Volume (1) No (10), 2025
Journal of Global Research in Multidisciplinary Studies (JGRMS)
Review Paper/Research Paper
Available online at https://saanvipublications.com/journals/index.php/jgrms/index

Predicting Customer Churn in Telecom: A Review of Advanced ML-Based Methods and Applications

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***Abstract*—The telecoms industry is developing rapidly, which has increased competition. Retaining customers is now a highly significant strategic objective. This article discusses the latest findings from studies that employ machine learning (ML) and deep learning (DL) to forecast the number of telecom customers who would switch. Based on the study, telecom operators are able to determine if customers are going to cancel their subscriptions based on their demographic, service usage, and behaviour information. This sequence deals with decision tree models, logistic regression, RNNs, support vector machines, and artificial neural networks (ANNs). The study also explores the application of churn prediction in real-life scenarios to improve customer retention, enable targeted marketing, and enhance service quality. The largest issues, such as data imbalance, explainability, and scalability, and directions for future research that encompass hybrid and explainable AI approaches. This study highlights the essential role of ML-driven churn prediction in ensuring customer loyalty and maximizing the performance of telecom businesses.**

***Keywords*—Telecom Customer Churn Prediction, Machine Learning, Predictive Analytics, Customer experience, Telecommunications Industry.**

I. INTRODUCTION

The telecommunications industry provides consumers a high level of control since they can access a variety of service providers and usually do. In this highly competitive industry, customers demand custom products and services at lower prices, while service providers are interested in expanding their bases through acquisitions and mergers [1]. Keeping existing customers not only generates income but also reduces associated costs, such as advertising and marketing. The telecommunication sector is losing customers at a speedy pace, and this is a serious issue. In a very competitive field like telecommunications, churned consumers are customers who switch from one provider to another [2]. Client turnover has been a key concern in the telecom industry due to its rapid expansion. The high cost has telecommunication providers more interested in retaining existing customers than in acquiring new ones.

A churning customer is one who switches between phone service providers. Telecommunications businesses face a significant challenge in customer turnover, defined as the proportion of existing customers who wish to terminate their service within the next few years. Both the company's quick expansion and its revenues could be impacted by this issue [3]. Consequently, despite the implementation of numerous Customer Churn Prediction (CCP) models, none of them have been able to achieve the expected level of CCP performance. This is because there are still unknown variation variables that could impact Customer Churn (CC). There are several factors that can influence a client's decision to leave a company. These include poor customer service, slow response times to complaints, negative press or social media reviews, software that doesn't meet their needs, more affordable options from competitors, or incompatibility with more advanced network types (4G, 5G, 6G).

Machine learning, in contrast, is a dynamic and ever-growing academic discipline. The report concludes that the telecom industry use nonparametric methods and machine learning models to catch up in the next years [4]. Machine learning goes beyond simple prediction when it comes to churn prevention. Businesses can leverage ML-driven insights to develop personalised engagement strategies that enhance customer satisfaction and loyalty. Targeted marketing, tailored loyalty programs, and proactive customer service are some of these tactics. Companies may also respond quickly to customer behaviour with real-time data, which means that intervention strategies are put into action on time and work [5]. By using machine learning (ML) and customer relationship management (CRM) systems along with business intelligence tools, companies may automate their retention activities and improve client experiences on a large scale, which helps them predict and stop customer churn. To develop data-driven ways to keep customers, need to spend a lot of attention to ML-based personalised marketing, segmentation, and real-time intervention tactics.

A. Structure of the Paper

The paper's structure is outlined below: Section II covers the basics of telecom customer turnover prediction. Machine learning techniques for churn prediction are covered in Section III, and their primary applications are highlighted in Section IV. Section V provides an overview of current research and obstacles, and Section VI finishes with important takeaways and recommendations for further study.

II. CONCEPT OF CUSTOMER CHURN PREDICTION IN TELECOM

Customer attrition in telecommunications refers to customers dropping services, which affects revenue through costly customer acquisitions and retention. Churns are categorized into voluntary, involuntary, contractual, and noncontractual, assisting telecom companies to isolate causes of customer loss and offer effective targeted retention strategies.

A. Role of Customer Churn in Telecom

"Churn" is an etymological derivative of "turnover" or "attrition." When two parties decide to end their relationship, this is known as "churn." term for when a client decides not to use service anymore is "churn." Churn A customer is the sum of all the present users who can cancel their service subscription at any moment within a given time limit. This group of buyers is known as churners. The primary goal of churn analysis is to quickly identify the causes of customer turnover and anticipate which customers are most likely to churn. Identifying and anticipating churnable consumers as quickly as feasible is the main objective of churn analysis. Use this information to fix the customer's problems [6]. The customer's needs met, and they continue to utilize that service, because of this. Customers continue to use the service because this helps meet their needs. Acquisition costs and retention costs are two types of promotional expenses in a telecommunications company.

