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| RESEARCH ARTICLE

An Ensemble of Advanced Machine Learning Models for Telecom Customer Churn Forecasting

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| ABSTRACT
In the rapidly evolving telecommunications sector, maintaining profitability and growth depends on customer retention. This study provides an in-depth analysis of customer churn prediction with the aim of determining the important factors impacting customer attrition and developing a practical predictive model. In order to make churn prediction more accurate and consistent, the authors of this paper suggest a hybrid ensemble model (LGBM + RF) that mixes LightGBM with random forests. The model makes use of both approaches to improve the accuracy and generalizability of its predictions. Testing on the IBM Telco Customer Churn dataset shows that the proposed model performs better than both traditional ML and DL models. Compared to its forerunners, LGBM + RF achieves better results with a lower AUC of 0.998%, a higher PRE of 98.85%, a recall (REC) of 99.12%, and an F1-score (F1) of 98.56%. These models were previously known as CatBoost, XGBoost, Random Forest, KNN, and Deep-BP-ANN. Ensemble learning is successful in capturing complicated patterns of consumer behavior, according to the findings. This method offers practical information that telecom companies can apply to develop targeted customer retention mechanisms and enhance customer loyalty, making it a useful and valid tool for churn forecasting programs.

| KEYWORDS

Customer churn, Telecom Industry, Churn Prediction, Machine Learning, Ensemble Learning, Predictive Modeling.

| ARTICLE INFORMATION

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1. Introduction

Customers' expectations of their online experiences have grown alongside the proliferation of mobile Internet options, and they now have a wider range of application providers from which to choose. Meeting the unique requirements of each customer, particularly those with high monetary value, and maintaining a steady stream of customers is a top priority for communication companies [1]. Some unhappy customers leave the telecom firm if it doesn't pay attention to their needs and care about maintaining customer relationships [2]. Managers are interested in knowing which users might quit and when they might quit [3]. Establishing a churn prediction model that incorporates both past and present data is crucial for the organization. This model will aid in decision-making, reveal previously unseen connections and patterns, and project future performance.

Enterprises can take proactive steps to care for customers and decrease customer churn [4]. Studies in the telecom sector have shifted their attention to the application of big data analysis tools for data mining, churn prediction, and churn mitigation [5][6]. With the current telecom environment, customer churn is not just a business consequence, but also a measure of the underlying service quality and accuracy of provisioning, network reliability and operational efficiency [7]. Large-scale OSS/BSS systems receive hundreds of millions of provisioning and configuration requests each month, and failures to align services bring about activation, policy, or network experience inconsistencies, which often result in customer churn. The outcome of AI-enhanced churn forecasting thus constitutes an important upstream intelligence alert in autonomous telecoms operations, permitting proactive remediation, service reconfiguration and specific provisioning interventions [8][9]. Through the integration of anticipatory intelligence into the operational processes, telecom operators can stop operating their retention efforts reactively and start operating proactively and at the system level to optimize customer experience.

Customer churn can occur for various causes, such as unhappiness, increased costs, poor quality, and so on [10]. Establishing and maintaining long-term connections with existing clients is a primary goal for many firms. This helps to retain customers by offering them enticing deals. To assist businesses in retaining customers, it is helpful to identify which consumers tend to churn. Some machine learning approaches have been specifically designed for churn prediction [11]. To determine which algorithm best divides customers into churn and non-churn groups, a range of machine learning techniques is used to classify customer data using labeled datasets. The telecom industry is plagued by client churn. A high customer turnover rate is characteristic of the telecom industry, which is caused by factors including fierce rivalry and the launch of new, appealing offers by rivals. There are instances when keeping existing customers is more cost-effective than finding new ones [12]. Predictive modeling approaches to deal with customer attrition prediction have been developed by the machine learning groups using the vast amounts of data available about the telecoms industry [13]. All sorts of consumer data, including local and international call logs, voicemail, demographics, financial information, and more, are at fingertips. Utilizing various data mining approaches, churners are forecasted.

1.1 Motivation and Contribution

There is a lot of competition in the telecom industry, and keeping current consumers is cheaper than finding new ones. Since churning is often linked to customer unhappiness, high prices, or low-quality service, it's crucial to identify probable churners in advance. Using historical and live data on customers, their usage, demographics, and billing information, ML models can identify hidden trends to forecast churn. Proper forecasting helps telecom operators implement retention measures tailored to the situation, enhance customer satisfaction, and minimize revenue loss. This inspires the creation of strong, effective churn prediction models using sophisticated data mining and ensemble learning algorithms. The paper has contributed significantly in the following ways:

- Introduces an effective exploratory analysis to identify major factors influencing telecom customer churn.
- Performs correlation and distribution analysis to identify key churn-driving features.
- Develops a structured data pre-processing pipeline to improve data quality and model performance.
- Proposes an ensemble LGBM + RF model to achieve robust and reliable churn prediction.
- Assesses the efficacy of the model by calculating its AUC-ROC, F1, REC, PRE, and accuracy (ACC).

This research is novel because it employs a composite of LightGBM and RF, which effectively improves customer churn prediction by combining the strengths of the two algorithms. This is in contrast to other traditional studies that have used only a single model or the traditional ML techniques and this work has shown a significant enhancement of the predictive performance and generalization. The findings justify this study, as the proposed ensemble model is more effective than past techniques across the most important measures and can better capture complex churn behavior, offering the telecom company valuable insights into how to enhance the customer retention strategy.

1.2 Paper Structure

The paper is organized as follows: Section II analyses the forecast for customer attrition. The methods that were employed in this investigation are detailed in Section III. The results and analysis of the research constitute the focus of Section IV. Lastly, Section V presents the conclusion and other alternative interpretations.

2. Literature Review

Telecom company churn prediction has been the subject of much research. While most used ML or data mining algorithms, some focused on a single feature-extraction approach, and others compared multiple algorithms to forecast customer attrition.

Shahimoon et al. (2025) examine how the telecom sector applies group-based learning models to forecast customer turnover. Customer retention strategies intended to tackle frequent loss of customers demand accurate churn predictions. The RF designs excelled all other models with a REC of 82.3%, PRE of 83.4% along with predicted ACC of 92.4%. These outcomes prove that the predictive algorithm can foretell employee turnover and pave the way for targeted, time-sensitive interventions powered by explainable AI (XAI) methods [14]. Singh and Gill (2024) investigate state-of-the-art ML classification methods for predicting telecom customer attrition. The three classifiers utilized had ACC rates of 79% for DT, 82% for RF, and 79% for KNN. Because it achieved the highest aggregate critical success rate (ACC), the RF classifier was the best tool for churn prediction.

Highlighting the remarkable effectiveness of the RF model, this study provides a reliable way for assessing customer turnover using ML classifiers [15].

Altairey and Al-Alawi (2024) identify the ML model that best predicts which customers will leave. Separating the dataset into a testing set and a training set was the subsequent stage after data preparation. Following the aforementioned four ML approaches, the prediction models were subsequently trained and tested. Histogram Gradient Boosting had the best ACC at 85.56%, followed by Random Forest at 85.41%, Gradient Boosting at 84.73%, and Logistic Regression at 81.45%. ML algorithms are quite good at predicting telecom customer attrition, according to the study [16]. Dhanawade, Mahapatra and Bhatt (2023) suggest that the telecom industry employ ML to predict client attrition. Select features and encode categorical variables. When dealing with imbalanced classes, a pipeline that uses SMOTE and Random Under-Sampler is employed. These algorithms include Logistic Regression, KNN, DTs, RF, XGBoost, and LGBM. Because it achieves the greatest ACC of 82.92%, this study suggests using LGBM with SMOTE [17].

Gupta et al. (2022). This study evaluated various classifiers for forecasting customers' likelihood of leaving a company using a downloadable data set from Kaggle. This study employed the Kaggle online data set to predict customer churn using several classifiers; the models achieved an ACC of 93.55%. The classifiers utilized were RF, Logistic, J48, Stacking, ADA Boost, Decision Table, and Logit Boost [18]. Saheed and Hambali (2021) suggest a novel approach to feature selection that integrates Ranker and Information Gain techniques. Employ 10-fold cross-validation, the ACC and PRE standard measures, and the F-measure to assess the model's performance. When feature selection is included, the results yield an ACC of 95.02%; without it, the ACC drops to 92.92%. When compared to the current approaches, models performed competitively in terms of F-measure and PRE [19].

Research Gap: Although previous research has demonstrated the effectiveness of ML methods such as RF, GB, and LGBM for predicting customer churn in telecommunications, the current literature lacks information on critical issues such as model interpretability, real-time scalability, and standardized performance of these models in the context of heterogeneous data. The majority of works focus on ACC measures without adequately incorporating explainable AI frameworks or demonstrating the model across a variety of telecom settings, thereby limiting its practical application. This void underscores the need for future studies that go beyond ACC-oriented solutions to develop lucid, scalable, and context-sensitive churn prediction methods capable of supporting actionable, time-sensitive interventions in dynamic industry environments.

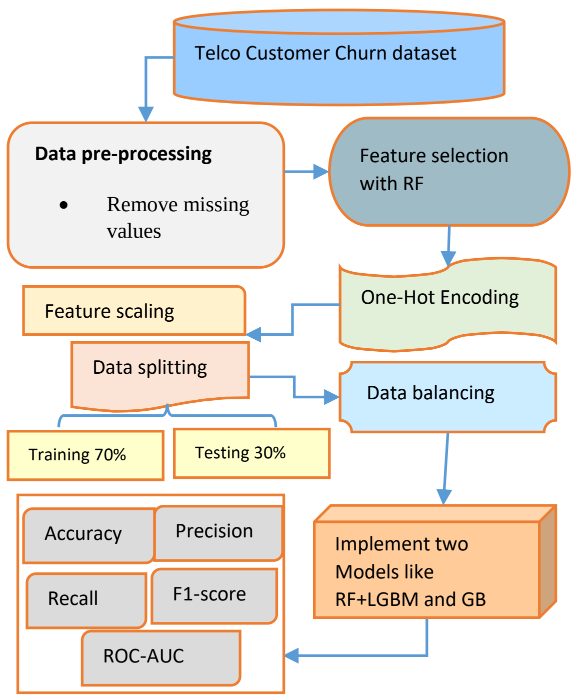

Fig. 1. Customer Churn Prediction Flowchart

3. Methodology

The paper utilizes a systematic ML framework shown in Figure 1 to forecast customer turnover using the Telco Customer Turnover dataset. The methodology includes data pre-treatment, which includes feature encoding, normalization, feature selection, and the removal of missing values, as well as exploratory data analysis, which is used to uncover influential characteristics. Class imbalance is addressed by splitting the data into training and test sets. The final step in ensuring effective churn prediction is to train and test ensemble models using metrics such as ACC, PRE, REC, F1, and AUC-ROC. One example of such a model is the Gradient Boosting Machine.

The details of these steps are clearly presented below:

3.1 Data Collection

This analysis relies on the Telco Customer Churn dataset, which was initially supplied by IBM Analytics. The information is organized in a logical way; it contains 7,043 rows of customer records and 21 columns of characteristics that describe customer qualities. Whether a consumer cancels their service is represented by the binary category variable churn, which is the goal variable. In this work, a correlation matrix was used to identify attributes.

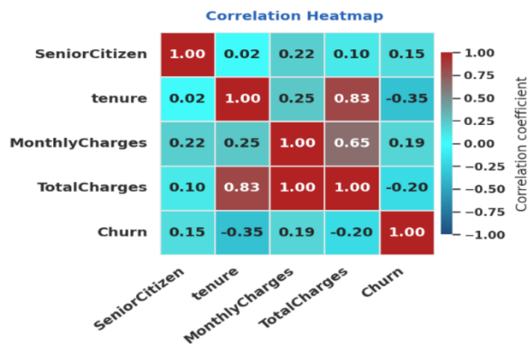

Fig. 2. Correlation Heatmap of features

Figure 2 presents the correlation heatmap of numerical features with churn in which tenure (-0.35) and Total Charges (-0.20) were found to be negatively correlated, whereas SeniorCitizen (0.15) and Monthly Charges (0.19) are weakly positively correlated, indicating that longer customer relations lower the churn, whereas older customers and those with higher monthly bills may be slightly more likely to churn. On balance, tenure and charges turn out to be the most effective characteristics.

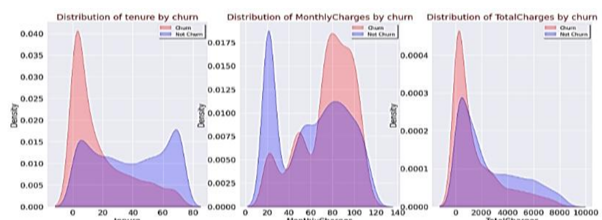

Fig. 3. Density Distribution Based on Churn

Figure 3 displays the tenure, monthly charges, and total charge distribution of both churned and non-churned customers. The churned customers are concentrated at low tenure values which means that the customer is likely to leave within the initial years of service. Greater monthly payments are linked better to churn whereas non-churned customers have longer tenure and greater aggregate payments indicating continued use of the service and improved retention.

Figure 4 illustrates that the customer churn is large among those using the services of the company without subscribing to supplementary services like Online Security, Tech Support, and Protection of Devices. The customers of Fiber optic internet have a higher churn rate than customers of DSL, and those who subscribe to value-added services and bundles have a lower churn rate; hence, retention is good. In general, the figure emphasizes the significance of bundled and security-oriented services in enhancing customer retention in telecom networks.

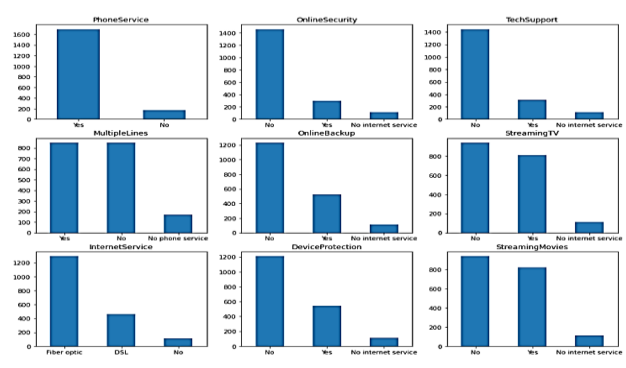

Fig. 4. Churn Customer by Telecom Service

3.2 Data Preparation

Missing value management, column lowering, feature selection, and encoding are all parts of this data preparation procedure. procedures for data standardization, data separation into training and test sets, data sampling from training data, and data balancing. These steps explained in below:

- **Remove missing values:** There are 11 missing values. The study dropped all missing values. 11 is a relatively small instance, so deleting the missing value.
- **Drop column:** Since "Customer ID" is useless for churn prediction, Pandas removed it from the dataset. void drop().

3.3 Feature Selection

One of the most important steps in extracting useful features from a dataset using domain knowledge is feature selection. In this study, use RF-based feature selection. Figure 5 shows a horizontal bar graph of the top 15 significant features of the RF model.

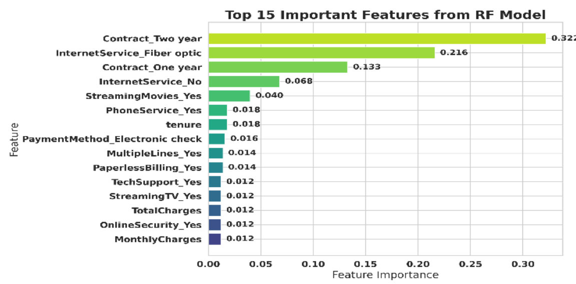

Fig. 5. Bar Graph for Selected feature with RF model

The most important feature is Contract_two year, then followed by InternetService_fiber optic, and Contract one year and this shows that contract type and internet service have a great bearing on the model predictions. Other salient characteristics are the tenure, payment method and the streaming services.

This visualization helps in emphasizing which features have the most effect on customer churn to choose the features and interpret the model.

3.4 One-Hot-Encoding

ML algorithms are not designed to handle categorical data directly. To transform categorical data into binary form, one-hot encoding is required. First of all, the. The next step was to convert the data in the target column "Churn" to binary form (Yes=1, No=0) using the replace() function from Pandas. Since one-hot encoding expands the column, it would cause issues when providing X and Y, hence it is not utilized in the target column. Next, used OneHotEncoder and make_column_transformer to encode and transform the category columns (aside from "Churn" column), and skipped over the remaining columns by setting remainder = 'passthrough'.

3.5 Feature Scaling

A normalization of the distribution of variable values is what feature scaling entails. Equation (1) shows that the Z-score, which is defined as the distance of the standard deviation (s) from the average ($\bar{x}$), was utilized for data normalization.

$$Z_i = \frac{x_i - \bar{x}}{s} \tag{1}$$

where x_i is the value of the i-th variable and Z_i is the i-th Z-score. In order to get the Z-score, this research makes use of the scale() function that is part of the R package.

3.6 Train-Test Splits

The following step is to divide the data in half, making a 70:30 split between the training and test sets. When building a model, one uses a training set and another uses a test set to see how well the model did. The majority of the data utilized for training the model in a 70:30 ratio, while a tiny piece is employed for testing the model.

3.7 Train Data Sampling

A popular and effective oversampling strategy, ROS helps with the problem of class imbalance. Overfitting is more likely to occur because this random oversampling strategy partially recreates the original minority dataset. Figure 6 shows that the dataset of churned customers is sampled to cover the distribution of classes. The Not Churn class has approximately 3500 cases, whereas the Churn class has approximately 1200 cases, which is highly unbalanced. Having used Random Over Sampler, Churn and Not Churn classes are balanced to about 3500 instances each, indicating that oversampling is effective in correcting the imbalance of the classes and improving the performance of the models.

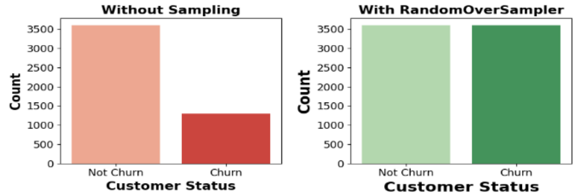

Fig. 6. Bar Graph for Class Distribution with and without sampling

3.8 Propose Models

The study looked at how well two tree-based ML ensemble models—the Ensemble RF+LGBM classifier and the GB classifier—predicted which way customers would leave. Here is a quick rundown of these classifiers that are based on ensemble trees.

1) Ensemble LGBM + RF

An ensemble model of LightGBM (LGBM) with Random Forest (RF) makes use of the advantages of both algorithms to enhance the predictive performance and strength. A gradient boosting framework called LightGBM is great at accurately processing massive amounts of data, while a set of decision trees called Random Forest provides stability and protects against overfitting caused by bagging. The Ensemble LGBM + RF model combines LightGBM's speed, ACC, and RF's strength. By optimizing hyperparameters like learning rate, num_leaves, max_depth, and n_estimators, the model improves its prediction and generalization performance.

2) Gradient Boosting Machine (GBM)

The acronyms GBRT and MART stand for "gradient boosted regression tree," which are other names for the gradient boosting machine [20][21]. A GBM enables training that is sequential, progressive, and additive. Unlike AdaBoost, which finds weak learners' flaws by analyzing high-weight data points, GBM does it by analyzing the loss function.

3.9 Model Performance Metric

The model's prediction ACC is proportional to the quality of the algorithm's input characteristics. The confusion matrix is used to conduct the evaluation. In contrast to off-diagonal cells, diagonal cells display the appropriately designated class. True positive rates are measured by the REC indicator, which indicates how reliable the result is, and positive predictive values with proper prediction are measured by the PRE indicator. The F1 indicator takes a harmonic average of the model's REC and PRE to show how reliable it is. ROC is a probability curve that graphically shows the trade-off between specificity and REC.

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \tag{2}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{3}$$

$$Recall = \frac{\mathrm{TP}}{TP+FN} \tag{4}$$

$$F1 - Score = \frac{2(Precision*Recall)}{\mathrm{Precision+Recall}} \tag{5}$$

Equations (2) through (5) are used to calculate the metrics, which are obtained by dividing the total number of observations by the sum of the correctly classified values. While TP stands for a genuine positive, TN stands for a genuine negative. The expected class (x-axis) and the true class (y-axis) in a 2×2 confusion matrix are used to derive these values.

4. Results and Discussion

A 32 GB RAM, 3.90 GHz Lenovo Legion Pro Core i9-13900HX PC running Windows 10 was used for the experiments and made use of the NVIDIA GeForce RTX 4070 GPU to speed up processing even further. Python modules such as Pandas, Numpy, Tensorflow, and Keras were utilized. Table I presents the comparison of performance of two models, LGBM + RF ensemble and Gradient Boosting (GB) in predicting customer churn. The ensemble model performs a little better than GB in all the metrics with a higher ACC (98.42%). These findings reveal that the predictive power and generalization of LGBM and RF are improved when they are used together and thus, they are more efficient in recognizing churned customers.

Table 1: Performance of proposed models for customer churn prediction

Measures	LGBM + RF	GB
Accuracy	98.42	98.25
Precision	98.85	98.36
Recall	99.12	98.57
F1-score	98.56	98.46

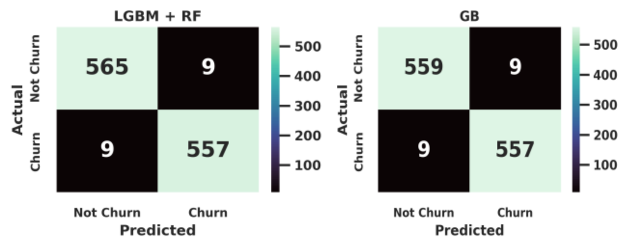

Fig. 7. Plot confusion matrix of Both Proposed Models

Figure 7 shows the confusion matrices of LGBM + RF and GB, demonstrating their performance in predicting customer churn. Both models are very strong in classification with a correctly identified churn and non-churn cases. In contrast to the GB model, which has 559 TN and 557 TP with 9 FP and 9 FN, the LGBM + RF model has 565 TN and 557 TP with 9 FN and 9 FN. These findings show that both methods provide almost the same predictive accuracy, with LGBM + RF having a slightly better performance in identifying non-churn customers.

Figure 8 provides the ROC curve between the classification in the two proposed models, namely, Ensemble LGBM+RF and Gradient Boosting. As illustrated in the curve both the models are highly predictive though the Ensemble model is somewhat higher than Gradient Boosting as the value of its AUC is 0.998 compared to 0.992. Model conditions between classes are increasingly effective as the curve approaches the upper left corner, proving that both methods are useful for predicting customer attrition.

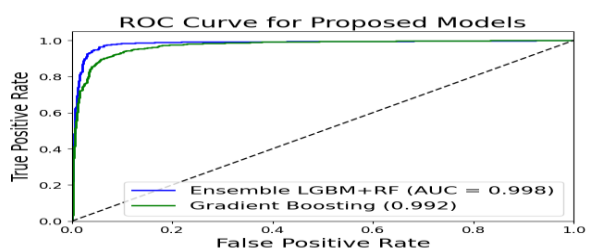

Fig. 8. Plot ROC Curve of Both Proposed Models

4.1 Comparative Analysis

Table II compares the current models to the proposed method of customer churn prediction. Previous research with more conventional ML and DL models including the CatBoost, XGBoost, KNN, DT, MLP, LR, RF, and Deep-BP-ANN report moderate-high performance, with a range of 62.27% to 95.54% ACC and typical F1 86.19%, which is indicative of a lack of ability to capture complex churn dynamics and class imbalance. Contrastingly, the hybrid models suggested have a great number of advantages over the current approaches. These findings clearly show that the proposed ensemble-based method is superior in providing more robust and reliable churn prediction than those previously reported.

Table 2: ML and dl models comparison for customer churn prediction

Ref	Data	Models	Accuracy	Precision	Recall	F1-score	ROCAUC
[22]	Iranian Churn dataset	CatBoost	95.54	90.10	80.72	85.03	-
[23]	Cell2cell	Deep-BP-ANN	73.90	68.15	89.74	77.47	73.90
[24]	Customer Churn Data	XG Boosting	89.60	76.04	62.82	61.63	-
[25]	**Telecom CUSTOMER Churn dataset**	KNN	0.7129	0.5805	0.8467	-	0.81
[26]		DTC	93.51	91.72	82.42	86.19	-
[27]		MLP	62.27	60.80	68.85	64.5 8	66.81
[28]		LR	87.52	82	81	81	-
[29]		RF	79.5	63.5	57.9	60.6	84.9
Propose		**LGBM + RF**	**98.42**	**98.85**	**99.12**	**98.56**	**0.998**
		GB	**98.25**	**98.36**	**98.57**	**98.46**	**0.992**

The study suggests that it has several significant strengths for predicting customer churn. The study has strong and consistent predictive performance through an ensemble model, which is superior to traditional ML and DL models. The methodology is efficient in handling class imbalance via oversampling, feature selection to identify the strongest predictors, and an extensive data pre-processing pipeline, which ensures excellent input to the model. The ensemble model is also enhanced with boosting and bagging, which help to further enhance generalization, minimize overfitting and effectively differentiate between churned and non-churned customers; therefore, the methodology is highly credible and can be effectively applied to real-life contexts in telecom settings.

Although the study has performed well, it is limited in several ways. The model is based on a single dataset, which can be a weakness for its application to other telecom markets or areas. Also, structured tabular data are employed only, no unstructured data, like customer communications, call logs, or feedback on social media, are used, which may bring more insights. Future directions might be to combine several datasets and to add unstructured and time-varying data, apply a sequence behavior analysis with DL models such as LSTM or transformer-based models and to apply the model in real-time environments to enhance predictive quality and usefulness in practice.

5. Conclusion and future scope

Customer churn prediction is finding out which customers will discontinue using a service. Companies in the banking, insurance, casino, and internet service provider industries are all dealing with the same problem of customer churn. This research focuses on telecom churn prediction as a means to identify the best categorization model. This work describes an ensemble-based model that uses LGBM, RF, and GB to forecast telecom customer turnover. Methods for enhancing the model's performance and dependability include balancing classes, reducing features, and cleaning data on a massive scale. The outcome of the experiments proves that the proposed ensemble models are good in terms of predictive performance, with an ACC of 98.42, and the GB model had an ACC of 98.25. The proposed ensemble shows superior predictive powers and strengths compared to standard ML and DL models such as the CatBoost, XGBoost, the RF, the KNN and the Deep-BP-ANN that were found to give lower ACC. The major drivers of churn identified included contract type, internet service and tenure, and they offer practical information to be used in the customer retention strategy. All in all, the paper confirms that ensemble learning along with efficient preprocessing of data and feature engineering is a really effective and feasible solution to telecom churn prediction.

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