proven structure through its proven capability of going beyond current frameworks, including RNN-LSTM and LightGBM, to generate actionable and data-driven insights to inform the policies and products of financial inclusivity. The study's main findings are as follows:

- Established an end-to-end analytical pipeline—from preprocessing to validation—providing a benchmark for future financial inclusion and policy research.
- Implemented the AdaSyn algorithm to effectively mitigate severe class imbalance, enhancing model learning for minority pension uptake cases.
- Developed and fine-tuned high-performance MLP and Decision Tree models through systematic hyperparameter optimization for robust financial behavior prediction.
- Applied a rigorous multi-metric assessment (Acc, Prec, Rec, F1Score, AUC-ROC) to ensure reliable and generalizable model performance.

V. Conclusion And Future Scope

The optimal allocation of wealth is required to provide financial security in old age, given trade-offs among investment risk, life insurance, spending, and bequest motivation. The interaction between income uncertainty, market volatility and behavioural properties such as panic selling and loss aversion is dynamic and can be largely overlooked by the traditional static models. The paper has been able to create a high-performance predictive model of pension uptake, which under optimized models, showed impressive metrics (MLP: 95.74% accuracy, 0.9968 AUC; DT: 95.25% accuracy, 0.9950 AUC) and was significantly better than the existing state of the art models (RNN-LSTM and LightGBM). The optimal wealth allocation during the retirement period, which is a dynamic issue needing more complicated modeling, can be used to estimate the future consumption, risk, and insurance of the retirement funds, but our approach presents a critical and data-driven basis of uptake behavior. But, the research has certain flaws, such as

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its cross-sectional design, which means it doesn't capture changes over time or behavioral factors like loss aversion that maybe impact long-term financial decisions. The way forward in the expectations of future labor is the use of longitudinal data to model wealth paths, incorporate behavioral economics variables into the predictive model, and apply this proven pipeline to predict strategies of dynamic retirement plans in the face of market fluctuations and income insecurity.

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