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An Intelligent Machine Learning Framework for Customer Churn Prediction in CRM Systems

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ABSTRACT: In today's highly competitive market environment, organizations face significant challenges in retaining customers due to increasing competition, evolving customer expectations, and unpredictable churn behavior. In order to address these concerns and predict customer turnover using the Telco Customer turnover dataset, this article suggests a CRM system that relies on clever machine learning techniques. To ensure high-quality data for model training, the proposed system incorporates thorough data pretreatment stages such ADASYN class balancing, missing value management, label encoding, and z-score normalisation. Build and test two supervised ML models, XGBoost and Random Forest (RF), to see how well they perform. The trials showed that the Proposed RF Model achieved 97.1% accuracy (ACC), 97.6% precision (PRE), 97.4% recall (REC), and 97.2% F1-score (F1), whereas the Model Proposed XGBoost Model generated 96.9% ACC, 96.7% PRE, 96.6% REC, and 96.3% F1-score. The suggested method outperforms state-of-the-art machine learning and deep learning models for predicting customer attrition. With the help of the suggested framework, businesses may pinpoint consumers who are likely to churn, which in turn allows for more proactive retention measures, happier customers, and more profits in the long run.

KEYWORDS: Customer Churn Prediction, Machine Learning, CRM, Predictive Modeling, Classification Algorithms, Customer Segmentation.

1. Introduction

The telecom industry (TCI) has expanded tremendously in recent decades, bringing with it new innovations in technology, fiercer rivalry, an increasing number of operators, and a plethora of new goods and services [1][2]. Every day, a large number of transactions take place on the online banking platform. There is a wide range of buying behaviours represented in the electronic banking transactions. The loss of customers to competing online retailers is a growing problem for entrepreneurs in the digital space [3]. Because of its significance, businesses should track their customer turnover rate on a regular basis. Customer relationship management focuses on retaining customers. Organisations that want to build lasting relationships with their customers and boost their overall performance have begun to rely on CRM systems [4][5]. Transactions, service usage, demographic information, purchase history, and customer contacts generate enormous amounts of customer data as a result of the fast development of digital technology [6][7]. The study of these data can help organizations better comprehend customer behavior, preferences, and satisfaction, which can guide decision-making and provide personalized services [8]. The traditional solutions to the analytical challenges of customer data are, however, proving to be less effective than they should be because of the quantity and complexity of the data [9][10]. This has made AI an effective solution for CRM systems, providing a means to analyze data efficiently, make informed decisions, and uncover valuable customer insights that can aid in the growth of the business and customer retention [11].

Predicting when a client depart is one of the most significant uses of AI in CRM. This makes sense because it is costlier to maintain an existing customer than to attract a new one [12]. The percentage of clients that opt to discontinue their relationship with a company is called client churn. While there are a variety of causes, the end result is the same: less money coming in, more money spent on acquiring new customers, and less money coming in in the future. Early churn identification could be useful for industries including subscription-based services, online banking, insurance, and telecommunications [13]. Churn prediction using ML models such as DTs, SVMs, and boosting models like XGBoost, LightGBM, and CatBoost, on the other hand, is best accomplished with structured data. Digital learning architectures such as ANNs, CNNs, LSTM networks, and Transformer-based models excel in modelling sequential and unstructured data, including customer contact histories and textual feedback [14][15]. These smart models help make timely customer retention decisions, boost the effectiveness of a CRM system, and increase customer satisfaction and business sustainability.

A. Motivation and Contribution

The study's goal is to find ways to stop customers from leaving in a business world where keeping customers is very important to success. The current traditional solutions are not successful in handling complex customer behaviors and predicting churn risks. Thus, the present study aims to create a ML based CRM framework for enhancing churn prediction and facilitating the proactive approach to customer retention along with data-driven decision making. The work carried out in this research has several significant contributions as outlined below:

- The development of a smart ML tool for CRM churn prediction.
- Applying the ADASYN approach to balance the data, handle missing values, encode labels, normalise z-scoring, and use the Telco Customer Churn dataset (TCCD).
- Implemented two supervised ML models, namely RF and XGBoost, for churn prediction.
- Conducted a comparative study with previous ML/dp models and proved the effectiveness of the proposed framework.
- Delivered a practical decision support model for real-world implementation of proactive customer retention and optimization of CRM performance.

