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Life Insurance Prediction and Its Sustainability Using Machine Learning Approach

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Abstract: Owning life insurance coverage that is not enough to pay for the expenses is called underinsurance, and it has been found to have a significant influence on the sustainability and financial health of families. However, insurance companies need to have a good profile of potential policyholders. Customer profiling has become one of the essential marketing strategies for any sustainable business, such as the insurance market, to identify potential life insurance purchasers. One well-known method of carrying out customer profiling and segmenting is machine learning. Hence, this study aims to provide a helpful framework for predicting potential life insurance policyholders using a data mining approach with different sampling methods and to lead to a transition to sustainable life insurance industry development. Various samplings, such as the Synthetic Minority Over-sampling Technique, Randomly Under-Sampling, and ensemble (bagging and boosting) techniques, are proposed to handle the imbalanced dataset. The result reveals that the decision tree is the best performer according to ROC and, according to balanced accuracy, F_1 score, and GM comparison, Naïve Bayes seems to be the best performer. It is also found that ensemble models do not guarantee high performance in this imbalanced dataset. However, the ensembled and sampling method plays a significant role in overcoming the imbalanced problem.

Keywords: life insurance; machine learning; sampling; ensemble; imbalanced data

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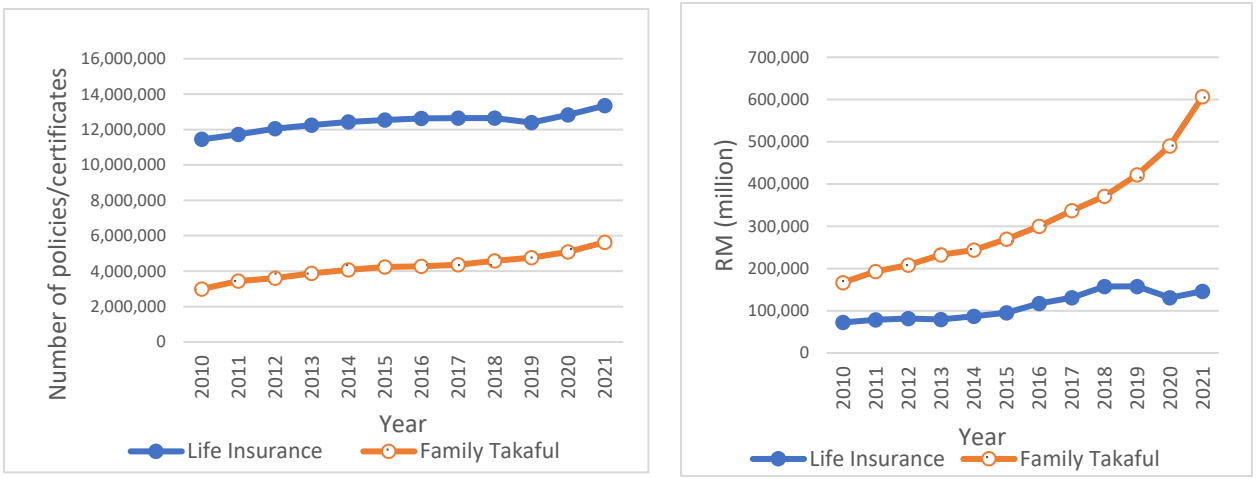
1. Introduction

Life insurance protects beneficiaries if any accidental death or unexpected event happens [1]. However, in countries with well-established social security systems, the demand for life insurance is frequently low [2]. The perception of mortality risk and attitudes toward life insurance plays a vital role in purchasing a life insurance policy. Most households are aware of the monetary risk posed by mortality. This does not, however, lead to the purchase of life insurance, which may affect the sustainability of their finances. A survey by the Swiss Re Institute (2020) [3] claims that households in all of the region's countries favor other strategies for boosting their financial security over life insurance, such as increasing their income or purchasing medical/critical illness insurance.

Due to the COVID-19 pandemic breakout, life insurance policies have drawn particular attention and interest among the numerous insurance products. The epidemic affects the global economy in both positive and negative ways. A series of surveys with the public were conducted between March and June 2020 in the UK, the US, and Spain. The results revealed that 30% of respondents said COVID-19 had increased their likelihood of considering buying life insurance [4]. However, based on the insurance barometer study conducted by LIMRA and Life Happens in 2021, life insurance ownership in the US decreased marginally in 2021, with only 52% of Americans claiming to have life insurance, a decrease from 54% in 2020 [5].

According to Bank Negara Malaysia (Central Bank of Malaysia), demand for life insurance has increased over the last decade, with per capita life insurance premiums rising 156% from RM 797.00 (USD 176.97)1 in 2010 to RM 1250.00 (USD 277.56) in 2021. Total premiums from new life insurance income rose from RM 7.9 billion to RM 40.75 billion, while new life insurance policies increased from 1.5 million to 17.5 million units. Meanwhile, in 1990, per capita insurance premium expenditure was only RM 92.00 (USD 20.43), while total new premiums (RM 573 million) and the number of new life insurance contracts (498,338) were significantly lower as compared to the period of 2010 to 2021 [6].

Figure 1a shows the number of policies and certificates in force from 2010 to 2021, which showed an increasing trend. However, there was a slight decrease in the number of life insurance policies in force in 2019. Meanwhile, Figure 1b presents the distribution of new sums insured for life insurance, and the sum participated for Takaful Family. In 2020, the distribution of life insurance's new sums decreased, possibly due to the COVID-19 crisis that affected the nation. The Malaysian life insurance market is still lagging compared to other established global and regional markets, notwithstanding the increase in active policies and premiums mentioned earlier. This is demonstrated by the persistently low insurance density per capita in USD between 2010 and 2021 compared to other Asian nations. Although Malaysia's insurance intensity climbed by nearly 157% from USD 282.8 in 2010 to USD 444 in 2021—above the world average of USD 382—it still lags behind other developed Asian nations such as Taiwan (USD 3772), Hong Kong (USD 8433), and Singapore (USD 5414). Additionally, in 2021, the Malaysian life insurance penetration rate (the proportion of life insurance premiums to GDP) was estimated to be 3.9%, which is significantly lower than the rates of other developed Asian nations such as Hong Kong (17.3%), Taiwan (11.6%), Singapore (7.5%), and Japan (6.1%) [7].



(**a**) (**b**)

Figure 1. (**a**) Number of policies/certificates in force. (**b**) Distribution of new sums insured/sum participated.

Based on the above facts, life insurance ownership is an interesting topic, especially in overcoming the low penetration rate problem. Families' sustainability and financial health were correlated to underinsurance, and one of the methods to overcome underinsurance is to increase the life insurance penetration rate. Hence, various measures must be considered to increase the penetration rate or to attract potential policyholders. One of the initiatives is to classify which one is the potential life insurance purchaser. Data mining techniques are commonly used to discover intriguing patterns in datasets and deliver future helpful information. Different data mining methods work well for classifying customers as potential or non-potential customers.

This study focuses on life insurance ownership in Malaysia, with the status of life insurance purchase as the main observation and Malaysian sociodemographic status as the

determinant. Hence, this article uses a data mining approach to classify customers based on their attributes to predict the class label for future customers, whether the potential customers will purchase a life insurance policy or not. This article's findings will redound to society's benefit, considering that insurance protection is vital to families' sustainability and financial health. It may assist insurance companies in better improving their underwriting process in selecting potential purchasers. Besides that, observing the descriptive analysis of the sociodemographic information of the respondents may provide a better overview of the Malaysian target market accordingly, which may increase the country's life insurance penetration rate. Apart from that, in machine learning and data mining, imbalanced datasets are a constant worry because they make it difficult for machine learning algorithms to efficiently learn minority classes. Hence, this study will also provide insight into the prediction with different sampling and ensemble methods throughout the classification process using data mining techniques because the dataset is imbalanced on a particular class label.

2. Related Work

2.1. The Life Insurance Ownership

For the past decade, a range of demographic factors, including age, gender, marital status, education level, number of dependents, ethnicity, and income, have been the subject of previous studies to determine whether they are significantly related to the decision to purchase (own) life insurance. Few cross-sectional studies have used the decision to buy or not to buy a life insurance policy as a proxy for life insurance demand. Life insurance ownership, the amount of life insurance coverage, the face value, the amount of life insurance premium paid, and the intention to purchase were the primary decision factors employed to estimate the purchasing behavior for life insurance [8]. Meanwhile, age groups, risk aversion, ethnicity, income, education, occupation, and marital status are significant predictors of life insurance in Malaysia. Additionally, to examine the determinants of life insurance demand among married couples in Malaysia, marital status, age, education, ethnicity, and family income are among the significant predictors of life insurance demand [9]. Grabova & Sharku, (2021) found that changes in the urban population, education level, and age dependency ratio statistically impact life insurance density. The penetration rate, however, does not appear to be affected by education level [10].

Several studies have investigated the determinants of life insurance ownership using various methods. A hurdle count-data model is one of the methods used to investigate the factors influencing Malaysians' life insurance consumption [11]. In 2014, Ref. [12] employed Cragg's two-part regression model to investigate the sociodemographic factors of household expenditures on life insurance in Malaysia. The study suggested that across ethnic groups, wealth and education levels are correlated with purchase probabilities and the amount of life insurance premiums purchased. However, only within ethnic groups are household size, geographical location, urbanicity, and employment type associated with life insurance demand. Besides that, a Logistic Regression model was used to study the behavior of life insurance purchase decisions among the Indian population. It found that financial circumstances were the most significant determinant of whether a household would purchase insurance or discontinue coverage [13]. Among the demographic factors, family size, gender, and the household head's education level impacted the likelihood of obtaining or surrendering insurance. Another popular method used by previous researchers is the econometric modeling such as [14,15] with the focus population in Brazil, Russia, India, China, and South Africa (BRICS countries), and the Czech Republic, Hungary, Poland, and Slovak Republic (V4 countries), respectively.

In recent years, machine learning has been proposed as an alternative method in life insurance studies, and it was one of the most trending topics in 2021 [16]. Most of the machine learning research that previous researchers have conducted focuses on life insurance lapse and non-life insurance [17,18].

2.2. Data Mining

There are quite a number of studies with data mining applications in classifying customers, and in this context, insurance customers. Data mining techniques were used by Yan and Xie [19] to study Chinese insurance firms. They suggested classifying data using decision trees and applying data mining to the CRM (Client Relation Management) methodology as well as for risk management. The requirement for insurance firms to operate a sizable data centre or warehouse to store information effectively was also noted.

Next, Thakur and Sing [20] employed a classification approach based on decision trees to create a prediction system based on customer data. They trained data on people who purchased auto insurance online and classified new clients for their interest in online insurance based on the characteristics of the customers. The accuracy and error rate of the classifiers were assessed. The primary goal was to classify customers according to their age, educational level, and the sort of car they drive. As a result, they created a system that offered all the information required for auto insurance online.

Besides that, a study with an imbalanced dataset showed that balancing improved performance significantly. Rahman et al. [20] stated that their objective is to identify a classifier that can distinguish between a regular client of an insurance company and a non-regular customer. They additionally apply balancing algorithms in order to balance the data. The general class mostly favors classification when balancing procedures are not used. However, after balancing, the outcomes obtained were reasonably satisfactory.

2.3. Life Insurance and Machine Learning

To date, numerous kinds of research have been conducted employing a machine learning approach using life insurance data. One of the most interesting research topics is customer behavior. According to Russell Higginbotham, CEO of Reinsurance Asia, understanding human behavior and how people choose insurance is a crucial first step in effectively addressing the policyholder protection gap [3]. Following this statement, the research presents the segmentation and classification technique for the insurance industry via data mining approaches, K-Modes Clustering, and Decision Tree Classifier. They concluded, using data mining approaches, that segmenting customers may be accomplished. The results of consumer segmentation have been improved by implementing both clustering and classification algorithms [21]. Recent research by Pereira, K. et al. [22] stated that the predictive ability of machine learning models may be hindered by privacy-preserving techniques and proved that discretization and encryption, two privacy-preserving methods, affect the accuracy of machine learning models using life insurance data.

Not only that, in 2021, a group of researchers carried out a study to discover significant and influencing variables for claim submission and approval through Exploratory Data Analysis (EDA) and feature selection methodologies using machine learning. The authors used Kaggle.com and Github.com as a means of obtaining the dataset. The study concluded that Random Forest is the most effective classifier with appropriate feature selection techniques. The Logistic Regression and Bernoulli NB classifiers outperformed all others for the first and second datasets. Furthermore, despite the Chi-Squared Test being a filter technique that only chooses features based on their connection with one another based on their frequency distribution, the KNN classifier has outperformed it in both datasets [23]. Apart from that, there was a study by Kaushik et al. [24] comparing the Artificial Neural Network (ANN) and linear regression model in predicting health insurance premiums with various parameters, such as age, gender, body mass index, number of children, and smoking habits, taken into consideration. The ANN was found to outperform the linear regression model in all performance metrics used.

2.4. Sampling for Imbalanced Dataset

Data mining has been widely used to predict binary target datasets. It includes predicting the churn of bank customers (churn vs. not churn), purchase decisions (purchase vs. not purchase), and patients diagnosed with certain diseases (yes vs. no). However, a

two-class dataset is often considered imbalanced (or skewed) when the minority class is significantly underrepresented in contrast to the dominant class. In machine learning and data mining, imbalanced datasets are a constant worry because they make it difficult for machine learning algorithms to learn minority classes efficiently [25]. Hence, the researcher should consider balancing the two-class data with trained data to avoid misrepresenting the minority class.

One method is to replicate the cases of the minority class using an oversampling method, such as the Synthetic Minority Over-sampling Technique (SMOTE), to obtain an equitable distribution [26]. Data balancing using the SMOTE algorithm was the most effective [27]. Another resampling method that previous researchers have widely used is Randomly Under-Sampling (RUS), which reduces the frequency of the majority class in the training set [28]. However, too much data removal may result in the prediction model training with inadequate data and poor performance [25,27]. However, [29] suggested that the effectiveness of balancing techniques varies widely depending on the classifier and feature set being used, and not all balancing strategies operate similarly. Depending on whether one balancing improves or weakens the classifier.

2.5. Ensemble Approaches (Bagging and Boosting)

Boosting is a popular machine-learning ensemble method that combines numerous models to obtain a powerful model. It completes this task by integrating a series of learning models that have been trained consecutively based on identified errors in learning models. The AdaBoost algorithm, a boosting method included in RapidMiner, creates a group of classifiers before applying voting logic, similar to Bagging. The AdaBoost develops classifiers consecutively and modifies the weights of the training cases based on the preceding classifiers, in contrast to Bagging, which builds the classifiers independently [30]. The primary aim of using AdaBoost is to demonstrate how well decision-making models perform and how accurate they are when using boosted methods versus those without boosted approaches.

Next, the bagging technique is based on the majority voting approach and builds base classifiers concurrently on several bootstrap subsets of the training dataset. This ensemble approach was chosen primarily to improve the performance of the classification model. Like boosting, bagging is a meta-algorithm renowned for its capacity to aggregate data [31]. Splitting the datasets primarily aims to build numerous models, which will be combined to form a powerful learner.

Vafeiadis et al. applied boosting in a customer churn prediction to improve a classifier's respective F-measure in assessing performance [32]. The weak classifiers are concatenated as subroutines to create an incredibly accurate classifier in the train set. They found that the Artificial Neural Network, Decision Tree, and Support Vector Machine with boosting ensemble improved accuracy and F-measure. Meanwhile, Wang et al. stated that model accuracy and false negative rate measurements could be improved by applying the ensemble method, and boosting has a more significant impact than bagging [33]. The application of these ensemble techniques is further explained in the next section.

3. Materials and Method

Data mining methods have been used extensively for solving the classification of customers, patients, or any predictive model, especially for an extensive dataset. Bhatia et al. studied consumer life insurance purchasing behavior and stated that researchers could apply advanced supervised and unsupervised machine learning and Artificial Neural Network methods [8]. Meanwhile, previous studies recommend employing alternative classification methods such as Random Forest, Naive Bayes, or even Artificial Neural Networks for consumer segmentation and profiling [21]. This paper will use five classification models: Decision Tree, Logistic Regression, Naïve Bayes, Random Forest, and Artificial Neural Network.

A Decision Tree is a classification algorithm with tree-based structure to classify data by splitting them. The primary goal of data splitting is to discover common dataset behavior, which also aids in measuring prediction accuracy. This approach builds and trains a classification tree with leaf nodes and decision nodes based on logical principles [31]. Logistic Regression is a classification technique using machine learning with binary dependent variables. In this approach, a logistic function is used to characterize the probabilities that describe the possible outcomes of a single experiment [34]. Meanwhile, the Naïve Bayes algorithm determines the probability for each class using several independent input variables and the Bayesian theorem [31].

On the other hand, Random Forest is a supervised learning approach that can handle classification and regression-related problems. It makes decisions by creating many trees, or a forest, to act as a collective. As an ensemble approach, Random Forest combines and associates several decision trees with a single basic learner model [31]. Next, Artificial Neural Network (ANN) is a mathematical or computer model based on biological neural networks. It processes information using a connectionist computation method and comprises a network of artificial neurons. An ANN is often an adaptive system that modifies internal or external information throughout the learning phase to affect how it is structured [35].

Table 1 presents several advantages and disadvantages of the selected machine learning approach. It is noted that every model shown has its pros and cons. However, these models are chosen due to the strength and recommendation of previous studies.

Table 1. The advantages and disadvantages of selected machine learning models.

Models	Advantages	Disadvantages
Decision Tree	1. The decision rules are simple to understand [34,36]. 2. Nonparametric, therefore, there is no requirement to use unimodal training data, and it is simple to add a variety of numeric or categorical data layers [36]. 3. Robust concerning training data outliers [36].	1. Decision trees frequently overfit training data, producing poor outcomes when used with the entire dataset [34,36]. 2. Predictions beyond the response variable's lowest and maximum limits in the training data are impossible [36]. 3. Prone to overfitting [36].
Logistic Regression	1. It was created for classification purposes, and its greatest use is in determining how various independent factors affect a single outcome variable [34].	1. Works only if the predicted variable is binary [34]. 2. Assumes all predictors are independent and data are free from missing values [34].
Naïve Bayes	1. Training and classification can be accomplished with one pass over the data [34]. 2. Perform effectively in various real-world circumstances, including spam filtering and document classification [34,37]. 3. Extremely rapid as compared to more advanced techniques [34].	1. Known to be a bad estimator [34]. 2. Extremely strong assumption of independence that it makes. Finding such datasets in the actual world is quite difficult [37].
Random Forest	1. Provide accurate predictions for many applications [34,36]. 2. Concerning the training dataset, it can measure the importance of each feature [36].	1. Biased for attributes with a different number of levels [36]. 2. For binary variables, smaller groups are favored over larger groups if the data contain groups of correlated features [36]. 3. A difficult technique and slow in real-time prediction [34].

Table 1. *Cont.*

Models	Advantages	Disadvantages
Artificial Neural Network	1. Able to approximate complex non-linear mapping [35]. 2. Flexible to incomplete and noisy data [35]. 3. Do not make prior assumptions about the data distribution [35]. 4. Overcome some limitations of other statistical methods while generalizing them [35].	1. The selection of the hidden nodes and training parameters is a heuristic [35]. 2. Estimating the network weights can be very computationally intensive because it requires large data [35]. 3. Useless to generalize new data if too many weights are used without regularization [35]. 4. Confidence interval and hypothesis testing are unavailable, lacking classical statistical properties [35].

Data mining involves six major steps, from data collection to model deployment.

Step 1: Data Acquisition—This study used the 2019 Malaysian Household Survey from the Department of Statistics, Malaysia (DOSM). The objective of this study is to predict whether individuals purchase life insurance, where the target attribute of Life Insurance Ownership can be No or Yes. A No means the head of household did not purchase a life insurance policy, and a Yes implies purchasing a life insurance policy. This prediction fits within the scope of classification problems. It will help to understand whether having a life insurance policy may or may not be related to income category and life expectancy. Suppose this connection is verified at the end of this study, measures may be taken by the competent entities so that the correct target customers can be identified for a life insurance policy.

Step 2: Data Understanding—This step begins with identifying the type of data using either quantitative or qualitative and determining the data measurement level used (nominal, ordinal, interval, and ratio). The data comprised 12 inputs with life insurance ownership status as the target of the study, which is presented in Table 2. The original income attribute is in the exact values; hence, this attribute has been categorized into three income categories (bottom 40%, B40, middle 40%, M40, and top 20%, T20). This is because the government frequently provides incentives or fund assistance based on the income category instead of exact values in Malaysia. Besides that, age has been grouped into two classes: non-prime working and prime working. Prime working age is assigned to those between 25 and 54.

Table 2. Description of variables.

Attributes	Measurement Level	Category	Description	Frequency	Percentage (%)
Life Insurance Ownership	Binary	Yes	HH has purchased a life insurance policy	12,947	90.73
		No	HH has not purchased a life insurance policy	1323	9.27
Gender	Binary	Male	HH is male	11,856	83.08
		Female	HH is a female	2414	16.92
Age	Binary	1	Non-prime working age	3408	23.88
		2	Prime working age (25–54)	10,862	76.12
Income category (IC)	Nominal	B40	Household income is in the bottom 40% category *	5904	41.37
		M40	Household income is in the middle 40% category *	5880	41.21
		T20	Household income is in the top 20% category *	2486	17.42
Expenditure	Interval	-	Household expenditure per month in Ringgit Malaysia	-	-

Table 2. *Cont.*

Attributes	Measurement Level	Category	Description	Frequency	Percentage (%)
Household Number (HN)	Interval	-	Number of family members in the household	-	-
Metropolitan Status (MS)	Nominal	Non-Metropolitan	Residing in the non-metropolitan West Malaysian	6732	47.18
		East Malaysia	Residing in the East Malaysian	4208	29.49
		Metropolitan	Residing in the metropolitan West Malaysian	3330	23.34
Strata	Binary	Urban	Residing in an urban area	10,889	76.31
		Rural	Residing in a rural area	3381	23.69
Ethnicity	Nominal	Bumiputera	Bumiputera	9609	67.34
		Chinese	Chinese	3125	21.90
		Indian	Indian	898	6.29
		Others	Others	638	4.47
Marital Status (MS)	Nominal	Married	Married	10,738	75.25
		Others	Others	3532	24.75
Education Level (EL)	Nominal	Tertiary	HH's highest level of education is a tertiary level	10,259	71.89
		Others	HH's highest level of education is other than tertiary	4011	28.11
Employment Status (ES)	Binary	Employed	HH is employed	13,426	94.09
		Unemployed	HH is unemployed	844	5.91
Collar Status (CS)	Binary	White-collar	HH has white-collar occupations (e.g., legislators, senior officials, managers, professionals);	8149	57.11
		Non-White collar	HH has a non-white-collar occupation	6121	42.89

Note 1. HH = Head of the household. Note 2. * DOSM classification of the income category.

Step 3: Data Preparation—The analysis will be performed using RapidMiner Studio Educational 9.10.011 (RM). The data preparation step covers all data preparation activities, such as cleaning, transformation, and modifying before modeling. These tasks include choosing which data should be included or excluded, considering the possibility of adding new attributes or changing those that already exist, and data cleaning [38]. The dataset comprised 16,354 household data. However, only 14,270 data have been considered for further analysis considering that the labor force age in Malaysia is between 15 to 64 years old. Hence, any household age outside the range will be removed. Since the dataset is too large to run the outlier detection using RapidMiner, the outlier is run using SPSS by calculating the Mahalanobis distance. Any p-value less than 0.001 is considered an outlier; hence, it is removed to produce a stable parameter. After removing the outlier, the total dataset used is 14,270. An overview of all the acronyms and their definitions is provided in Table 3.

Table 3. List of acronyms used.

Acronyms	Definitions
DT	Decision Tree
LR	Logistic Regression
NB	Naïve Bayes
RF	Random Forest
NN	Neural Network
k-NN	k-Nearest Neighbours
SMOTE	Synthetic Minority Oversampling Technique
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
ROC	Receiver Operating Characteristics
RUS	Random Under-Sampling

As shown in Figure 2, the label attribute was not balanced. Therefore, it was necessary to use the pre-processing method to avoid any misrepresentation of the minority class. In this paper, we split the dataset using 5-k fold cross-validation. Pre-processing sampling techniques, such as under- and over-sampling, were only used on the training set. SMOTE operator was the oversampling technique used. When creating synthetic samples for the dataset, SMOTE employs the k-NN approach by choosing the k nearest neighbors from sample data and connecting them. SMOTE may help the majority–minority class border become distinguishable since it solely relies on minority class observation. After the SMOTE process, the class label became balanced with Yes = 12,947 and No = 12,947. For RUS techniques, the operator Sample has been used with three different ratios; 1:1 (No = 1323, Yes = 1323), 2:1 (No = 2646, Yes = 1323), and 3:1 (No = 3969, Yes = 1323).

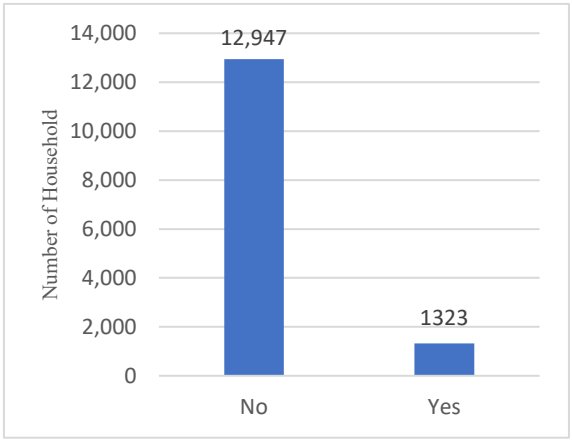


Figure 2. Life insurance ownership distribution (target).

Step 4: Modelling—In this stage, five predictive models are used to predict whether the customer will purchase a life insurance policy. The classifiers include DT, LR, NB, RF, and ANN. Classifiers are chosen based on a literature review from past studies on data mining models and the five best models in ROC evaluation. In this paper, we propose to compare the full model without any sampling process with the models that have undergone resampling and ensembled process as follows; (i) five classifiers with different sampling techniques, (ii) classifiers with bagging ensemble learning method, and (iii) classifiers with boosting ensemble method.

There are two stages in predictive modeling for life insurance ownership. Figure 3 illustrates the user interface of life insurance ownership modeling without the ensemble learning method used in this study. Many copies of the data were produced in the initial stage because the dataset needed to be connected with multiple classifiers. A 5-fold cross-validation strategy was also used to apply the model. The data file is called in the first interface, and the attributes are selected based on the explained attributes in Tables 2 and 3. Next, the cross-validation operator with 5-fold validation is used. The "Cross Validation" operator, sometimes called a nested operator in RM, comprises the training and testing subprocesses. The dataset for this cross-validation process was divided into K (number of fold) subsets. Each iteration used one subset for testing, and the remaining dataset divisions were used for training. As the testing dataset was unseen, applying the model's training and validation in one procedure was considered a fair test.

Next, the data are divided into training and testing inside the cross-validation operator. The input port (on the left) received the training dataset and connected with the DT, as shown in the figure. After the learning phase, the trained model was sent to the testing phase, where testing data were used to apply the testing procedure further. Finally, the model was verified using the "Apply Model" operator, which was connected to the "Performance" operator to help measure various characteristics of the classification model. Various parameters can be chosen for each of the classifiers in the RM. Hence, the

authors experimented with various parameter combinations throughout implementation to evaluate the models' performance. Then, the parameters with the highest accuracy are chosen. Similar to Figure 3, other classifiers with different sampling techniques adhere to the same process.

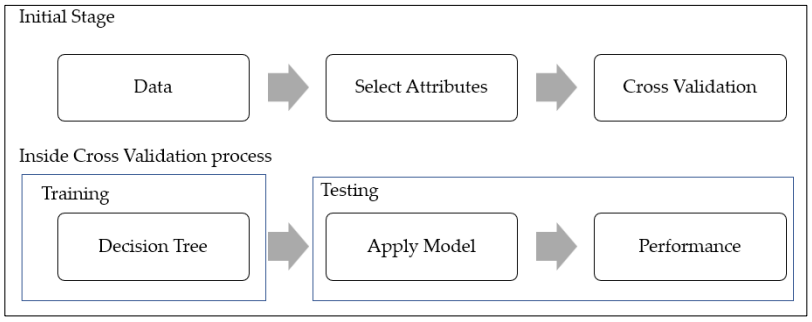


Figure 3. The RapidMiner's user interface of life insurance ownership modeling without ensemble learning method.

Meanwhile, the ensemble learning method is divided into three stages: (i) the initial stage, (ii) inside the cross-validation process, and (iii) inside the bagging/boosting process. Bagging and boosting (AdaBoost) were used as the ensemble learning method to see the differences in the performance metrics for each classifier. Figures 4 and 5 demonstrate the implementation of bagging and boosting in the ensemble learning method. As for bagging, enhancing the performance of the classification model is the key motivation behind choosing this ensemble method [31]. A meta-algorithm known as bagging is renowned for its aggregation capabilities. The working scenario for this technique is based on bootstrapping, which separates the original dataset into numerous training datasets known as bootstraps. The datasets were divided to develop numerous models, which will eventually be combined to produce a powerful learner. The sub-process of this operator, which will use various learner models, is known as a nested operator.

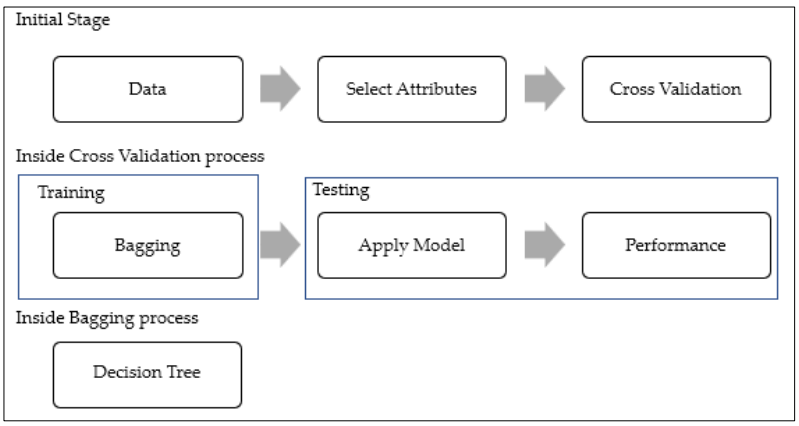


Figure 4. The RapidMiner's user interface of the life insurance modeling with bagging ensemble learning method.

Boosting is a popular ensemble strategy in machine learning that combines numerous models to obtain a robust model. It achieves this goal by merely training several learning models consecutively, then combining them based on discovered learning model errors. Besides that, according to research by Nazemi et al., boosting is helpful in reducing bias and variance [39]. One of the boosting algorithms that can be used with other learning algorithms is called AdaBoost, which stands for adaptive boosting [31]. The meta-algorithm used to implement AdaBoost in the RM tool can run the process by adding another algorithm as a sub-process. After running and training numerous models, it combines weak

learners to form a single strong learner, adding extra calculation and running time. In this study, the classification model is trained using AdaBoost's ensemble method that combines five additional algorithms as sub-processes. The primary goal of using AdaBoost is to compare decision-making models with and without boosted approaches in terms of performance and accuracy. The results and discussion section examines the model's overall performance. Similar to Figures 4 and 5, other classifiers with different sampling techniques follow the same process.

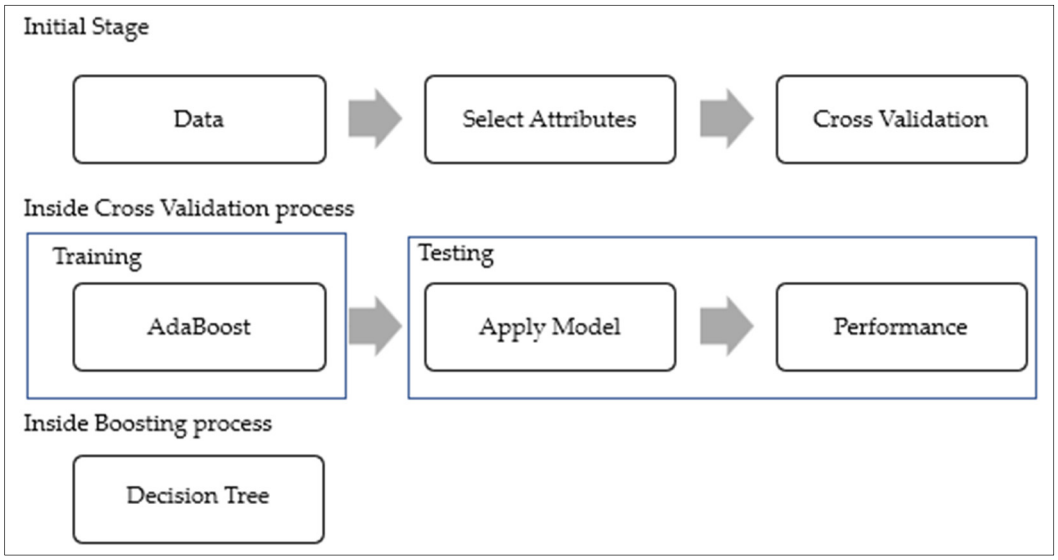


Figure 5. The RapidMiner's user interface of the life insurance ownership modeling with boosting ensemble learning method.

Step 5: Model Assessment and Comparison—In the final phase, it is necessary to evaluate the results and review the steps performed in detail [38]. The performance of each tested model was assessed using the confusion matrix, which includes the number of TP, FP, TN, and FN. The accuracy, precision, and recall measures can be calculated using these parameters. Accuracy measures the model's ability to capture true positives as being positive and true negatives as being negatives. Precision is calculated by dividing the true positives by anything predicted as a positive. In contrast, Recall is calculated by dividing the true positives by anything that should have been predicted as positive. The formulas for the performance metrics used in our analysis are shown in Table 4.

Table 4. Performance metrics used.

Symbol	Metric	Formula
ACC	Accuracy	$(TP + TN)/(TP + TN + FP + FN)$
BA	Balanced Accuracy	$(TPR + TNR)/2$
GM	Geometric Mean	$(TPR + TNR)^{1/2}$
F_1	F_1-score	$2 \times (Recall \times Precision)/(Recall + Precision)$
AUC	Area Under the ROC Curve	Plotted with TPR against the FPR

Note 1. TPR = sensitivity, TNR = specificity, FPR = false negative rate.

The tools from which various accuracy measures are derived include an ROC chart and statistics such as accuracy, F_1-score, and ROC index. Tékouabou, Alaoui, et al. (2022) [40] state that the F_1-score balances recall and precision (also known as sensitivity), accounting for both minority and majority classes. Hence, it is one of the good indicators for choosing the best model for classification problems. Other useful metrics are BA and GM. BA is the average of the two rates for accurately classifying positive and negative events. Contrary to accuracy, the BA is strong for evaluating classifiers on imbalanced datasets [41]. GM is also an effective indicator for imbalanced data classification binary problems.

4. Discussion

This section will further discuss the result and analysis by describing the nature of the dataset, followed by the best model comparison.

4.1. Descriptive Analysis

As presented in Table 2, the average age for households involved in this dataset is 44.04. Most of the respondents are male (83.08%), as most of the heads of households in Malaysia are male. The income category was dominated by the B40 category, with 41.37%, followed by M40 (41.21%) and T20 (17.42%). More than half of the households are Bumiputera (67.34%), followed by Chinese (21.90%) and Indian (6.29%). Most families (47.18%) reside in a non-metropolitan area, and only 23.34% reside in a metropolitan area. Meanwhile, 29.49% live in East Malaysia. Besides that, only 4011 (28.11%) households have other than tertiary as the highest level of education, which concludes that the majority of the households taking part in this survey have tertiary as their highest level of education. Besides that, 57.11% of the households work in a white-collar industry. The prime age group (age 25 to 54), also known as the active working age group, appears to dominate, with 76.12%.

Table 5 shows the interval input summary. The average monthly household expenditure is RM 4187.44, with a minimum spending of RM 472.14. This shows that the average household in Malaysia falls in the B40 category. Meanwhile, most of the respondents have three members in a household.

Table 5. Interval input summary.

Attribute	Missing	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Expenditure	0	4187.442	2450.359	472.14	17978.06	1.642446	3.713083
Number of Households	0	3.668325	1.289895	1	5	−0.53572	−0.91988

Figure 6 presents an overview of categorical attributes and perhaps indicators of the factors that should be paid particular attention to in determining life insurance ownership. The bar chart in Figure 6a demonstrates that those with tertiary education are more likely to own a life insurance policy than others. In contrast, Figure 6b shows that Chinese and Indian individuals outnumber Bumiputera individuals in life ownership status. Even though Bumiputera participants outnumber other ethnicities in this survey, as shown in Table 2, they do not contribute to the high percentage of life insurance ownership. It may be an indicator that Chinese and Indian individuals have more interest in owning a life insurance policy compared to Bumiputera. Figure 6c indicates that four times as many households in the highest 20% income levels will purchase life insurance policies as in the bottom 40%. The household in Figure 6d in a metropolitan area is likelier to have a life insurance policy than in a non-metropolitan location and East Malaysia.

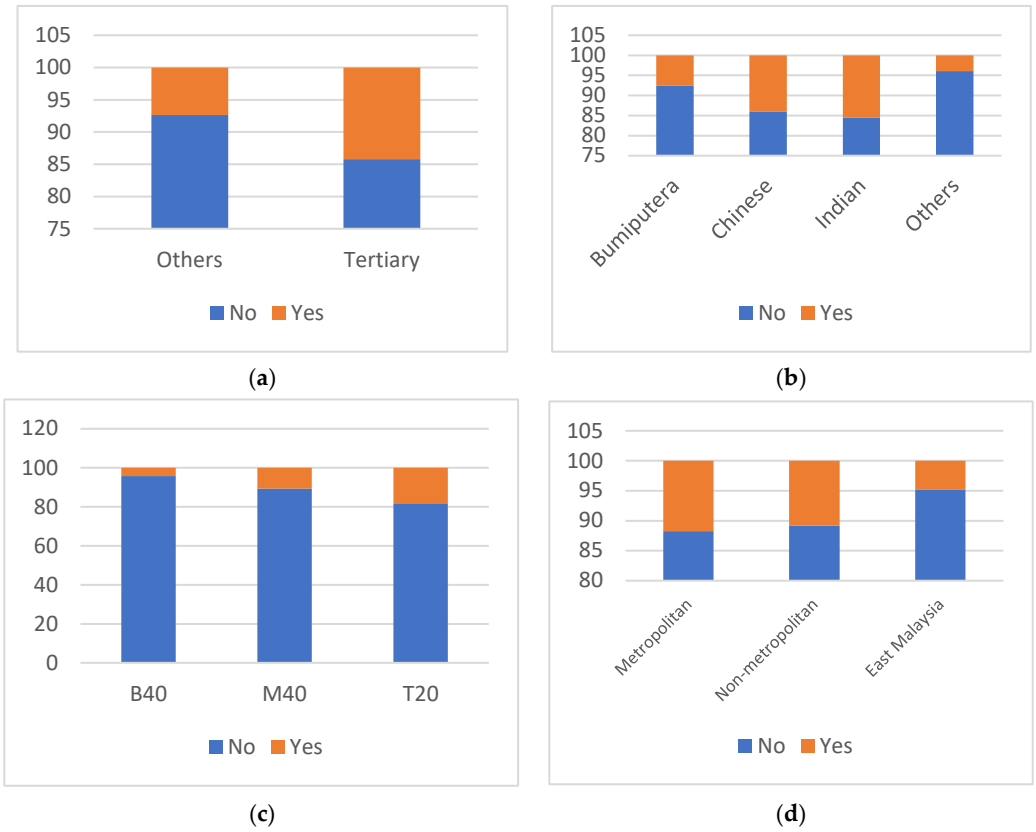


Figure 6. Percentages of life insurance ownership by (**a**) Education, (**b**) Ethnicity, (**c**) Income Category, and (**d**) Metropolitan Status.

4.2. Best Model Comparison

The area under the ROC curve is frequently used to evaluate the accuracy of classification models. A good model's range value area under the curve (AUC) should be between 0.5 and 1. A greater AUC value will result in a more accurate model [18]. The classification classifiers used for the Compare ROCs were DT, NB, LR, RF, and ANN, using the whole dataset without modifying the data and sampling technique. This is to give an early overview of the performance of the model. The model accurately predicted the data if the curves' climbed rapidly to the top-right [42]. Figure 7 presents each model's ROC charts, showing that all models have almost the same performance except for the decision tree model. Based on Figure 7, it is recommended that if the researcher would like to use the whole dataset without considering the imbalanced data, then the decision tree would be the best classifier to use.

The summaries of the model comparison based on accuracy and balanced accuracy are presented in Tables 6 and 7, respectively. It is shown that the bigger the difference between class labels, the more significantly the accuracy increased. This is due to there being too few data points for the model to learn from; the model tends to be biased towards the majority class and would be unable to identify fraud in the majority class. Classifiers with no sampling applied have the highest accuracy, the lowest at 86.06% and the highest at 90.66%, and classifiers with SMOTE have the lowest accuracy, ranging from 65.21% to 72.45%. Based on the accuracy, LR outperformed other classifiers with high accuracy rates for all the classifiers with different sampling and ensemble methods.

Meanwhile, NN has the highest accuracy rate in the SMOTE dataset, with and without the ensemble method. However, by looking at the balanced accuracy performance, NB showed the best model for an imbalanced dataset. Meanwhile, for the balanced dataset, RUS ratio 1:1 and SMOTE, LR showed the highest rate, with LR-SMOTE and LR + bagging SMOTE having slightly higher accuracy rates than other classifiers.

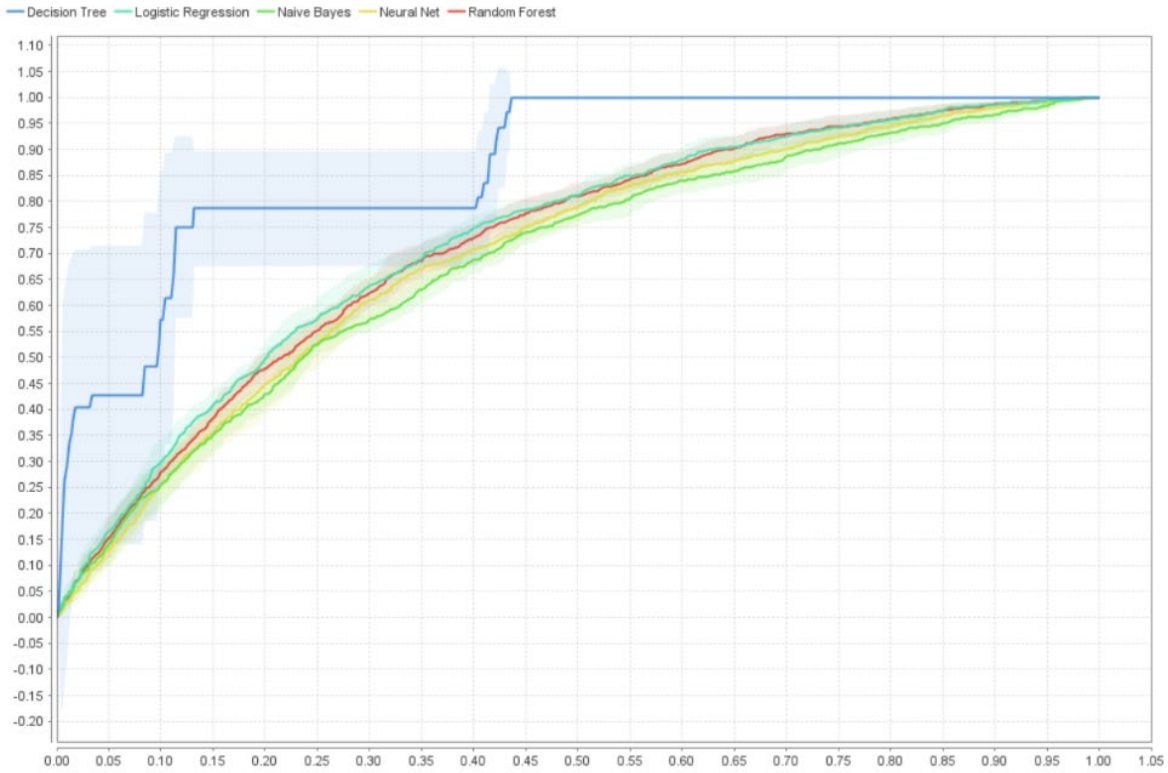


Figure 7. ROC charts for model comparison without ensemble and sampling.

Table 6. Model's accuracy comparison between different sampling and ensemble methods.

Model	No Sampling (Ratio 9:1)	RUS (Ratio 3:1)	RUS (Ratio 2:1)	RUS (Ratio 1:1)	SMOTE
DT	89.44%	86.09%	81.13%	66.90%	65.21%
LR	90.66%	89.21%	86.26%	73.40%	66.32%
NB	86.13%	81.18%	78.37%	71.16%	66.70%
RF	90.50%	88.35%	82.93%	68.19%	69.19%
NN	90.50%	85.96%	79.60%	68.40%	69.75%
DT + Bagging	89.49%	86.59%	81.42%	67.34%	66.38%
LR + Bagging	90.65%	89.26%	86.21%	73.57%	66.36%
NB + Bagging	86.06%	81.21%	78.38%	71.17%	66.67%
RF + Bagging	90.64%	88.82%	84.37%	69.60%	69.57%
NN + Bagging	90.59%	87.43%	82.21%	68.56%	72.45%
DT + Boosting	89.44%	86.09%	81.13%	66.90%	65.21%
LR + Boosting	90.66%	89.21%	86.26%	73.40%	66.32%
NB + Boosting	88.85%	84.27%	79.13%	71.66%	66.29%
RF + Boosting	90.50%	88.35%	82.92%	68.19%	69.19%
NN + Boosting	90.24%	84.82%	79.21%	67.30%	71.75%

Table 8 represents the AUC index for all classifiers. LR showed consistent performances for all the models except classifiers with boosting ensemble. NB + boosting has the highest AUC (0.701) in RUS 1:1; other AUCs in boosting ensemble showed values less than 0.700. It can be observed that the AUC value for LR and LR + bagging and NB and NB + bagging has the same performance. The other models showed different values for the model without ensemble and the model with bagging ensemble.

Table 7. Model's balanced accuracy comparison.

Model	No Sampling (Ratio 9:1)	RUS (Ratio 3:1)	RUS (Ratio 2:1)	RUS (Ratio 1:1)	SMOTE
DT	50.79%	53.15%	57.02%	61.81%	64.24%
LR	50.13%	53.61%	57.99%	66.27%	67.02%
NB	57.00%	60.14%	61.81%	64.66%	64.96%
RF	50.42%	53.47%	56.32%	64.25%	64.63%
NN	50.31%	54.81%	60.46%	64.13%	64.47%
DT + Bagging	50.78%	52.98%	56.95%	62.66%	63.94%
LR + Bagging	50.13%	53.77%	57.86%	66.19%	66.97%
NB + Bagging	57.00%	60.19%	61.93%	64.64%	64.90%
RF + Bagging	50.36%	52.55%	56.68%	64.89%	65.21%
NN + Bagging	50.13%	53.75%	59.15%	64.96%	65.31%
DT + Boosting	50.79%	53.15%	57.02%	61.81%	64.24%
LR + Boosting	50.13%	53.61%	57.99%	66.27%	67.02%
NB + Boosting	52.15%	57.19%	61.56%	65.38%	66.39%
RF + Boosting	50.42%	53.47%	56.32%	64.25%	64.63%
NN + Boosting	50.45%	56.04%	59.19%	63.55%	63.06%

Table 8. Model's AUC index comparison.

Model	No Sampling (Ratio 9:1)	RUS (Ratio 3:1)	RUS (Ratio 2:1)	RUS (Ratio 1:1)	SMOTE
DT	0.672	0.660	0.640	0.621	0.661
LR	0.728	0.727	0.727	0.727	0.727
NB	0.708	0.708	0.708	0.707	0.706
RF	0.691	0.692	0.688	0.694	0.705
NN	0.704	0.698	0.686	0.683	0.691
DT + Bagging	0.678	0.673	0.672	0.662	0.675
LR + Bagging	0.728	0.727	0.727	0.727	0.727
NB + Bagging	0.708	0.708	0.708	0.707	0.706
RF + Bagging	0.699	0.704	0.705	0.710	0.709
NN + Bagging	0.723	0.714	0.713	0.704	0.710
DT + Boosting	0.510	0.548	0.619	0.667	0.676
LR + Boosting	0.693	0.662	0.660	0.674	0.690
NB + Boosting	0.668	0.684	0.678	0.701	0.699
RF + Boosting	0.506	0.550	0.599	0.682	0.671
NN + Boosting	0.681	0.672	0.668	0.674	0.670

In comparing the models with imbalanced datasets, F_1 is also a good indicator, as presented in Table 9. F_1 values showed that for a balanced dataset RUS ratio 1:1, LR + bagging is the best model, with a slightly higher performance, 0.2865, than LR + boosting and LR (0.2863 each, respectively). F_1 values enable a model to be evaluated using a single score that accounts for precision and recall, which is useful when reporting model performance and comparing models.

Table 10 presents the GM values for all the models. Balanced datasets (SMOTE and RUS 1:1) performed better than the imbalanced dataset, with LR outperforming other models. Meanwhile, as shown in the table, the NB model outperformed the imbalanced dataset. GM is a metric that compares the classification performance of the majority and minority classes. A low GM indicates poor performance in categorizing positive cases, even if negative cases are successfully classified. LR and LR + boosting showed the same and highest GM performance of 0.6701, followed by LR + bagging, 0.6697.

Table 9. Model's F1-score comparison.

Model	No Sampling (Ratio 9:1)	RUS (Ratio 3:1)	RUS (Ratio 2:1)	RUS (Ratio 1:1)	SMOTE
DT	0.0551	0.1447	0.2125	0.2370	0.2515
LR	0.0074	0.1432	0.2382	0.2863	0.2722
NB	0.2212	0.2525	0.2642	0.2672	0.2592
RF	0.0230	0.1450	0.2039	0.2573	0.2618
NN	0.0188	0.1785	0.2509	0.2567	0.2626
DT + Bagging	0.0541	0.1396	0.2116	0.2441	0.2515
LR + Bagging	0.0074	0.1473	0.2358	0.2865	0.2719
NB + Bagging	0.2210	0.2532	0.2635	0.2671	0.2588
RF + Bagging	0.0177	0.1177	0.2113	0.2650	0.2669
NN + Bagging	0.0089	0.1541	0.2426	0.2632	0.2759
DT + Boosting	0.0551	0.1447	0.2125	0.2370	0.2515
LR + Boosting	0.0074	0.1432	0.2382	0.2863	0.2722
NB + Boosting	0.1048	0.2157	0.2620	0.2747	0.2682
RF + Boosting	0.0230	0.1450	0.2038	0.2572	0.2618
NN + Boosting	0.0292	0.2005	0.2354	0.2507	0.2558

Table 10. Model's GM comparison.

Model	No Sampling (Ratio 9:1)	RUS (Ratio 3:1)	RUS (Ratio 2:1)	RUS (Ratio 1:1)	SMOTE
DT	0.1809	0.3448	0.4874	0.6149	0.6423
LR	0.0616	0.3104	0.4645	0.6569	0.6701
NB	0.4439	0.5431	0.5837	0.6417	0.6492
RF	0.1098	0.3202	0.4588	0.6407	0.6438
NN	0.0988	0.3924	0.5570	0.6391	0.6414
DT + Bagging	0.1787	0.3323	0.4837	0.6240	0.6386
LR + Bagging	0.0616	0.3151	0.4621	0.6557	0.6697
NB + Bagging	0.4444	0.5438	0.5854	0.6413	0.6486
RF + Bagging	0.0953	0.2789	0.4534	0.6463	0.6499
NN + Bagging	0.0670	0.3433	0.5193	0.6481	0.6471
DT + Boosting	0.1809	0.3448	0.4874	0.6149	0.6423
LR + Boosting	0.0616	0.3104	0.4645	0.6569	0.6701
NB + Boosting	0.2627	0.4654	0.5765	0.6492	0.6639
RF + Boosting	0.1098	0.3202	0.4587	0.6406	0.6438
NN + Boosting	0.1257	0.4349	0.5384	0.6338	0.6214

The overall model performance comparisons of SMOTE models without the ensemble learning method are presented in Figure 8a. Figure 8b illustrates the best model comparison in SMOTE for classifiers with the bagging ensemble learning method. In contrast, Figure 8c shows the best model comparison in SMOTE for classifiers with the boosting ensemble learning method. It can be seen in Figure 8a–c that the LR performances showed slightly higher performances in most performance criteria. However, in Figure 8c, Naïve Bayes showed better performances in AUC for classifiers with boosting ensemble. Regardless of whether the dataset used ensemble and sampling techniques or not in this dataset, the F_1 scores showed almost the same performance, below 30%. The F_1 scores might improve if the variables undergo feature selection [29], which can be interesting in future research. The study found that the SMOTE will perform better after feature selection.

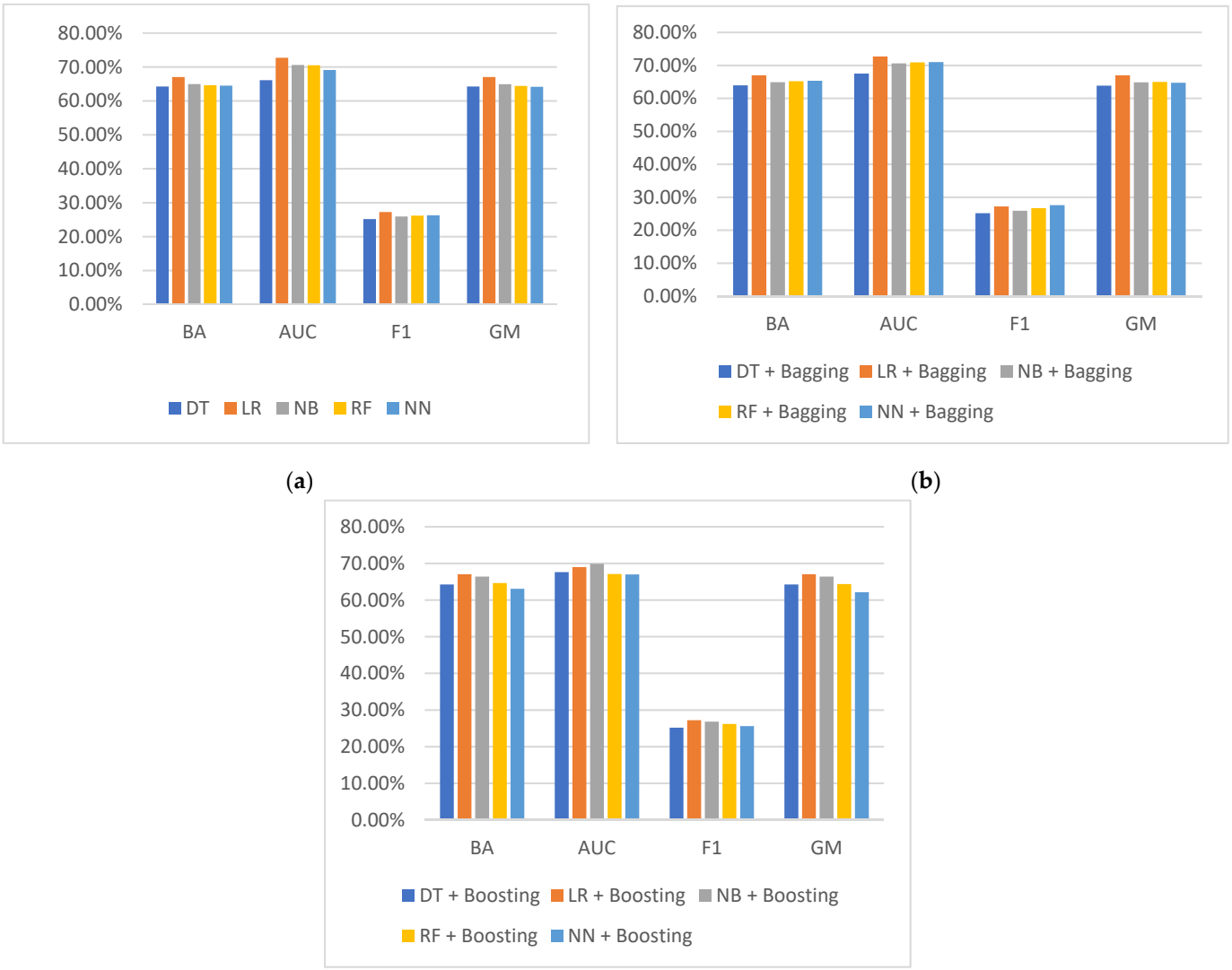


Figure 8. Best model comparison in SMOTE: (**a**) for classifiers without ensemble learning method, (**b**) for classifiers with bagging ensemble, and (**c**) for classifiers with boosting ensemble.

4.3. Model Scoring

Considering all the performance metrics above, it is quite debatable which model is the best. The decision will depend on what one believes it means to have better performance. Based on Figure 8, LR showed slightly higher performances in all performance metrics, except for AUC, with boosting. Hence, we illustrate the Logistic Regression model for predicting life insurance purchasers in the model scoring step. Model scoring is performed to assess the accuracy and efficiency of the chosen model. Another dataset is used for the model scoring purpose. The dataset is another form of secondary data obtained from a DOSM, Malaysian Household Survey. Output for model scoring is as tabulated in Table 11.

Table 11 displays that a customer will be predicted to purchase a life insurance policy when the predicted value of Y = Yes is more than and equal to 0.5 and is predicted not to purchase when the person has a predicted value of Y = No more than or equal to 0.5. The prediction for observations 4, 5, and 10 would be incorrect. Meanwhile, other observations correctly predicted not to purchase life insurance. Thus, the model accuracy is 70%, and the prediction error rate is 0.3 (30%). The formula for the LR model to predict the life insurance purchaser is given as follows:

$$\begin{aligned}\log \frac{p}{1-p} = \; & -0.347 + 0.4488\ (Income\ Category\ T20) + 0.5652\ (Income\ Category\ M40) - 0.5818\ (Metropolitan) \\ & -0.8716\ (East\ Malaysia) - 0.2099\ (Age\ Group1) - 0.3700\ (Rural) + 0.2199\ (Male) \\ & +0.2476\ (Unemployed) - 0.3214\ (Non - White\ Collar) - 0.2123\ (household) + 0.0002\ (expenditure)\end{aligned} \quad (1)$$

Table 11. Summary of model scoring.

No	Y Status	Predicted: Y = No	Predicted: Y = Yes	Prediction for Y
1	Yes	0.4988	0.5012	Yes
2	Yes	0.3004	0.6996	Yes
3	Yes	0.2971	0.7029	Yes
4	No	0.2691	0.7309	Yes
5	No	0.4774	0.5226	Yes
6	No	0.5804	0.4196	No
7	No	0.7665	0.2335	No
8	No	0.6339	0.3661	No
9	No	0.8418	0.1582	No
10	No	0.4208	0.5792	Yes

5. Conclusions

Based on the results obtained in Section 4, it can be concluded that the performances of all classifiers that have undergone a sampling method are almost identical. SMOTE has slightly higher performance in balanced accuracy, AUC index, and GM. Even though the accuracy of the original dataset with no sampling applied has the highest accuracy value, other performance measurements showed the lowest. Hence, the imbalanced dataset proved to be highly accurate but misrepresented the majority class. Logistic Regression showed consistent performance with or without ensembled (bagging and boosting) for SMOTE and RUS 1:1. Even though the LR model in RUS 1:1 showed the highest value in F_1 measures compared to other models, LR + SMOTE has been outperformed in most of the criteria. Hence, it can be concluded that SMOTE is the best sampling method [29], and it is pretty challenging to determine which model is the best to predict the potential life insurance purchasers in these data. Without feature selection in the dataset, LR has performed better, which is supported by Kaushik et al. [24] research. However, similar studies on classifying financial decisions show that nonlinear methods such as Neural Networks [24] and Random Forest [23] perform significantly better. Moreover, the analysis shows that the decision tree is the best performer according to ROC and, according to balanced accuracy, F1 score, and GM comparison, Naïve Bayes seems to be the best performer. Hence, the decision will depend on which performance criteria a researcher wishes to focus on.

By applying the ensembled method, we believe that it presented various performance comparisons. The performance of the ensembled models (bagging or boosting) significantly improves the models' performances. However, the performances differ from one model to another. Based on the results discussed in Section 4.2, the researchers should evaluate each model with different ensembled methods to determine which classifier and ensemble method is appropriate for the dataset being studied. The findings of this study will be beneficial to society since insurance protection is important to the sustainability and financial well-being of families. It may help the insurance business select potential buyers more effectively through a better underwriting process. Additionally, this study will shed light on the prediction using various sampling and ensemble approaches throughout the classification process employing data mining techniques with an imbalanced dataset.

Despite the beneficial findings, this study has been conducted based on this limitation. It does not consider feature selection, which may affect the study's outcome. Feature selection may provide a more thorough comparison, as it only considers the most significant attributes in the study. Perez et al. [29] stated that SMOTE performs better after applying feature selection. However, since this study aims to compare the different sampling and

ensemble methods on the imbalanced dataset, the feature selection criteria have been excluded from this study. Hence, we recommend that future research considers the feature selection for a better understanding and comparison. This study proposes an approach to determine the usefulness of various artificial intelligence approaches using machine learning to predict life insurance ownership. This approach may also be used in countries with roughly identical life insurance penetration rates. Further improvements may also be achieved by including more socioeconomic status parameters and economic factors.

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