B. Classification of Customer Churn

Churns can be classified into a variety of categories based on their characteristics. They are the second category of customers, referred to as "unintentional" or "involuntary." One way to classify aware churners is as either inadvertent churners or deliberate churners (see Figure 1). People who churn on purpose do so because they are dissatisfied with the services and recharge/monthly plans offered by one company and want to move to another that offers better plans [7]. Incidental churners are customers who cancel due to circumstances beyond their control, such as relocating to an area without access to the service provider, departing the nation, or being required to use a specific provider for employment. Finding customers who are considering leaving is the goal of the churn prediction model [8]. One way to improve the accuracy of forecasts regarding purposeful churners is to examine their historical behavior with the service provider.

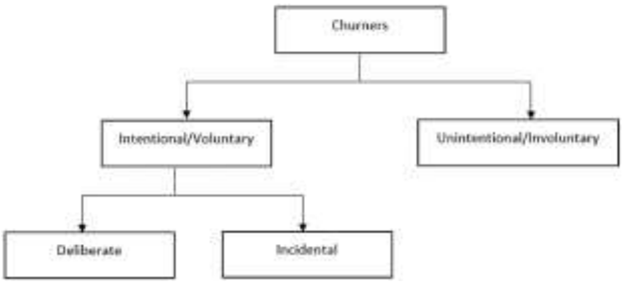

Fig. 1. Categorization of Churners

Churns are classified as follows:

- **Voluntary:** This churn happens when the customer decides to cancel their service contract subscription. There are essentially two categories here: intentional and accidental [9]. Deliberate factors for churn include technological ones, such as customers seeking more modern or innovative solutions, as well as factors like excessive cost, poor support quality, and housing. Most people focus on trying to fix this one problem. Simply put, incidental churn occurs when a change in a customer's circumstances negatively affects their ability to subscribe to a service.
- **Involuntary Churn:** The company decides to end the customer's monthly service because of this type of churn. Expiration of a credit card, nonpayment, or abuse of the service are among the grounds for termination. It is easier to find involuntary churn than voluntary churn.

III. Machine Learning Approaches for Churn Prediction

ML represents a significant advancement over traditional methods for predicting customer turnover and retaining customers in the telecom industry. ML approaches for churn prediction employ supervised models like SVM, DT, and Random Forests, ensemble and hybrid methods for improved accuracy, and DL architectures such as CNNs and LSTMs to capture complex behavioral patterns and enhance customer retention strategies.

A. Machine learning approaches

The algorithm is fed a bunch of instances together with their associated replies; in other words, the model is built from its output [10]. This is an example of automatic learning. Decision trees, SVMs, and AI, specifically MLPs, are the most common supervised approaches. In figure 2 shows the supervised learning.

- **Logistic Regression**: LR is a widely used statistical framework for applications that involve binary classifications. Even though it sounds like a regressive strategy, it's actually a categorization methodology. Determining whether an input belongs to a certain class is the main objective. The LR model uses the logistic function to convert expected values into possibilities. Outcomes of the logistic function include the integers 0 and 1.
- **Support Vector Machines:** The two-class classification challenges were addressed by proposing SVM. When it comes to reducing its generalization error, the SVM takes structural risk minimization into consideration. For each set of classes, it seeks out the best possible separating hyperplane (OSH) [11]. The primary objective is to maximize the gap between the training sample classes. Promisingly, SVR extends SVM to address regression issues.
- **Decision Tree:** DT, an adaptive ML approach, are useful for DT Model the Testing and regression tasks. In their decision-making frameworks, each node represents a choice and the chain of possible outcomes that could result from it. Within the decision tree, the model's features are represented as nodes, and the decision-making rules are embodied in the branches that connect these nodes to the outcome leaves. At each node, data is partitioned according to the features that, when evaluated, yield the most homogeneous subsets.
- **Random Forest Model:** DT' overfitting problem was resolved by the introduction of ensemble decision-tree-based algorithms, while random forest remains a highly accurate and practicable alternative. After building many decision trees, random forest classifiers vote to combine their predictions [12]. After implementing both the bagging and feature random sub-setting techniques, randomization is achieved. Bootstrapping makes use of a variety of data sources to build trees, while feature subset

selection uses two-way randomization to create consolidated weak learner models.

- **K-Nearest Mean (KNN) Model:** This approach revealed novel fraud patterns that improved the institution's fraud prevention capabilities by facilitating the identification of trading fraud activities [13]. Analysis of trading behaviour allowed unsupervised anomaly detection systems to identify transactions with suspicious patterns. Successfully identifying insider trading violations that were missed by standard inspection techniques, the firm achieved its goal. Identifying possible insurance claim fraud. Examining their claims data, the insurance company employed association rule learning for study.