The study is necessary because of the urgent need for intelligent customer churn prediction systems that help organizations detect customer churn risks and act proactively to prevent customer churn. The development of an ML-based CRM framework is the study's distinctive contribution. This strategy integrates data balancing, ensemble learning models, and cutting-edge preprocessing techniques to enhance churn classification performance. This proposed solution is data-driven and can be used to analyze customer behavior patterns and make proactive decisions in CRM systems, providing a reliable solution.

B. Organization of the Paper

The remaining paper is summarized as follows. Section II includes works that are related. In Section III, describe the methodology of the study. Section IV delves into the analysis and findings of the experiments. In Section V, the paper is finished.

2. Literature Review

The purpose of this literature study was to fill in research gaps and enhance the suggested methodology for predicting customer turnover in CRM systems.

Kishore Varma Alluri, (2026) proposes a Data-to-Action architecture for implementing AI in a CRM environment similar to Salesforce, which may help automate business decisions in real-time. There are 7,043 customer records and 21 characteristics in the IBM TCCD. Several machine learning methods were evaluated, including LR, SVM, RF, Gradient Boosting, XGBoost, and LightGBM. Afterwards, a five-layer stratified cross-validation model was employed. LR has proposed an ideal REC of 0.7834, F1 of 0.6136, performance-to-ROC-AUC ratio of 0.8413 for a churn-sensitive application in a corporation [16]. Another work by Alluri, 2026) recommended comparing CRM churn prediction with different ML techniques on the IBM TCCD. LR appears to have the best REC performance and maximum ROCAUC (0.8413) according to the experimental data, making it a good fit for retention-based CRM strategies. Model transparency and business interpretability are both enhanced by SHAP-based explainability [17].

After this Hudli et al., (2025) The purpose of this EDA is to find trends in a dataset consisting of telecom customers that might indicate cause of churn. Among six ML algorithms used to simulate churn behaviour, the RF Classifier had the best results, increasing ACC from 84% to 92.8%. Useful applications of these findings include proactive retention campaign design and predictive modelling [18]. Then, Kuramannagari et al., (2025) offers a contrast of ANN, LR, RF, and XGBoost, four ML models that were trained on the TCCD. The other models were beaten by XGBoost, which achieved a ROC-AUC of 92.4%, an F1 of 82.8%, and an ACC of 87.5%. The application of SHAP (Shapley Additive Explanations) further improved the data's interpretability, drawing attention to the fact that the contract type, monthly costs, and client were the most important factors in determining churn [19].

Subsquently, Alteer and Alariyibi, (2024) suggested that ML approaches, utilised for a multitude of purposes, constitute the backbone of data science. Five different classifiers were utilised in the method that was suggested. In particular, techniques such as LR, DT, RF, GBM tree method, and XGBoost are relevant in this prediction context. With an AUC of 94%, the XGBoost tree model produced the best results in the experiments [20]. Also, Raman Chandan et al., (2024) provides a ML-EWDS to decrease commercial client attrition. A RF classifier is part of the ML-ensemble EWDS's learning model, which allows it to solve this challenge by analysing historical consumer data enhanced with RFM features. After extensive data preparation, model training, and cross-validation, the system achieved an impressive 87.5% ACC and an amazing ROC-AUC of 0.92. The groundbreaking potential of ML-EWDS in CRM is demonstrated in this work, which has implications for both academia and industry and suggests several avenues for further research [21]. Then Adiputra and Wanchai, (2023) A system that utilises a combination of preprocessing approaches and an ensemble of the XGBoost and RF ML models is the aim of this study. A public dataset platform is utilised in this research to draw upon data acquired from two separate industries: insurance and telecoms. The insurance industry got a 0.947 F1 and a processing time of 28 seconds, while the telecom sector dataset got a 0.850 F1 [22].

Finally Singh et al., (2023) one of the most vulnerable sectors to income loss due to customer churn and ecological footprint is the telecoms companies. How well ML algorithms mimic actual telecoms data, as opposed to the freely available dataset, may also affect their efficiency. Consequently, XGBoost was one of several prediction models utilised by the researchers with this dataset. An ACC of 82.80% was attained using the original dataset. The results demonstrate that the highly technified prediction model is successful [23]. Lastly, Galal, Rady and Aref, (2022) offers a classifier-based approach for churn prediction using customer profile data. Many supervised classification techniques were employed and evaluated in the research. These algorithms included KNN, LR, AdaBoost, Gradient Boosting, and RF. The RF model ranks the characteristics based on their importance. With a dataset of 10,000 records, the model was able to get an 87% success rate in the given experiment [24].

Table I provides a concise overview of current research on CRM churn prediction, including papers, models, datasets, important results, and limitations.

TABLE I. RECENT STUDIES ON CUSTOMER CHURN PREDICTION IN CRM SYSTEMS USING MACHINE LEARNING TECHNQIUES

Author	Proposed Work	Dataset	Results	Limitations & Future Work
Kishore Varma Alluri (2026)	Proposed a Data-to-Action AI architecture integrating machine learning with Salesforce CRM for automated churn prediction and decision-making.	IBM Telco Customer Churn (7,043 records, 21 features)	Logistic Regression achieved ROC-AUC: 0.8413, Recall: 78.34%, F1-score: 61.36%.	Limited evaluation on a single dataset; future work should validate the framework on larger datasets and advanced deep learning models.
Alluri (2026)	Developed a scalable, secure, and explainable machine learning framework with SHAP-based interpretation and differential privacy.	IBM Telco Customer Churn	Logistic Regression achieved ROC-AUC: 0.8413 with high recall while preserving privacy.	Future work should improve privacy-utility trade-offs and evaluate additional explainable AI techniques.
Hudli et al. (2025)	Performed exploratory data analysis and compared multiple machine learning models for telecom churn prediction.	Telecom Customer Dataset	Random Forest achieved 92.8% accuracy after preprocessing.	Limited to traditional ML models; future work can incorporate deep learning and real-time prediction systems.
Kuramannagari et al. (2025)	Compared Logistic Regression, Random Forest, XGBoost, and ANN with SHAP-based interpretability.	Telco Customer Churn Dataset	XGBoost achieved 87.5% accuracy, 82.8% F1-score, 92.4% ROC-AUC.	Future work should improve model generalization and evaluate hybrid ensemble techniques.
Alteer & Alariyibi (2024)	Applied oversampling methods and evaluated five classifiers for ISP customer churn prediction.	Libyan ISP Customer Dataset	XGBoost achieved 94% AUC.	Performance evaluated on a single ISP dataset; future work should explore multi-domain datasets and real-time deployment.
Raman Chandan et al. (2024)	Proposed an ML-based Early Warning Detection System (ML-EWDS) using Random Forest with RFM features.	Commercial Customer Dataset	87.5% accuracy, 0.92 ROC-AUC, reduced customer turnover by 70%.	Future work should investigate adaptive learning and larger enterprise deployments.

Adiputra & Wanchai (2023)	Developed an ensemble framework combining Random Forest and XGBoost with preprocessing optimization.	Telecom & Insurance Datasets	F1-score: 85.0% (Telecom), 94.7% (Insurance).	Processing time remained high for large datasets; future work should optimize computational efficiency.
Singh et al. (2023)	Evaluated XGBoost and other predictive models on a telecommunications churn dataset.	Telecommunications Customer Dataset	Achieved 82.8% accuracy.	Limited handling of class imbalance; future work should investigate advanced balancing and ensemble methods.
Galal, Rady & Aref (2022)	Proposed a voting-based ensemble with hyperparameter optimization for customer churn prediction.	Customer Churn Dataset (10K records)	Achieved 87% accuracy.	Future work should validate the model on larger datasets and improve feature selection and scalability.

Research gaps: ML methods like XGBoost, LR, RF, and ensemble techniques have been shown to effectively detect possible churn consumers in recent research on Customer Churn Prediction in CRM systems. The current methods have limitations due to class imbalance, lack of generalization ability for the models, lack of scalability, and the desire for models with better prediction ACC and real-time decision support. Many studies focus mainly on model comparison without integrating advanced preprocessing and balancing techniques to enhance minority class prediction. This study suggests a ML framework that uses effective data preprocessing, ADASYN-based balancing, and optimised ensemble learning models to make it easier and more accurate for CRM systems to predict when a customer leave.

3. Methodology

A systematic strategy encompassing data collecting, data preprocessing, model construction, and model assessment is suggested for predicting customer attrition. The first step is to gather and analyse the TCCD in order to learn more about its features and spot any issues with its cleanliness. Data balancing utilising the ADASYN approach for addressing class imbalance is conducted during the preprocessing step, along with missing value imputation, categorical feature encoding, and Z-score normalisation of numerical features. The stratified train-test split approach, which divides the dataset into a training set of 75% and a testing set of 25%, is then applied to maintain the class distribution. Two supervised ML models, XGBoost and RF, trained and evaluated next for the purpose of predicting client turnover. The proposed models are evaluated using a variety of measures. These encompass PRE, ACC, REC, confusion matrix, ROC-AUC, and F1. The proposed method's general outline is depicted in Figure 1.

The next section provides a comprehensive outline of the steps that make up the proposed technique:

A. Data Collection and Exploration

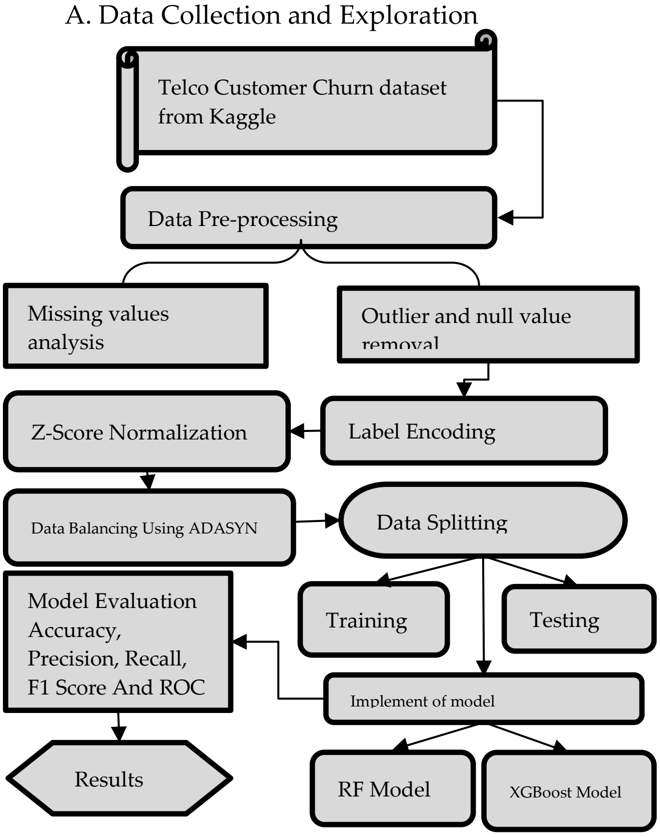

Fig. 1. Proposed flowchart for customer churn prediction in CRM Systems using machine learning

The TCCD [25] has been downloaded from Kaggle and has been utilized to implement and test the suggested customer churn forecasting models. Within 7,043 client records, 21 attributes are used to characterise customer demographics, account details, subscription services, billing information, and churn status data. In order to start getting to know the data, the distribution of customer turnover, and the linkages between the variables of the dataset, an EDA was performed as a preliminary step. In order to prepare the data for preprocessing and model construction, visualisation approaches such as correlation heatmaps and bar charts were used to examine feature patterns, class distribution, and correlations.

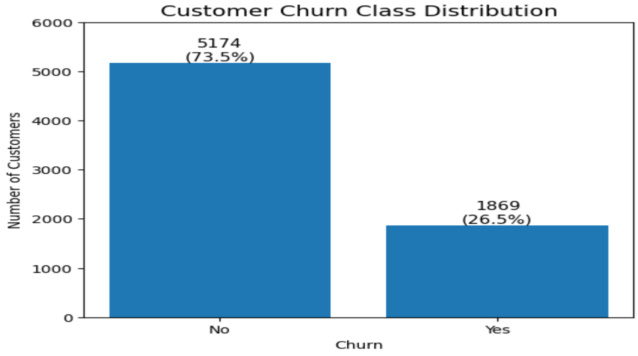

Fig. 2. Bar graph of class distribution

The TCCD shows the churn of customer instances in the bar graph in Fig. 2. Furthermore, out of all the data, 5174 (or 73.5% of the total) are marked as "No customers," while 1869 (or 26.5% of the total) are marked as "Yes customers.". The churn class is greatly outnumbered by the non-churn class, indicating a severe class imbalance. Because of this disparity, ML models may fail to recognise churned consumers and fail to adequately serve the minority class.

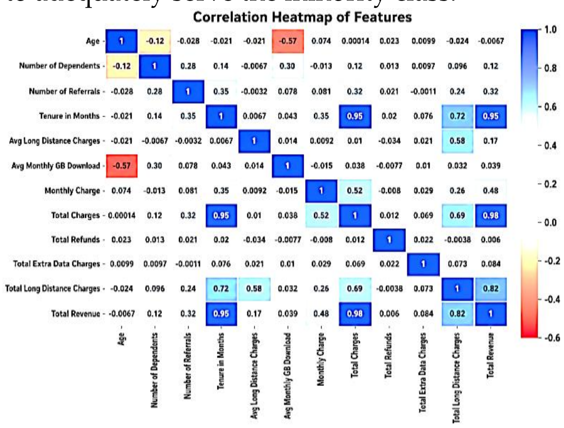

Fig. 3. Correlation Matrix Heatmap of Features

Figure 3 is a heat map that shows the correlation between data characteristics; greater positive or negative correlations are shown by deeper colours, while weaker positive or negative correlations are shown by lighter colours. It shows that Total Charges, Tenure in Months, and Total Revenue have a strong positive correlation, thus offering insight into feature selection and development of the predictive model, whereas the remaining features have either weak or moderate correlation.

B. Data Pre-processing

The TCCD was used in a data preparation process that included data cleansing and feature engineering. During the preprocessing phase, missing value analysis, outlier and null value removal, data labelling, and normalization were performed to enhance data quality and prepare the dataset for effective ML. The main procedures for pre-processing are summarized below:

1. Missing values analysis

The missing values in all features were checked in the dataset. There were no explicit nulls found, but some customers in the TotalCharges feature had empty values. The blank values were those customers with tenure = 0, who had not accumulated any charges. The missing data in the blank fields were replaced with NaN values and then dropped during data preprocessing for consistency. Following this, the dataset here was complete and valid data for modelling.

2. Outlier and null value removal

All the TotalCharges feature had missing values which were converted to null values and then removed. The data set was mainly categorical and the data pertaining to customer accounts, so extreme numerical outliers were very few in number. There were no notable outliers detected while examining the data of the numerical characteristics (tenure, MonthlyCharges, and TotalCharges). This pre-processing was important to provide a clean and reliable data set for the customer churn prediction problem.

3. Label Encoding

The TCCD contains several category variables. Label Encoding was used to convert the binary category variables Churn, PhoneService, Dependents, Partner, and PaperlessBilling into numerical values. Class attributes of more than two types, such as InternetService, Contract, PaymentMethod, and others that are particular to services, were appropriately encoded numerically. These conversions allowed for efficient processing of categorical data by the ML models and also maintained the relationships between feature values.

C. Z-Score Normalization

This study used Z-score normalisation (standardisation) to normalise the numerical characteristics, ensuring that all the data was assessed on the same scale. To prevent features with high numbers from "dominating" the learning process, this technique rescales them all to a distribution with a mean of 0 and a standard deviation of 1. Many ML algorithms are also more efficient and perform better when they are standardized. The Z-score normalization is defined as Equation (1):

$$E' = \frac{E-\bar{M}}{\sigma_M} \quad (1)$$

The standardised value is denoted as E', where E is the feature value, μ is the feature mean, and σ is the feature standard deviation. Numbers in the TCCD (tenure, MonthlyCharges, TotalCharges) were only normalised using Z-scores. The categorical features were encoded into numerical representations first and were not standardized. This pre-processing step ensured that all the numerical features had the same contribution in the training of the ML models and thus made the models more stable and predictable.

D. Data Balancing Using ADASYN

One of the most significant problems with churn prediction modeling is class imbalance, because churn often occurs at a very low rate and dominates the data. This section describes the systematic way this imbalance was addressed to achieve strong model performance for both majority and minority classes. The synthetic samples generated by the ADASYN (Adaptive Synthetic Sampling) technique are added only to the training dataset to form a more balanced class distribution, which improves the classification ACC, reduces prediction bias, and makes the identification of churn customers more effective.

After applying the ADASYN approach, the class distribution of the TCCD is shown in Fig. 4, a bar graph. The No (non-churn) class has 5,174 records, or 50% of the total, and the Yes (churn) class has 5,174 records, or 50% of the total, after synthetic minority samples are generated. The balanced distribution eliminates the original class imbalance and enables the ML models to learn the characteristics of both classes equally.

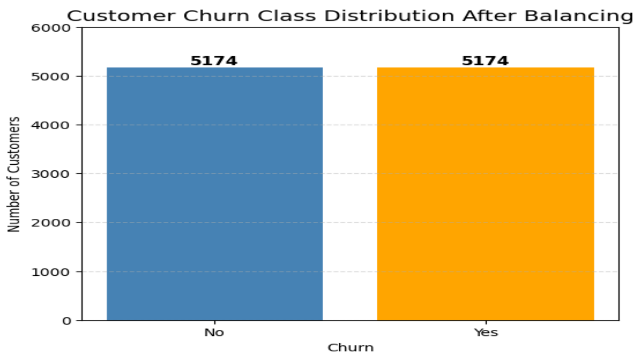

Fig. 4. Bar graph of class distribution after ADASYN

E. Data Splitting

Employing the Stratified Train-Test Split technique, the balanced and preprocessed dataset was divided into two parts: one for training (consisting of 75% of the total) and the other for testing (25% of the total). Thanks to stratified sampling, which keeps the percentage of each class in the training and testing sets constant, each subset accurately represents the overall distribution of classes in the balanced dataset.

F. Implement of model

The purpose of this study is to create two supervised ML models for use in customer relationship management systems: the Proposed RF and the Proposed XGBoost.

A. Proposed Random Forest (RF) Model

A proposed RF uses a random selection of training data and characteristics to generate a number of decision trees, making it an ensemble ML technique. The input sample is classified by each decision tree independently and the class label is chosen based on maximum voting. This ensemble approach reduces overfitting, boosts generalization ability, and ensures the reliability of churn classification predictions.

$$\hat{y} = mode\{T_1(x), T_2(x), \dots \dots, T_n(x)\} \quad (2)$$

The predicted class is denoted by $\hat{y}$ the prediction of the i^{th} DT is denoted by $T_n(x)$, and the total number of trees in the RF is represented by n. The outcome is determined by the forecast that gets the most votes from all the decision trees, as shown in Equation (2).

$$G = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \sum_{j=1}^{C} p_{ij}^2\right) \quad (3)$$

This is where G stands for the average Gini impurity, N for the number of nodes, C for the number of classes, and p_ij for the probability of class j at node iii. The Gini impurity is used in tree construction when determining the best feature split, so as to achieve better classification ACC and more discriminative decision boundaries as expressed in Equation (3). Optimized parameters used for the Proposed RF model are n_estimators = 200, criterion = "gini", max_depth = 20, min_samples_split = 2, min_samples_leaf = 1, and random_state = 42. The parameters settings are more stable, less overfitting, and better classification ACC in predicting customer churn.

B. Proposed Extreme Gradient Boosting (XGBoost) Model

The Proposed XGBoost model is an advanced boosting algorithm that is used to sequentially grow decision trees; the prediction errors made by the previous trees are corrected by the newly grown trees. XGBoost models are fine-tuned by reducing an objective function that includes a regularization term and a training loss term; this enhances prediction performance while reducing model complexity and overfitting.

$$\mathcal{L}(\emptyset) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (4)$$

The prediction loss is denoted by the function $l(y_i, \hat{y}_i)$, the regularisation function for the k^{th} tree is denoted by the function $\Omega(f_k)$, and K is the number of boosting trees. The XGBoost, as mentioned in Equation (4), reduces both prediction error and model complexity to create an optimal predictive model.

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i) \quad (5)$$

In this context, $\hat{y}_i^{(t)}$ represents the updated prediction at iteration t, η signifies the learning rate, and $f_t(x_i)$ denotes the output of the fresh decision tree. Equation (5) shows that the prediction is improved with each boosting iteration by changing the residual errors of the preceding model. This makes the learning process more efficient and the performance of generalisation better. Here are the hyperparameters that were specified for the proposed XGBoost model: n_estimators = 200, learning_rate = 0.05, max_depth = 6, subsample = 0.8, colsample_bytree = 0.8, goal = "binary: logistic", and random_state = 42. These optimized values allows to achieve effective boosting, generalization and prediction ACC for churn classification.

G. Evaluation metrics

The efficacy of the proposed customer attrition prediction models was evaluated by calculating the ACC, PRE, REC, F1, and AUC-ROC. The assessment metrics give a comprehensive picture of the models' efficacy in forecasting client retention or churn rates. On top of that, analysed the prediction results in depth by creating a confusion matrix for every classifier. There are four columns in the confusion matrix that provide information on the amount of occurrences that were properly and incorrectly labelled as churn and non-churn, respectively: TP, TN, FP, and FN. Equations (6)-(9) are used to compute the evaluation metrics:

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (9)$$

ACC is a measure of the model's prediction power and the proportion of correctly categorised customer records. To reduce the number of false churn warnings and show how accurate the positive churn predictions are, PRE is measured as the proportion of persons who were correctly projected to churn. For customer retention techniques that lose money when customers don't leave, REC—also called sensitivity—is an important aspect to examine. It shows how well the model can identify customers who are likely to quit. For unbalanced datasets in particular, the F1—the harmonic mean of REC and PRE—is used to assess the model. Also, the TPR and FPR over different classification thresholds were shown by drawing ROC curves for each ML classifier. A greater AUC indicates stronger classification and prediction capacity, which is how the model was evaluated for its ability to distinguish between churned and non-churned clients.

4. Results and Discussion

The experimental setup and performance assessment of the projected ML models on the TCCD are detailed in this section. Experiment setup and suggested ML model performance on TCCD are detailed in this section. The experiments were conducted on a Windows 11 PC with an Intel Core i5 CPU, 8 GB of RAM, and Google Colab installed. Python libraries used included Seaborn, Scikit-learn, NumPy, Matplotlib, and Pandas. The ADASYN technique was used to preprocess this dataset in order to fix missing values, encode categorical data, normalise data with Z score, and make it oversampled-balanced. Finally, using stratified train-test splitting, a balanced data set was separated into two parts: 75% for training and 25% for testing. All things considered, the ACC, PRE, REC, F1, confusion matrix, and AUC-ROC were used to evaluate the suggested classifiers' performance in predicting customer turnover.

TABLE II. RESULTS OF PROPOSED MODELS FOR CUSTOMER CHURN PREDICTION

Matrix	Proposed RF	Proposed XGBoost
Accuracy	97.1	96.9
Precision	97.6	96.7
Recall	97.4	96.6
F1-score	97.2	96.3

The suggested RF and XGBoost classifiers for customer churn prediction in the CRM system are compared in Table II. Across the board, the models' performance was excellent. When contrasted with the XGBoost model, the suggested RF model achieved better results in terms of ACC (97.1%), PRE (97.6%), REC (97.4%), and F1 (97.2%). In comparison, the suggested XGBoost model obtained 96.9% ACC, 96.7% PRE, 96.6% REC, and 96.3% F1. Both models are excellent in churn prediction, according to the results; however, the RF classification model is somewhat more predictable. Both methods are applicable to CRM churn prediction.

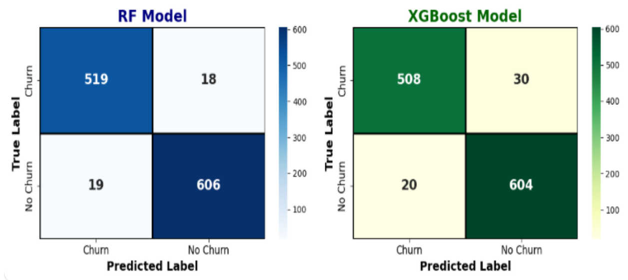

Fig. 5. Confusion Matrix for the Proposed Models

The confusion matrices for the RF and XGBoost models are displayed in Fig. 5. The average classification ACC of both models is high, having correctly classified most of the churn and non-churn cases with few numbers of misclassifications. The RF model achieved 519 correct predictions for churn and 606 correct predictions for non-churn, whereas the XGBoost model made 508 churn and 604 non-churn predictions. The overall results showed that both models have good predictive ACC, with the RF model having slightly better classification ACC because it makes fewer false predictions.

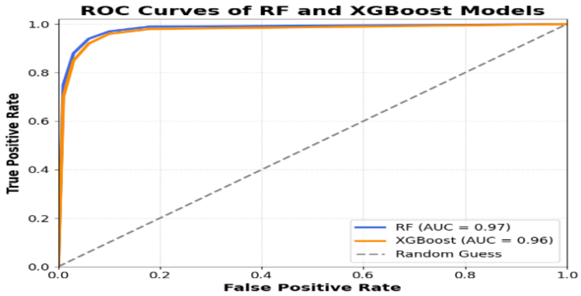

Fig. 6. ROC Curve for the Proposed Models

ROC curves for RF and XGBoost models in forecasting customer attrition are displayed in Figure 6. The XGBoost model had an AUC of 0.96 and the RF model had an AUC of 0.97, indicating that both models have great classification capabilities. The low FPR and high TPR for different categorisation thresholds are indicated by the proximity of both ROC curves to the upper left corner. Both models had excellent discriminative performance in accurately identifying client attrition, according to the data.

A. Discussion

The efficiency of the presented models may be assessed by comparing them to other models, as shown in Table III. Among the models tested, the Proposed RF model had the best results in terms of ACC (97.1%), PRE (97.6%), REC (97.4%), and F1 (97.2%). The Proposed XGBoost model is trained with these highest performance values and then achieves the highest ACC of 96.9%. The baseline models, including CatBoost, Decision Tree (DT), LightGBM, SVM, and ANN, were performance-wise worse in comparison. These results show that the suggested models achieve better prediction of customer churn. In conclusion, the proposed method proved to be effective and robust for CRM systems, as reflected by the overall assessment metrics.

TABLE III. Comparative Analysis Of Customer Churn Prediction Models

Model	Accuracy	Precision	Recall	F1-score
CatBoost[26]	72	70	72	71
DT[27]	80.04	79.07	81	-
LightGBM[28]	0.84	0.84	0.84	0.84
SVM[29]	92	91	92	91
ANN[30]	93.5	-	69	-
Proposed RF	97.1	97.6	97.4	97.2
Proposed XGBoost	96.9	96.7	96.6	96.3

The experimental results clearly show that Proposed RF and Proposed XGBoost models have been performing very well in the prediction of customer churn. The Proposed RF had the best ACC of 97.1%, whereas Proposed XGBoost had an ACC of 96.9%, showing that Proposed RF is more effective at correctly classifying churn and non-churn customers. The high PRE, REC, and F1 values were also obtained on both the models, proving the strength, consistency, and generalization capability of both models. Predicting client attrition and enabling proactive retention efforts are two areas where the models suggested in this study shine within the framework of intelligent CRM systems.

B. Limitations and Future Work

The study's limitations include relying on a single source of customer churn data, potentially restricting the applicability of the results to different customer types and industries. Furthermore, the developed models are based on historical customer attributes but lack temporal or real-time behavioral data. Future studies examine the framework with various public and real-world datasets for customer churn, explore more sophisticated ML and DL models, such as CatBoost, LightGBM, LSTM, GRU, Transformer, and hybrid ensemble models, and include XAI models and methods, including SHAP and LIME, to improve the transparency, interpretability, and trust of the churn predictions.

5. Conclusion and Future Study

CRM and data-driven marketing have become essential in today's dynamic market environment and fiercely competitive business landscape. The most important part of CRM is to keep existing customers. Customer churn prediction is achieved in this work by use of ML algorithms. An churn prediction model based on classifiers that is customer-centric is proposed in this research. Experimental findings demonstrate that the suggested RF model outperformed other models in terms of ACC, with a score of 97.1%. This model outperformed current models like CatBoost (72%), DT (80.04%), LightGBM (84%), SVM (92%), and ANN (93.5%). As a consequence of its improved prediction ACC, the suggested RF model can aid organisations in identifying churn consumers, which in turn can aid in the development of strategies for timely customer retention and relationship management. Future research will involve leveraging the framework with different datasets, incorporating advanced DL and explainable AI methods, and creating real-time churn prediction systems for better CRM decisions.

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