Performance Enhancement of Hybrid Algorithm for Bank Telemarketing

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Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: Telemarketing is an interactive direct marketing system in which telemarketers encourage customers to leverage the resources by notifying, imparting knowledge of online products, latest business offers via direct interaction or through a telephone call. In the contemporary global pandemic spell telemarketing has become dominant backbone to increase the online banking business to withstand for the reducing retail business. It has gained prominence in the banking and financial sector with the enormous adoption and availability of cellular connections amongst customers. The contemporary work has scrutinized conventional classification as well as data mining methods have a problem of ill-fitting with multiple features and are prone to data leakage during re-training of the machine learning model. A local Indian bank were designated, contemplating the current economic slowdown and crisis. A discussion on three machine learning (ML) models is performed along with the Hybrid ML model, Logistic Regression ML model (LR), Naive Bayes ML model (NB), Decision Trees ML model (DTs). The three ML models were tested and analysed with proposed Hybrid ML model on an evaluation set, the data is partitioned as training, validation and test set. The hybrid model first identifies important features of subscribed customers and predicts response for a potential customer, both existing and new who will eventually subscribe again through the direct marketing campaign. The hybrid model is trained to predict the response of new customer who will subscribe to the product or service offered via a direct marketing campaign through transfer learning. The hybrid model API shows new customer response on the front-end screen. To overcome the problem of ill-fitting and data leakage, the model is trained on a large dataset and tuned on a validation set. The proposed hybrid machine learning technique presented the best results (Accuracy 98.69%). Python language is used to develop the model. Financial institutions and organizations can use the hybrid model for predictions of product direct marketing response with customer transaction information.
Keywords: Machine learning, Deep learning, Banking, Financial services, Transfer learning

1. Introduction

In the banking and financial services domain, marketing is the prime business to promote newly developed products, impart knowledge and notify the customers regarding the latest online products, features or facilities. Marketing is the procedure of recognizing the profitable and non-profitable customers thereby preserving long term association with the customers by understanding their needs and wants. It accomplishes a successful trade in by understanding what the market needs and developing products that fit and survive in the current market situation [1]. Marketing emphasizes on timely instigating the products which the customers require. The per diem purchase transactions performed by customers are logged in the bank database. Banking institutions maintain a comprehensive and organized details of the transactions which assist in granular analysis of individual customer behavior, needs and understand the market demands [2]. This enables reaching out to the right customers. It has increased easy enrollment for profit enhancing financial services like loan, deposits [3]. The comprehensive objective is to enhance the number of bank investors by purchasing the product bank term deposit and thereby enhancing the market stability of the financial organization. It has been a stable and trustworthy bank product for customers to invest and receive returns from it. There are multiple ways to advertise and promote banking products like Television ads, Newspapers, social media marketing, Short message service, electronic mails and give services to customers like chatbots which are used for cost effective promotion by analyzing real time telemarketing data. Countries around the world have increased their research in machine translation and tech giants like Amazon, Salesforce, Microsoft, Zendesk, Google have publicized the bot technology and machine learning for tele assistant services [4]. However, reaching out to the potential customers at the right time during direct marketing campaigns still has challenges due to huge customer databases available with banks and thereby reaching out to right customers often is very difficult by scrutinizing the database records manually, information security restrictions or by data mining, processing methods [5]. Machine learning has therefore become evident to assist banks in scrutinizing the right customers by learning, analyzing and finding out the potential customers for direct marketing by supervised, unsupervised learning methods. In supervised learning the previously gathered information is learned to identify the patterns in the information acquired by banks through various means like surveys, initial customer enrollments with the bank for account opening, credit card purchase. This information assists the supervised machine learning method to perform decision making and predictions on the future and real time information. It includes Linear regression, DT, LR, ANN, NB techniques [6]. Unsupervised learning method builds the machine learning model based on previous data which has input information but it has no required outputs [7]. It includes clustering technique which is further described as connectivity based as hierarchical clustering, agglomerative, centroid based which is K means clustering [8]. This has drastically reduced the calling efforts of telemarketers as previously they had to go through errant customers who were not interested and were compelled to approach them during campaigns due to monthly sales target pressure and to generate new leads [9]. It has paved an era that has increasingly started leveraging Artificial intelligence in the Financial Sector [10]. Machine learning researchers have engrossed on development of models which can bring forth real time functional solutions and clarifications for the financial sector. Computational intelligence has led to deep learning implementations in the financial industry. Deep learning encapsulates several layers of artificial neural networks which enable data abstraction [11]. The objectives of this work are to overcome the problem of ill-fitting due to multiple features in the dataset, overcome the problem of data leakage caused during retraining of the machine learning model, for the new transactions recorded by the bank in the dataset predict the new customer response by the trained model. Three Machine Learning models were used, and a comparative study is produced to investigate bank telemarketing dataset which was recorded previously to take a decision. The ML Software development life cycle is implemented in Python.

2. Related Work

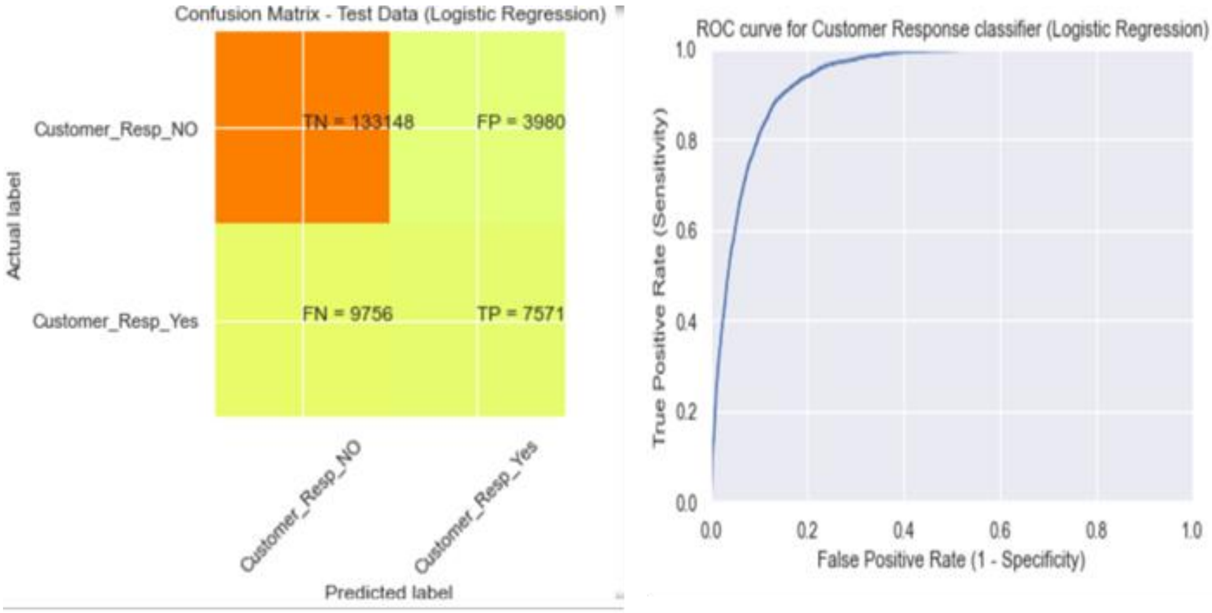
This segment illustrates the prior work performed in classification by employing data mining and ML techniques. An evaluation is conducted upon the diverse articles, research contributions, comprehensive exploratory techniques and accomplishments. The several implementation and development contradictions, contributions, contrast achievements and research techniques were assessed. A glossary of data mining and ML systems, methods is prognosticated with cognizance of contemporary along with prominent drifts within this sector as a domain of interest especially for researchers. In study [12], the author addressed an automated system to identify potential term deposit investors. The authors proposed a DL oriented hybrid model which loads convolutional, RNN layers. The classification methods applied in their study are KNN, Decision Tree, Multilayer Perceptron network (MLP) from which the hybrid model outperforms other classification algorithms. The results of these algorithms were measured by accuracy and mean squared error metrics. In manuscript [13], the authors have demonstrated three models of MLP to decrease the complexity of neural network based on principal component and factor analysis technique. The authors utilized bank marketing dataset and showed that the model which inserted the factors in the hidden layers and preserved the high loading factors only is better in respect to complexity, accuracy. In manuscript [14], the authors have utilized bank telemarketing information to identify potential customers interested in time deposits. The algorithms used in their study were DT, K-nearest Neighbour (KNN), ANN, Random forest (RF), LR, SVM out of which SVM outperformed other techniques in terms of accuracy and AUC metrics. In manuscript [15], the author has utilized hybrid sampling technique and stacked deep network (SDN) to resolve the problem of class imbalance using bank marketing information. The SDN method demonstrated better results in terms of accuracy, recall and precision than LR, RF, SVM, NN and DT. In manuscript [16], the authors have demonstrated Recursive General Regression (NN) Oracle technique which is an enhancement of the original GRNN Oracle technique. It demonstrated superior results in accuracy, F1-score, sensitivity, precision, AUC, specificity than other techniques utilized like SVM, PNN, GNB, KNN, MLP, RF. In study [17], the authors have utilized PCA and classification techniques AdaBoost (AB), Gradient Boosting (GB), SVM RBF, NB, RF to identify potential customers for offering bank credit and optimize the operational cost of the call centers and enhance the profits in the meantime by using bank marketing data. The Adaboost classifier demonstrated better results than other classifiers in accuracy and performance metrics. In study [18], the authors have analyzed and reviewed in detail the deep learning (DL) technology in bank marketing, customer relationship management, risk management addressed DL implementation instances of chatbots for personalized marketing, and have discussed the DL techniques RNN, CNN, DBN, AE, GAN utilized in recognizing face, voice and optimizing the processing of images. In study [19], the authors demonstrated hybrid clustering technique to minimize the training efforts and reduce the accuracy losses. The techniques used in their study were K means, SVM, MLP, BIRCH out of which the hybrid approach gave satisfactory results with bank telemarking dataset. In manuscript [20], the researchers put forth a Hybrid bidirectional DL model to predict bitcoin investment trends and compared the outcomes with other ML and DL models wherein the Hybrid bidirectional DL model got better investment outcomes. In manuscript [21], the researchers have addressed the issues of elucidation and accuracy of machine learning models and have utilized predicate-based models to achieve better accuracy and elucidation of ML models. In manuscript [22], the research scholar has investigated ML algorithms through big data for analyzing wealth information. The ML models put forth in the study were MMDB, SHAP-MRMR+, SOM which showed the effectiveness of DL algorithms on financial wealth data. In study [23], the work aimed to foreshow the achievements of bank telemarketing, amongst the classifier algorithms used in the experimental study Random forest performed better than others and the enhancements were achieved through sampling techniques. In manuscript [24], the authors computed and evaluated the performance of several machine learning algorithms which were further utilized to evaluate the Machine learning platforms like Microsoft Azure ML, IBM SPSS, Apache Spark ML, Python, R, SAS. The performance of the ML algorithms was evaluated based on accuracy, F-score, AUC. The datasets used in their study were from Kaggle, UCI ML repository and the platforms were compared using 13 multiclass and 16 two class problems and demonstrated that all platforms performed equivalently efficient. In study [25], the authors utilized K nearest neighbor technique to classify bank telemarketing customers and have discussed and evaluated Euclidian, Manhattan distance formulas to achieve optimum results. In manuscript [26], the authors have proposed a multi-level ensemble model to predict the financial instability of companies to survive the future financial crisis. The model proposed in their study encapsulates six machine learning models SVM, LR, DT, RF, ANN, RRF to predict the financial instability. In manuscript [27], the authors have proposed a hybrid technique encapsulating Ant colony optimisation, Decision Trees, Decision forests developed to classify email messages. The ant colony decision forest method was tested on enron email dataset and was compared with existing ant colony optimization methods and better results were obtained in terms of accuracy and stability. In manuscript [28], the authors have utilized GA-ENN and GEP techniques for coronary artery disease forecast wherein the GEP models demonstrated better accuracy results and outperformed the other models.

3. Methodology

In this segment the proposed mechanism is discussed. The methodology utilized in the work is in manuscript [29]. The data set used in this work is an Indian bank data set. The Indian bank dataset has 1029700 records and 21 attributes. Previous research has the problem of ill-fitting with multiple features, data leakage during re-training of the ML model, less accurate and could not achieve the high customer conversion rate with direct telemarketing campaigns. Ill-fitting of data occurs whilst the number in respect to attributes within the dataset are more and the number with reference to data points are less. The various permutations that are possible between those attributes are huge, while the number of data points are comparatively less. Not all possible permutations and combinations amongst these independent attributes can be represented in the data set. This possesses reverberation upon the target variable and leads to curse of dimensionality. In this situation, the feature space or mathematical space has multiple dimensions, and the data points are spread far and wide from each other. The ML algorithm cannot understand the type of a surface which needs to be produced in those areas where there are no data points. As the feature space or mathematical space is sparse, the ML algorithm finds it difficult to understand the relationship between target and independent attribute in those empty spaces. To understand the relationship between the attributes and the target variable, sufficient amount of data is required. Due to insufficient information, the model under performs during the testing phase and tends to be unstable to be deployed in production environment. This reduces the accuracy of the model and the customer conversion rate. The model gets prone to data leakage during re-training phase. To overcome the problem of ill-fitting due to multiple features, less accuracy and data leakage during re-training of the model, the model is trained on a large bank dataset, tuned on a validation data set. For the new transactions recorded by the bank in the database, prediction of the new customer response is performed by the trained model through transfer learning.

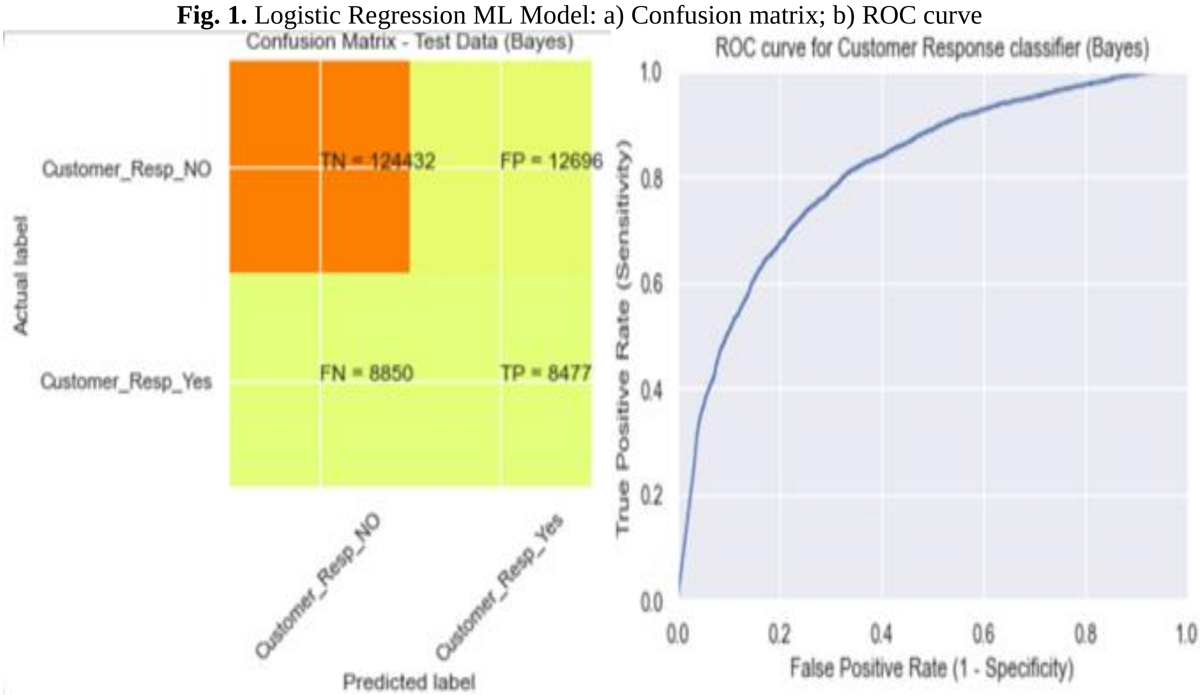
A. Prediction Results of Machine Learning Models on Indian Bank Dataset

In this segment prediction results of the ML models are demonstrated and examined. The Fig. 1. (a), and Fig. 1. (b), demonstrates confusion matrix, roc curve produced through code for Logistic Regression ML Model. The Fig. 2. (a), and Fig. 2. (b), demonstrates confusion matrix, roc curve produced through code for Bayes ML model. The Fig. 3. (a), and Fig. 3. (b), demonstrates confusion matrix, roc curve produced through code for Decision Tree ML Model. The Fig. 4. (a), and Fig 4. (b), demonstrates confusion matrix, roc curve produced through code for Hybrid ML model wherein true positive (TP) depicts that actual, predicted customer behavior for purchasing bank product term deposit is positive. False positive (FP) denotes that perceived customer behavior is negative and predicted customer response for purchase of bank product term deposit is positive. True negative (TN) which foreshows that actual observation is negative and estimated customer response for purchasing bank product term deposit is also negative. False negative (FN) denotes that customer response for purchase of bank product term deposit is perceived as true and estimated as false. The confusion matrix exhibits the efficiency estimate of the ML models with perceived and estimated results referring to bank product term deposit subscription by the customer. The roc curve demonstrates a brink which manages specificity and sensitivity of the ML model. The auc is beneficial to foreshow model efficiency through unique ordinal synopsis.



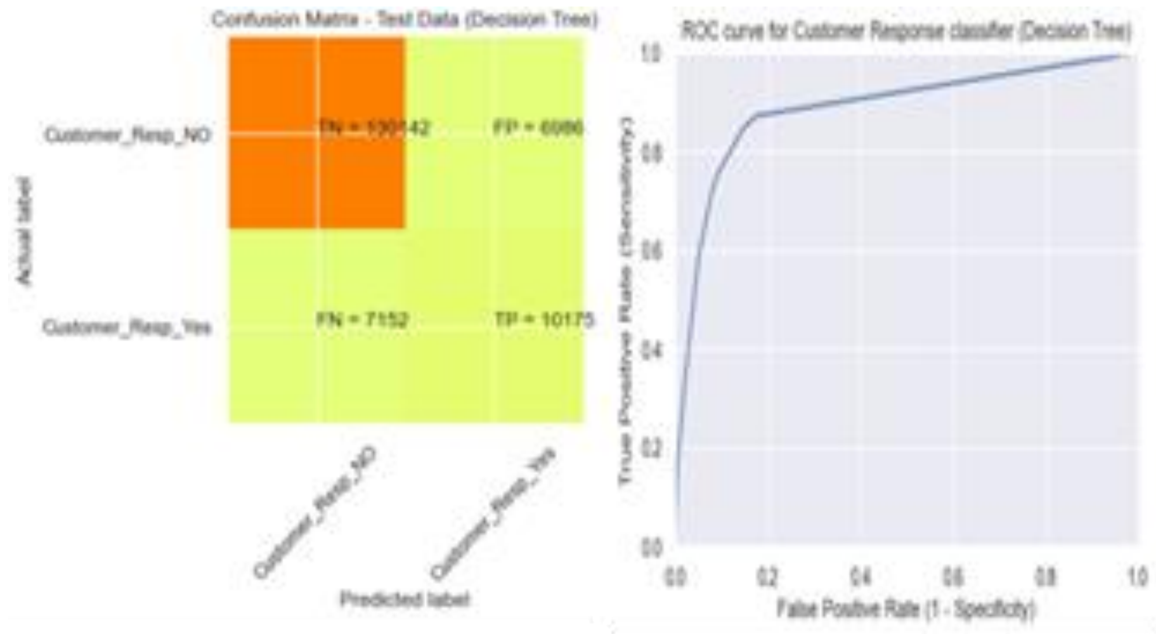
(a) **(b)**

Fig. 1. Logistic Regression ML Model: a) Confusion matrix; b) ROC curve



`(a) **(b)**

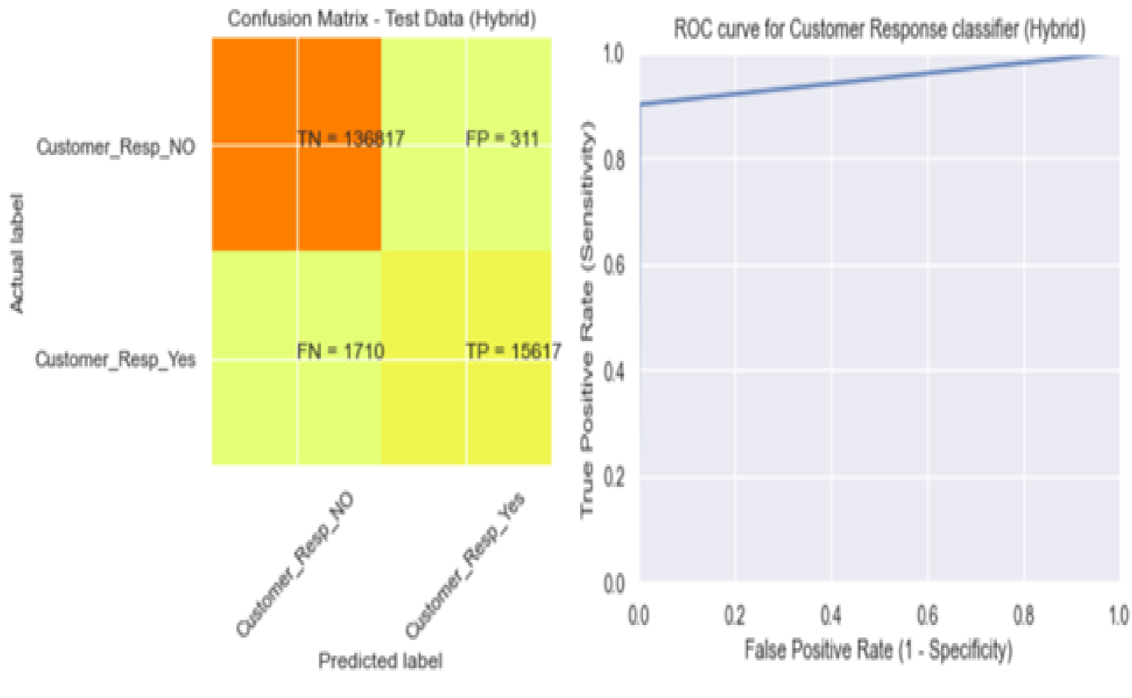
Fig. 2. Bayes ML Model: a) Confusion matrix; b) ROC curve



`(a) (b)

Fig. 3. Decision Tree ML Model: a) Confusion matrix; b) ROC curve

The Table I. below demonstrates the performance metrics of Logistic Regression ML Model, Bayes ML Model, Decision Tree ML Model and Hybrid ML Model.



`(a) (b)

Fig. 4. Hybrid ML Model: a) Confusion matrix; b) ROC curve

Table I. Performance metrics - Machine learning models

Performance Metrics	**Logistic Regression ML Model**	**Bayes ML Model**	**Decision Tree ML Model**	**Hybrid ML Model**
Accuracy	91.10	86.05	90.84	98.69
Sensitivity	65.74	51.33	87.18	90.13
Specificity	94.07	89.63	82.37	99.77
Roc Auc Score	93.81	81.18	88.61	94.95
True Positive	7581	8477	10175	15617
False Negative	9756	8850	7152	1710
Precision Score	65.54	40.03	59.29	98.04
Recall Score	43.69	48.92	58.72	90.13

The equation (1) manifests the degree to which model is accurate in predicting the customers who desire to subscribe for product bank term deposit. The equation (2) depicts ML models sensitiveness in identifying positive occurrences. The equation (3) evaluates the specificity of the ML model in recognizing the positive customer records. The equation (4) evaluates the ML models correctness in predicting positive customer records. The equation (5) evaluates the recall of the ML models which expresses that if the perceived customer record is positive then how frequent the prediction is legitimate.

$$ACCURACY = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

$$SENSITIVITY = \frac{TP}{TP + FN} \qquad (2)$$

$$SPECIFICITY = \frac{TN}{TN + FP} \qquad (3)$$

$$PRECISION = \frac{TP}{TP + FP} \qquad (4)$$

$$RECALL = \frac{TP}{TP + FN} \qquad (5)$$

The Fig. 5, below represents the testing accuracy of ML models on Indian bank data set. The Logistic Regression ML Model gives 91.10% accuracy, Bayes ML model gives 86.05% accuracy, Decision Tree ML Model gives 90.84% accuracy. The Hybrid ML Model gives 98.69% accuracy as compared to other models.

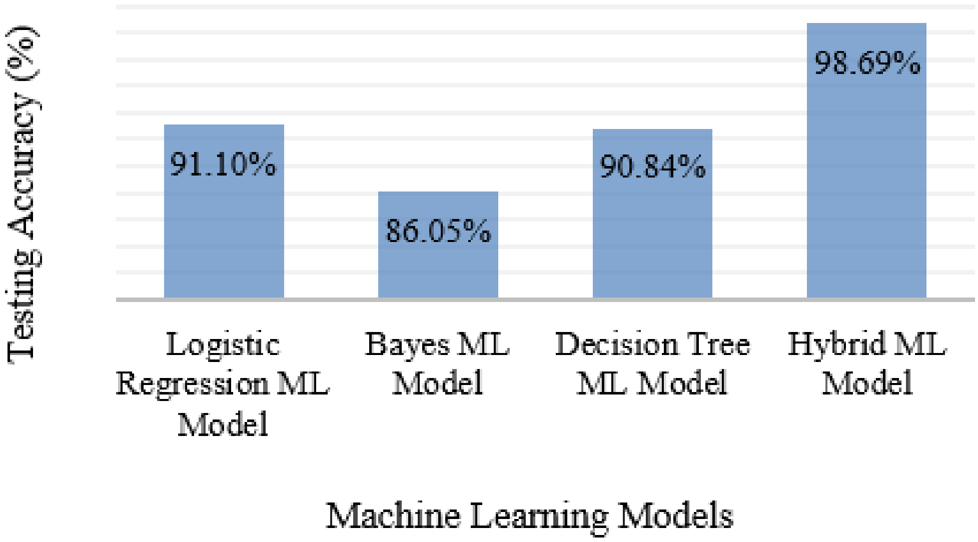


Fig. 5. Testing accuracy on Indian Bank Dataset

The Fig. 6, and Fig. 7, below demonstrates Bank product AIML user front end API sending request to Hybrid ML model API with new customer information and the Hybrid ML model API performing the prediction on the new incoming data from the Bank product AIML user front end API by using the trained Hybrid ML model and sending back successful response of prediction that the customer will subscribe for the product bank term deposit to the Bank product AIML user front end API. The response of the new customer by the trained hybrid model by performing practical predictions on new customer transaction information is demonstrated by the trained hybrid model through transfer learning. Thus, the hybrid model is useful for practical use and can perform real time predictions and respond to request done by the marketing team thereby reducing the cost and time and assisting them with immediate responses to latest customer transactions records.

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**************                                                                                          *************
**************          Bank Product Artificial Intelligence & Machine Learning User Front End API      *************
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*********************************************************************************************************************
*********************************************************************************************************************
**************                                                                                          *************
**************      Prediction Request for New Customer Record Added to Bank Database Sent from User Front End API  *************
**************                                                                                          *************
*********************************************************************************************************************
{"Age": 1.43, "call_time": 1.99, "Promotion": 0.25, "last_contact": 0.2, "no_of_deposits": 0.4, "occupation_change_scale": 0.94,
"customer_cost_indicator": -0.29, "customer_trust_indicator": 0.97, "interest_rate": 0.8, "quarterly_emp_count": 0.99, "Job Type"
: -0.92, "Marital Status": 0.73, "Education": -1.22, "Education loan": -0.51, "Housing loan": -1.06, "Personal loan": -0.44, "Con
tact Type": 0.76, "Month": -0.04, "Day": -0.74, "promotion_result": 0.39}
*********************************************************************************************************************
**************                                                                                          *************
**************          Prediction Response Received from Hybrid Machine Learning Model API             *************
**************                                                                                          *************
*********************************************************************************************************************
1
*********************************************************************************************************************
**************                                                                                          *************
**************             !!! Customer will Subscribe to Product Bank Term Deposit !!!                 *************
**************                                                                                          *************
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Fig. 6. Bank Product AIML User Front End API sending new customer information to Hybrid ML Model API for prediction and receiving successful prediction response.

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**************                                                                                        *************
**************                           Hybrid Machine Learning Model API                            *************
**************                                                                                        *************
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*******************************************************************************************************************
**************                                                                                        *************
**************  Prediction Request for New Customer Record Added to Bank Database Received from User Front End API  *************
**************                                                                                        *************
*******************************************************************************************************************
{'Age': 1.43, 'call_time': 1.99, 'Promotion': 0.25, 'last_contact': 0.2, 'no_of_deposits': 0.4, 'occupation_change_scale': 0.94,
'customer_cost_indicator': -0.29, 'customer_trust_indicator': 0.97, 'interest_rate': 0.8, 'quarterly_emp_count': 0.99, 'Job Type'
: -0.92, 'Marital Status': 0.73, 'Education': -1.22, 'Education loan': -0.51, 'Housing loan': -1.06, 'Personal loan': -0.44, 'Con
tact Type': 0.76, 'Month': -0.04, 'Day': -0.74, 'promotion_result': 0.39}
*******************************************************************************************************************
**************                                                                                        *************
**************              Hybrid Machine Learning Model Prediction Output 1:Yes, 0:No               *************
**************                                                                                        *************
*******************************************************************************************************************
**************                                                                                        *************
**************            The Prediction Output of the Hybrid Machine Learning Model is : [1]
**************                                                                                        *************
*******************************************************************************************************************
**************                                                                                        *************
**************               The Customer will Subscribe for Product Bank Term Deposit                *************
**************                                                                                        *************
*******************************************************************************************************************
**************                                                                                        *************
**************              Prediction Successful!!!! Response sent to User Front End API             *************
**************                                                                                        *************
*******************************************************************************************************************
127.0.0.1 - - [16/Mar/2021 03:50:42] "POST /api HTTP/1.1" 200 -
```

Fig. 7. Hybrid ML Model API performing prediction on new customer transaction information and sending response back to Bank Product AIML User Front End API

4. Conclusion and future scope

In the banking and financial services domain, enhancement and maximization of the efficient and effective targeting of right clients for telemarketing is a widespread issue considering the economic slowdown and crisis during the pandemic spell thereby soaring the rate of work pressure to reduce the business losses and to gain profits to make the businesses survive be it in the retail marketing business, online marketing business, food and beverages marketing business, technology marketing business all industries being drastically impacted. However, telemarketing has gained much widespread attention and has been the support system to the businesses during such economical crunch period. Taking into account the reverberations of the economic crisis of the Indian Bank were obliged to acquire capital investments by acquiring term deposits. In this research, an efficient machine learning procedure is recommended for the detection of bank telemarketing customers. A current and sizeable Indian Bank dataset was examined and analysed through the machine learning models: Logistic Regression ML model, Naive Bayes ML model, Decision Tree ML model. These models were compared with Hybrid machine learning method using accuracy and performance metrics. For both parameters and phases, high and valid outcomes were achieved by the Hybrid technique. The models were trained on large Indian bank data to overcome the problem of ill-fitting due to multiple features in the dataset and tuned on validation set to prevent the data leakage. The models were trained, validated and tested on Indian bank data set. After achieving the desired accuracy, the hybrid model can be deployed for practical use. This allows bank to predict the customers who may agree to subscribe to the new product. The hybrid model can be used for new customers and can predict the response of the customer and displays the response on the Bank product AIML user interface front end. The hybrid model can be used by financial institutions and organizations for predictions of product direct marketing response with customer transaction information. After achieving the desired accuracy and customer conversion rate the model can be used for practical predictions. Future work in this domain is focused on applying and utilizing the hybrid ML model for various business problems to meet the demand of the financial institutions to achieve the subscription targets for future banking products. In future the model can help the social and economic arenas of the society and can be trained and used for real time and immediate prediction to contribute AI to the society. .

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