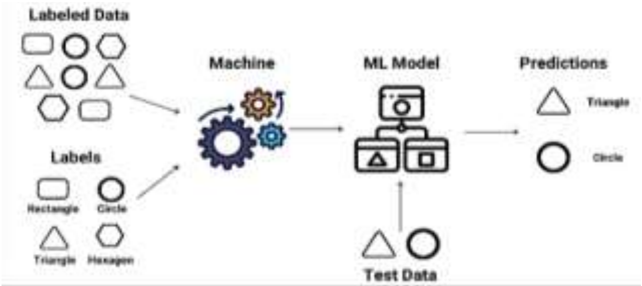

Fig. 2. Supervised learning

B. Ensemble and Hybrid ML Approaches

The use of hybrid and ensemble approaches has greatly improved consumer churn prediction across many different industries. These approaches combine different classifiers, clustering algorithms, and sophisticated feature engineering techniques to solve problems that single algorithms cannot. Hybrid could involve clustering of customers based on segmentation, and then further breaking down the segment into a classification using CNNs or feature engineering using CNNs with a temporal model using LSTM. Hybrid systems tend to be more tailored and usually domain-specific, whereas ensemble methods adhere to standard rules of combining, such as majority voting or weighted averaging.

C. Deep Learning Approaches

A variety of methodologies capable of addressing complex user behavioural patterns and industry retention problems have been provided by deep learning methods, which have significantly contributed to the advancement of the business attrition prediction framework. Updates include new models for representation learning and feature interaction, CNNs applicable to structured data, efficient feedforward neural networks, deep reinforcement learning, sequential modelling using architectures like LSTMs, and hybrid and ensemble algorithms that combine multiple DL paradigms [14]. Proactive and successful churn management solutions can benefit from the benefits of each of these areas, such as improved accuracy, interpretability, and computing efficiency.

IV. Applications of Telecom Customer Churn Prediction

The main applications of telecom customer churn prediction are customer retention strategy, targeted marketing and personalized offers, resource optimization and cost reduction, and customer experience and loyalty enhancement. Through the proper estimation of the possible churners, the telecom firms can be proactive in keeping the good customers, increasing satisfaction, and having competitive advantage in the market.

- **Customer Retention Strategies:** A prerequisite for the development of effective consumer retention strategies in the telecommunications sector is the ability to predict churn. Through customer behaviour, trends of service consumption and contact with the company, telecom operators can determine customers who have a high risk of switching to competitors [15]. With the help of churn prediction, businesses have the ability to improve loyalty by actively applying relationship marketing strategies such as targeted communication, personalized customer care and trust-building engagements. Individualized offers, improved quality of networks and quick service complaint resolution are just some examples that can make the customer happier and reduce attrition [16]. With the help of churn prediction data, telecom companies can manage resources better, provide high-value clients with the priority, and design cost-effective and effective retention campaigns, which can keep them afloat in terms of long-term income and competitiveness in the market.
- **Targeted Marketing and Offers:** Telecom company businesses can design personalized offers and targeted marketing campaigns, which are effective in retaining consumers through churn prediction. Telecom providers can detect subscribers who are at risk of switching to competitors through the analysis of consumer behaviour, service usage, and history of interactions with the service via machine learning [17]. Companies can utilize this data to tailor their loyalty plans, small business promotions, discounts, and personalized service enhancements to satisfy the needs and interests of every specific consumer. In circumstances where one of the clients complains of the quality of their service, like when they complain about the quality of their network, they can be offered network enhancements or incentives based on usage, and a client who is exploring competitor plans can be offered special loyalty rewards.

A. Implications for Telecommunications

The high accuracy of forecasts provided by the framework enables telecom providers to subsequently adopt specific retention strategies such that their effort centers on retaining customers who are most likely to churn [18][19]. This is a targeted approach that maximises the utilisation of resources and the retention campaigns are more effective. Customer satisfaction and loyalty can be maximised through proactive customer management enabled by early churn prediction. This means offering customers personalized offers, improved service, and targeted messaging. Telecommunications firms can enhance the alignment of their products, customer care policies, and promotions with customer needs by applying the framework's insights into the drivers of customer churn.

B. Future Research Directions

Future studies can explore different mechanisms for enhancing methods of predicting churn. Incorporating real-time data, including call centre records and social media sentiment, can enhance prediction accuracy by providing companies with more current customer information. Applying Explainable AI (XAI) methods to the ensemble model may also help people better comprehend what makes people depart, enabling them to make better decisions. Since the model is adaptable, it can be applied to various industries beyond telecommunications. It's necessary for most companies to be able to foretell when the customers departing. This one might be applied in the banking industry, retail, and subscription services, among others. Finally, subsequent studies should aim to develop tailored and adaptable retention approaches that apply real-time churn estimates and particular client portraits.

V. Literature Review

Present studies on telco churn forecasting with machine learning emphasize the necessity for risk assessment among customers, optimization of retention efforts, and data-based decision-making to reduce customer loss and improve business performance.

Kumar, Kakkar and Chouhan (2025) uses KNN, SVC, RF, LR, DT, AdaBoost, Gradient Boosting, a Voting Classifier, and a LSTM network to see how well machine learning algorithms can predict customer turnover. The LSTM model surpasses standard prediction methods by processing time-based patterns which includes customer data activity combined with service pattern usage and payment records. Experimental data shows the LSTM model surpasses standard classifiers by producing testing accuracy results of 89% and precision results of 0.86 together with recall results of 0.85[20].

Azhar, Saikhu and Buliali (2025) The research suggests a machine learning ensemble method that combines XGBoost and LightGBM, with the addition of SMOTE-ENN and GridSearchCV for hyperparameter optimisation, to improve upon the strengths of each method. While GridSearchCV methodically finds the best parameter settings, SMOTE-ENN integrates to produce synthetic minority samples and remove noisy or borderline occurrences, successfully addressing class imbalance. Experimental results demonstrate that the optimized XGBoost and LightGBM models achieved high prediction accuracies of 96.49% and 96.32%, respectively[21].

Toprak, Berfin Mercan and Osmanca (2025) conducted on open-source IBM Telco, Orange Telecom and Maven Analytic Telco datasets. 16 different ML classification models were evaluated separately on the datasets and the 3 models that gave the best results were selected and their customer churn prediction performances were evaluated with classification metrics. The most successful models were the Linear Discriminant (80% test accuracy), Gradient Boosting (94% test accuracy), and Linear Regression (99% test accuracy) on the following datasets: IBM Telco, Orange Telecom, and Maven Analytic Telco [22].

Haroon P S *et al.* (2024) paper and it is preprocessed by one hot encoding. At this time, the data is converted into numerical form. The TSA is used for feature selection which overcomes dimensionality detection and vanishing gradient issues. Then, the SVM-IRF is used for predicting churn customers at early stage. Model performance is estimated using the f1-score, recall, precision, and accuracy. With respect to f1-score (97.59%), recall (98.86%), precision (96.64%), and accuracy (96.82%), TSA-SVM-IRF surpasses state-of-the-art algorithms like GWO-ENN and S-RNN [23].

Verma (2024) for telecommunications corporations, customer attrition is a chief trouble that outcomes in large revenue losses and better costs of customer acquisition. by using putting in place cantered retention programmers, corporations who can as it should be forecast attrition can reduce these losses. in this work, improved device learning classification methods are used to predict customer attrition inside the telecom sector. Three classifiers were used to build predictive models: DT, RF, and KNN. The models produced, in turn, accuracy of 79%, 82%, and 79%. The RF classifier proved to be the only approach for forecasting viable client churn due to its superior performance in extra correctly predicting such turnover [24].

Aravinda *et al.* (2024), use adaptive k-means clustering to ascertain the decrease directly in relation to the quality of data in each class. A new balanced dataset is created by combining the datasets with class labels. This dataset is then utilized for classification in the SVM technique, which differentiates between non-churn and churn customers in telecom sector prediction. The SVM algorithm is capable of handling high-dimensional data, improving generalization, and performing both linear and non-linear classification using a kernel function. The results show that the proposed technique improved upon the telecom churn dataset in every way: accuracy (95.70%), precision (56.01%), recall (55.05%), and F1-score (96.05%) [25].

H M *et al.* (2023) provides telecom operators with a thorough study of customer churn by integrating customer segmentation with churn prediction. Organizations can save money, retain consumers through tailored interventions, and gain a competitive edge by leveraging data-driven insights to increase profits and enhance customer satisfaction. Throughout the trials, four ML classifiers are utilized. These ML classifiers are initially employed to forecast the consumer's attrition state. The proposed SMOTE is used to concentrate on the imbalanced datasets challenges. Gradient Boosting Classifier is the most effective method, according to the experimental inquiry, since it has attained an accuracy of 95.13% [26].

Table I examines telecom churn prediction using ML and DL, highlighting key approaches, findings, accuracy, limitations and future directions including teleco churn prediction.

TABLE I. Summary Of Literature Review Of Machine Learning Approaches For Telecom Customer Churn Prediction

Author(s)	Study On	Approach	Key Findings	Accuracy	Limitations/Future Work
Kumar, Kakkar & Chouhan (2025)	Customer churn prediction using traditional ML and DL models	Implemented KNN, SVC, RF, LR, DT, AdaBoost, Gradient Boosting, