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Telemarketing outcome prediction using an Ensemblebased machine learning technique

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Abstract

Business organisations often use telemarketing, which is a form of direct marketing strategy to reach a wide range of customers within a short time. However, such marketing strategies need to target an appropriate subset of customers to offer them products/services instead of contacting everyone as people often get annoyed and disengaged when they receive pre-emptive communication. Machine learning techniques can aid in this scenario to select customers who are likely to positively respond to a telemarketing campaign. Business organisations can use their CRM-based customer information and embed machine learning techniques in the data analysis process to develop an automated decision-making system, which can recommend the set of customers to be communicated. A few works in the literature have used machine learning techniques to predict the outcome of telemarketing, however, the majority of them used a single classifier algorithm or used only a balanced dataset. To address this issue, this article proposes an ensemble-based machine learning technique to predict the outcome of telemarking, which works well even with an imbalanced dataset and achieves 90.29% accuracy.

Keywords Telemarketing, data mining, machine learning, ensemble methods, stacking.

1 Introduction

Direct marketing has several definitions (Nash, 1984; Bauer & Miglautsch, 1992), however, Page and Luding (Page & Luding, 2003) suggested that this marketing strategy usually establish an advertising and response channel to communicate with existing and potential customers to evoke their intention to purchase a product and/or service, and the data gathered through the campaign is recorded and analysed to explore purchasing behavior and to better target potential customers. In both the US and UK, direct marketing is being extensively used as a standard operating procedure to reach a large customer base and they are effective (Page & Luding, 2003). Telemarketing is a form of direct marketing strategy, which is becoming very popular among brand owners to promote their products and services. It provides a cost-effective solution to reach a wider customer base within a short time and being used in various industries, such as telecommunication service providers, financial institutions, banks, and insurance companies (Lahmiri, 2017). However, an empirical study conducted by Page and Luding (Page & Luding, 2003) also suggested that more than 80% of the customers considered telephone marketing as annoying, and about 75% of the customers were concerned about their invasion of privacy. Therefore, it is highly important to ensure the campaigns are conducted to target a specific set of customers based on their personal, social, and financial information rather than reaching out to everyone.

Data mining and machine learning techniques can be used to predict the likelihood of customers positively responding to a telemarketing campaign. However, the selection of an appropriate set of customers that are likely to subscribe to an advertised product/service is considered NP-hard (non-deterministic polynomial-time hardness) (Nobibon, Leus, &

Spieksma, 2011), and the problem of selling long term deposits through telemarketing campaigns to an appropriate set of users requires further attention (Moro, Laureano, & Cortez, 2011; Moro, Cortez, & Rita, 2014; Lahmiri, 2017). In a global market with high competition and low response rate, it is immensely important for organisations to select the appropriate strategic decision making policy to sell the right product to the right customers at the right time to increase profit and revenue (You, et al., 2015). Therefore, the use of data mining techniques can be embedded with customer relationship management systems (CRM) to formulate a business strategy and influence customer behaviour through meaningful communications to improve profitability, customer satisfaction, customer retention, and customer loyalty (Bahari & Elayidom, 2015). The use of advanced data analytics techniques can also be employed by analysing structured data to make automated decisions (Intezari & Gressel, 2017) that can be used in daily operations to determine whether to approach a customer with a particular offer or not. Therefore, in this article, we focus on predicting the outcome of telemarketing based on the information of customers. Here, a successful outcome would indicate that the customer will subscribe to the advertised product and an unsuccessful outcome would indicate otherwise.

Several works (Moro, Laureano, & Cortez, 2011; Moro, Cortez, & Rita, 2014; Bahari & Elayidom, 2015; Apampa, 2016; Lahmiri, 2017; Parlar & Acaravci, 2017; Jiang, 2018) have investigated the use of machine learning techniques to predict the success of telemarketing. Moro *et al.,* (Moro, Laureano, & Cortez, 2011) considered the context of telemarketing campaigns conducted by a Portuguese bank to attract customers to subscribe to a long-term deposit plan and used the CRoss Industrustry Standard Process for Data Mining (CRISP-DM) methodology to predict the successful outcome. The authors used data mining techniques, such as Naïve Bayes (NB), Decision tree (DT), and Support vector machine (SVM) for their prediction. Javaheri *et al.* (Javaheri, Sepehri, & Teimourpour, 2014) investigated the impact of a mass media campaign on customers' buying habits and used the SVM classifier to model customer response. Their model achieved 81% accuracy while using 26 features for prediction. Moro *et al.,* (Moro, Cortez, & Rita, 2014) conducted another investigation to predict the success of telemarketing with a semi-automatic feature selection of 22 features and measured the performance of four data mining models, including logistic regression (LR), DT, Neural network (NN) and SVM. Their performance analysis suggested that NN achieved the best results with 80% accuracy. Along a similar line work in (Bahari & Elayidom, 2015) used a CRM-data mining framework to predict the behavior of customers in the decision-making process to improve customer retention. This work employed NB and NN models to predict customer behavior and concluded that the NN method achieved superior performance compared to the NB method.

The above-mentioned models only use a classifier to classify the customers as prospective subscribers. They can be further improved with the incorporation of ensemble techniques. The ensemble techniques combine the predictions of multiple baseline learning algorithms to improve the generalizability and robustness of the system. Although a few works (Pan & Tang, 2014; Apampa, 2016; Lawi, Velayaty, & Zainuddin, 2017) have used ensemble methods, they are based on bagging and/or boosting ensemble methods, which uses homogenous base models to combine learning. The previous works also used a partial dataset (Lawi, Velayaty, & Zainuddin, 2017) to overcome the class imbalance problem (i.e., a dataset having a higher number of entries belonging to a specific class) or achieved poorer performance with imbalanced classes. Their performance can be further improved by employing an appropriate ensemble technique based on stacking, which combines multiple heterogenous weak learners as a base model and then uses another classifier in the meta-model to produce the final output.

This paper proposes a stacking-based ensemble machine learning model to predict the outcome of telemarketing. We consider that customer data (personal, financial, and social) is available through a CRM-based system and the machine learning model can be employed in the data analysis phase to develop an automatic decision-making system, which can recommend whether to contact a particular customer or not based on the likelihood of that customer subscribing to the advertised product. In this case, only the customers classified as potential subscribers are recommended by the decision-making system. The proposed machine learning model considered three different combinations of classifiers for stacking and compared their performances. The simulation results show that our proposed approach outperformed existing ensemble-based methods (Apampa, 2016) and achieved 90.29% accuracy.

The rest of the article is organised as follows. Section 2 highlights the existing literature that addresses the problem of telemarketing outcome prediction using machine learning and data mining techniques, and Section 3 discusses our proposed methodology. Section 4 explains the details of the dataset used for our evaluation and the outcome of the experiments while section 5 presents the concluding remarks.

2 Literature Review

Direct marketing has been widely used by different organisations to offer promotional products and services to customers (Page & Luding, 2003). Telemarketing is a form of direct marketing strategy that helps to reach a wide customer base within a short time and hence adopted in many organisations, including banks, financial institutions, retails, and insurance companies. It is imperative to target a specific set of customers to increase the potential benefit of a telemarketing campaign rather than reaching out to everyone (Asare-Frempong & Jayabalan, 2017). Several data mining and machine learning models (Moro, Laureano, & Cortez, 2011; Elsalamony, 2014; Pan & Tang, 2014; Parlar & Acaravci, 2017; Lahmiri, 2017; Jiang, 2018) have been used by researchers to predict the outcome of a telemarketing campaign. The proposed techniques can be broadly categorised as a single classifier-based model and an ensemble-based model. The single classifier-based model uses a specific machine-learning algorithm to predict the outcome while an ensemble model combines the strength of multiple classifiers in the prediction. The proposed approaches are highlighted in Table 1 and discussed below.

Most of the existing literature used a single classifier-based model to predict the outcome of telemarketing. They compared multiple such models and suggested the best one for a specific dataset. Moro *et al.,* (Moro, Laureano, & Cortez, 2011) proposed a CRISP-DM based methodology to predict the outcome of the telemarketing campaign in a Portuguese bank. More specifically, they considered 16 features, used the NB, DT, and SVM algorithms to predict the outcome, and concluded that the SVM algorithm produced the best result in their dataset. Along a similar line, Javaheri *et al.* (Javaheri, Sepehri, & Teimourpour, 2014) concluded that their SVM-based model was able to achieve 81% accuracy while predicting the outcome of a mass media campaign on customers' buying habit. In another work, Moro *et al.,* (Moro, Cortez, & Rita, 2014) considered the telemarketing outcome prediction with 150 features and found that the NN algorithm produced the best result with 79% accuracy. In contrast, Bahari and Elayidom (Bahari & Elayidom, 2015) suggested that the MLPNN algorithm produced superior results compared to other models when applied to the testing dataset and achieved an accuracy of 88%. Random forest classifier-based models have also been found effective in a few studies (Asare-Frempong & Jayabalan, 2017; Muppala, Dandu, & Potluri, 2020). Asare-Frempong and Jayabalan (Asare-Frempong & Jayabalan, 2017) suggested that their RF-based model was able to achieve 86% classification accuracy when applied to the bank telemarketing data while a recent work by Muppala *et al.* (Muppala, Dandu, & Potluri, 2020) suggested that the random forest model achieved 88% accuracy. In contrast, an LR model was employed in (Jiang, 2018) and obtained a superior classification accuracy compared to other methods.

The above-mentioned works used all the features within a dataset for outcome prediction. In contrast, Parlar *et al.* (Parlar & Acaravci, 2017) considered the problem of optimal feature

Article	No of features	Models used	Best model	Performance metric calculated
CRISP-DM (Moro, Laureano, & Cortez, 2011)	16	NB, DT, and SVM	SVM	AUC, ALIFT
Bank direct marketing (Elsalamony, 2014)	16	MLPNN, Bayesian network (TAN), LR, and DT (C 5.0)	MLPNN	Accuracy, Sensitivity, Specificity
Ensemble methods (Pan & Tang, 2014)	16	NN and LR for bagging and gradient boosting	N/A	Sensitivity, Specificity, and ROC curve
CRM-Data mining (Bahari & Elayidom, 2015)	16	MLPNN, and NB	MLPNN	Accuracy, TPR, FPR, ROC area, time taken to build the model
Customer response prediction (Apampa, 2016)	16	LR, DT, NB, and RF ensemble	RF ensemble	Accuracy, AUC, Precision, Recall, F1-score
Important feature detection (Parlar & Acaravci, 2017)	5-15	NB	N/A	Precision, Recall, and F measure
AdaBoost SVM (Lawi, Velayaty, & Zainuddin, 2017)	20	Adaboost SVM and SVM	Adaboost SVM	Accuracy, Sensitivity
Customer response to direct telemarketing (Asare-Frempong & Jayabalan, 2017)	16	DT, RF, LR, and MLPNN	RF	Accuracy, AUC
Two-step system (Lahmiri, 2017)	20	BPNN-PSO	N/A	Accuracy, Sensitivity, Specificity, AUC
Logistic regression (Jiang, 2018)	20	LR, NB, SVM, NN, and DT	LR	Accuracy, AUC
Asymmetric financial data (Muppala, Dandu, & Potluri, 2020)	20	RF, and LR	RF	Accuracy, Precision, Recall, F1-score

Table 1 Existing Literature on telemarketing prediction

selection for the customer selection process of direct marketing in the banking section. They used Chi-square and information gain feature selection methods and evaluated the performance of the Naïve Bayes machine learning algorithm by varying the number of features from 5 to 15. Their evaluation section showed that the result of both feature selection methods was very close even though they produced a different set of features, and the performance of the classification slightly improved with a reduced number of features. Lahmiri (Lahmiri, 2017) proposed another interesting work of telemarketing outcome prediction with a two-step process. In the initial step, multiple backpropagation neural networks (BPNN) were independently trained with different information (personal and social information of a customer, and campaign information), and in the latter step prediction from previous models were used in a BPNN to make a final prediction. The performance results indicated that the two-step prediction system outperformed each of its individual components.

The above-mentioned works used a single classification algorithm based model to predict the outcome of a telemarketing campaign. However, these models suffer from a class imbalance problem as the number of positive responses from the telemarketing campaign is usually quite low (Pan & Tang, 2014). Ensemble-based methods can be employed in this case to increase the performance of the models as they train multiple classifiers sequentially or parallelly on the same dataset to overcome this. A few works (Pan & Tang, 2014; Apampa, 2016; Lawi, Velayaty, & Zainuddin, 2017) in existing literature have used ensemble-based methods. Pan *et al.* (Pan & Tang, 2014) compared the performance of bagging and boosting based ensemble methods and suggested that the bagged neural network model achieved the best performance in their experiments. In contrast, Lawi *et al.* (Lawi, Velayaty, & Zainuddin, 2017) suggested that the AdaBoost SVM algorithm achieved better performance compared to the normal SVM algorithm. Another work by Apampa (Apampa, 2016) suggested that the ensemble random forest method outperformed other methods (DT, NB, and LR), and achieved an accuracy of 89%.

In summary, existing literature mostly used a single classifier based learning algorithm or bagging/boosting based ensemble learning to develop the output prediction model. A single classifier-based learning model can suffer from the class imbalance problem, which can be improved with an ensemble model. The proposed bagging/boosting ensemble model also uses homogenous learning algorithms in their base model to combine the output from multiple learners. In this regard, employing a stacking ensemble model can further improve the performance as it incorporates the prediction of heterogeneous learners in the base model to make a final prediction. Therefore, this paper proposes a stacking ensemble model for telemarketing outcome prediction.

3 Proposed Methodology

This article proposes the development of an automatic decision-making system for telemarketing outcome prediction, which can be embedded in the CRM system. The proposed system collects customer information including their personal, social, and financial information as well as their attitude towards previous campaigns. The collected information is processed in the pre-processing step to identify important features and/or missing values. To achieve this, feature selection techniques, such as information-gain, chi-squared method, ANOVA correlation coefficient, and Kendall's rank coefficient method. We have used the information-gain feature selection method in our evaluation in Section 4 to observe its impact. Finally, the training dataset is extracted and provided as input to our proposed classification model, which predicts whether the customer is expected to provide a positive or negative response. Based on the predicted outcome, a relevant recommendation is provided as an output by the decision-making system to the CRM.

Figure 1 represents the framework of the proposed system. The figure suggests that the proposed decision-making system extracts training data after obtaining relevant information from the CRM and provides it to the proposed stacking ensemble classifier in the form of features with associated values after selecting the appropriate features using a feature selection method. Afterward, the classifier uses this test data and the meta classifier model to make the final prediction and provide it as an output to the recommendation module, which provides a positive (i.e., contact the user) or negative (i.e., do not contact the user) recommendation.

As alluded in Section 2 that the state-of-the-art single classifier-based machine learning models are inefficient to predict customer behaviour in the massive business data scenario. In this regard, a hybrid multi-model solution can enhance performance by producing accurate predictions. Ensemble methods combine many base models to generate one optimal predictive model. Taking a multitude of models into account, ensemble methods combine these models to generate one final model. Previous research has demonstrated that the ensemble model produces better performance compared to the single classifier- based models (Wolpert, 1992). Therefore, this paper proposes an ensemble method using meta-classification allowed by stacked generalization. The proposed classification model aims to achieve accurate predictions of customer response based on the stacking ensemble method.

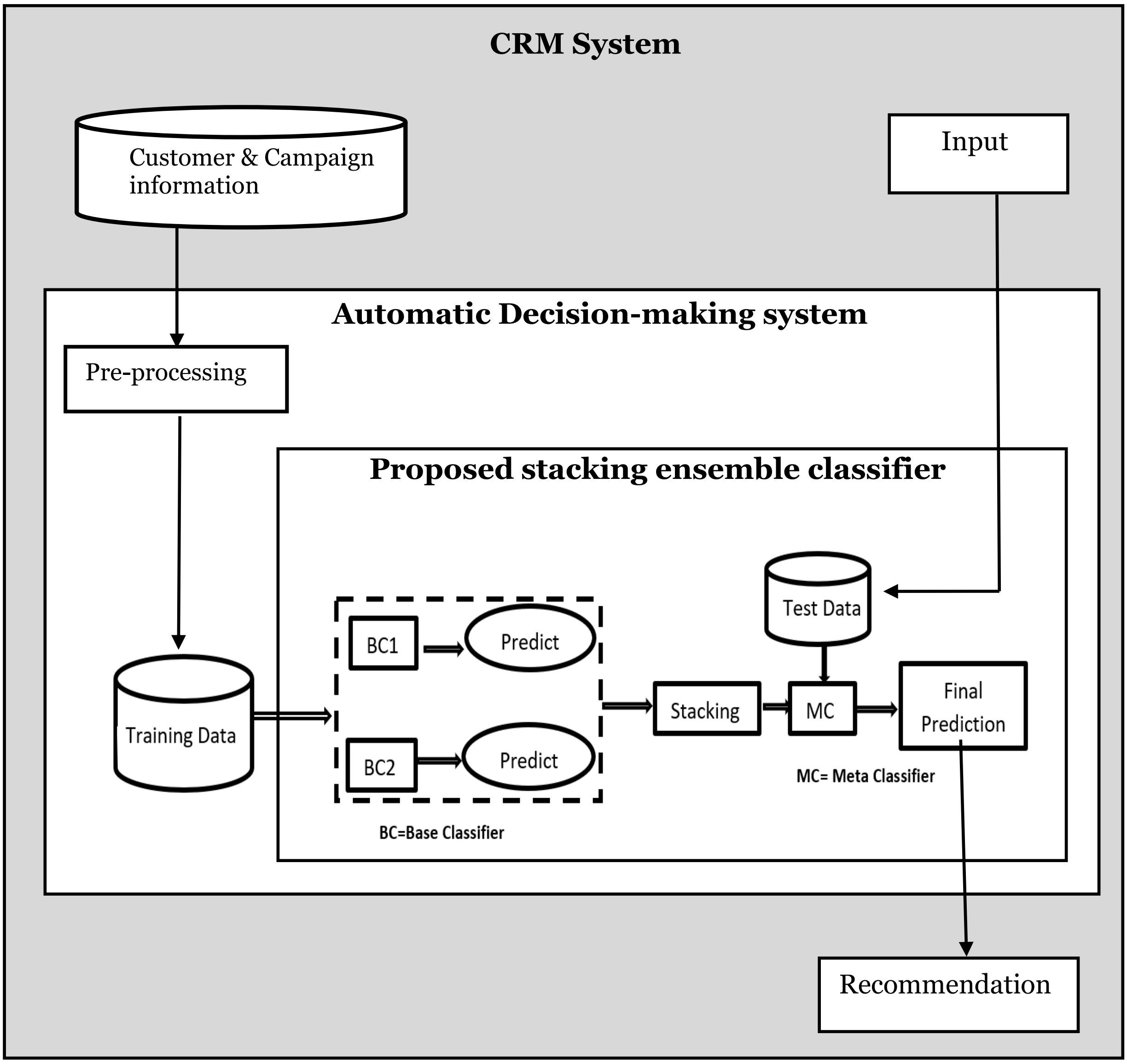

Figure 1: The proposed framework for telemarketing outcome prediction

The proposed stacking ensemble classifier in *Figure 1* consists of two classifiers: Base Classifier (level 0 classifier) and Meta Classifier (level 1 classifier). The base classifier receives the whole training data from the decision-making system and independently makes a prediction. Please note that multiple models (i.e., single heterogeneous classifier) can be a part of the base classifier and each of them independently makes a prediction. The fundamental principle of stacking is to use the meta classifier to predict the samples by learning from base classifiers. In the case of an unbalanced dataset, stacking ensemble can enhance the prediction accuracy (Yan & Han, 2018). In our proposed ensemble classifier, the prediction output of the base classifiers is fed into the meta-model, which is yet another classifier and receives the test data to make the final prediction. In this case, the different combinations can be used for stacking. For example, Random forest (RF) and Artificial neural network (ANN) can be used as the base classifier and SVM can be used as the meta classifier. Our performance evaluation in Section 4 shows the comparison of three different combinations.

4 Performance Evaluation

The performance of the proposed stacking ensemble classifier is evaluated using the following well-established metrics for outcome prediction.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1),$$

where *TP* = true positive, *TN* = true negative, *FP* = false positive, and *FN* = false negative,

$$Precision = \frac{TP}{TP + FP} \quad (2),$$

$$Recall = \frac{TP}{TP + FN} \quad (3), \quad \text{and}$$

$$F1\ score = \frac{2 * TP}{(2 * TP) + FP + FN} \quad (4).$$

4.1 Dataset used

We employed a publicly available telemarketing dataset from the University of California at Irvine Machine Learning Repository[1] to evaluate the performance of our proposed model. This dataset has been introduced by Moro *et al.* (Moro, Laureano, & Cortez, 2011) and it shows the telemarketing outcome of an unnamed Portugues bank who conducted 17 campaigns between May 2008 and November 2010 to offer an attractive long-term deposit plan. The dataset contains 45,211 instances where the customers were contacted and out of these instances, 5289 attempts were successful where the customer subscribed to the advertised product. Therefore, the success rate of this campaign was around 11.69% and it produced an imbalanced dataset with a high number of negative responses (88.30%). For each of the instances, 17 features are provided without any missing values. The details of the attributes in the dataset provided by Moro *et al.* (Moro, Laureano, & Cortez, 2011) is presented below in *Table 2*.

4.2 Experiments and Results

The proposed stacking ensemble classifier was implemented using python program language using several libraries, such as pandas, NumPy, sklearn, and Keras on an HP (ELITEBOOK) laptop with Windows 10 operating system. The processor was an Intel(R) Core (TM) i5-8350U CPU (1.70GHz and 1.9 GHz) with 16 GB RAM. We have considered three stacking combination for performance comparison. In the first staking combination (SC1), we have used RF and ANN as base classifiers and SVM as the meta classifier. The second staking combination (SC2) used KNN and ANN as base classifiers and SVM as the meta classifier while the third staking combination (SC3) used KNN and RF as base classifiers and ANN as the meta classifier. We used two scenarios for performance evaluation. The first scenario (Case 1) used all features from the dataset while the second scenario (Case 2) used only the important features obtained from the information gain feature selection method. Results obtained from these two cases using the stacking combinations are discussed below.

[1] https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

Information Type	Feature	Description	Type
Customer Information	age	age of the customer at the time of contact	Numeric
	job	the type of job currently undertaken by the customer, e.g., admin, management, etc.	Categorical
	marital	marital status of the customer	Categorical
	education	the highest education level of the customer	Categorical
	default	has the customer any credit in default?	Binary
	balance	average yearly balance of the customer in euros	Numeric
	housing	does the customer have any housing loan?	Binary
	loan	does the customer have any personal loan?	Binary
Previous campaign contact	contact	the type of previous communication, e.g., telephone or cellular	Categorical
	day	day of the month when the last communication was made	Numeric
	month	the month of the year when the last communication was made	Categorical
	duration	the duration of the last contact in seconds	Numeric
Other information	campaign	the number of contacts performed during the current campaign for this customer	Numeric
	pdays	the number of days that have passed after the customer was last contacted from a previous campaign	Numeric
	previous	the number of contacts performed before this campaign for this customer	Numeric
	poutcome	the outcome of the previous marketing campaign	Categorical
Output variable (Target class)	y	has the customer subscribed to a term deposit?	Binary

Table 2 Description of features in the bank dataset

Table 3 shows the result of employing the proposed stacking ensemble method on the evaluation metrics for Case 1. The impact of different stacking combinations is also presented here. SC1 achieved the best result by attaining a higher accuracy compared to SC2 and SC3. On the other hand, precision, recall, and F1-score of SC1 and SC3 were similar and much higher than Sc2.

Table 3 Evaluation metrics for case 1

Staking Combination	Accuracy	Precision	Recall	F1-Score
SC1	90.29%	89%	90%	89%
SC2	88.33%	78%	88%	83%
SC3	90.03%	89%	90%	89%

The performance of the proposed stacking ensemble method for Case 2 is presented in ***Table 4***. For this scenario, we considered 9 important features based on the information gain scores and compared the performance of different stacking combinations. The information gain score (Quinlan, 1986) for the selected 9 features are presented in ***Table 5***. From ***Table 4***, we can see that the accuracy for SC1, SC2, and Sc3 has slightly improved compared to the previous case, i.e., Case 1. However, the values obtained for precision, recall, and F1-Score for both Case 1 and Case 2 are quite similar.

Staking Combination	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SC1	90.40%	89%	90%	89%
SC2	88.58%	78%	89%	83%
SC3	90.05%	89%	90%	89%

Table 4 Evaluation metrics for case 2

Feature	**Score**	**Feature**	**Score**	**Feature**	**Score**
balance	0.137	duration	0.132	pdays	0.048
poutcome	0.042	month	0.035	contact	0.019
age	0.0184	previous	0.018	housing	0.0139

Table 5 Information gain score for different features

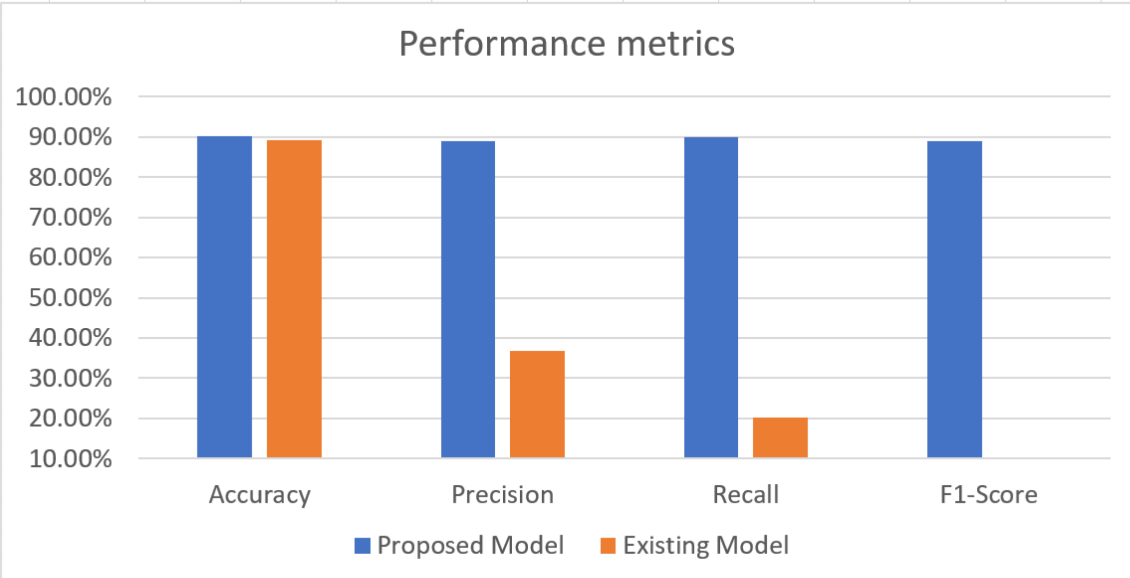

Figure 2 Performance comparison with Apama (Apampa, 2016). Proposed Model indicates the the proposed stacking ensemble with the first combination (SC1) and Existing model represent the model present in Apama (Apampa, 2016).

We compared the proposed stacking ensemble classifier with an existing ensemble-based model proposed by Apama (Apampa, 2016) and the results are presented in ***Figure 2***. The accuracy, precision, and recall of our proposed model and existing model (Apampa, 2016) are 90.29% and 89.10%, 89.00% and 36.7%, 90.00%, and 20.2%, respectively. Apama (Apampa, 2016) did not present the F1-Score measure, while the value achieved for this metric by our model was 89.00%. ***Figure 2*** demonstrates that our model significantly outperforms the existing ensemble model especially in terms of Precision and Recall, which are important metrics to ensure that potential customers are not missed, and uninterested customers are not recommended during the prediction process. Although our analysis shows that the proposed stacking combination achieves higher accuracy, precision, and recall, it should be highlighted that the dataset used for this analysis does not contain any missing values. In real-life settings, some of the information may not be readily available, and hence missing feature values might cause slight performance degradation. Our future work will investigate the implication of such missing values and a more extensive analysis related to a balanced dataset, AUC and ROC also remain as a part of our future work.

5 Conclusion

Direct marketing is extensively used by business organisations to reach potential or existing customers to offer them products and/or services. Telemarketing is a popular form of direct marketing strategy that allows companies to communicate a large customer base within a short time. However, the telemarketing campaign needs to target a specific set of customers who are more likely to subscribe to the advertisement to increase profitability and customer loyalty. Existing literature mostly employed a single classifier-based learning algorithm or bagging/boosting ensemble methods to predict the outcome of telemarketing and find potential subscribers. However, they suffer due to class imbalance problems and their performance can be further improved by using a stacking ensemble method. In this article, we proposed the development of an automatic decision-making system, which can be embedded within the CRM. The proposed decision-making system employs a stacking ensemble method, which combines the prediction outcome from multiple base classifiers to make a final prediction. The performance results indicated that the proposed ensemble classifier was adept in handling the class imbalance problem and achieved higher accuracy, precision, recall, and F1-score when compared to an existing algorithm. Our future work will focus on further improving the accuracy and investigate the impact of the proposed model on larger datasets.

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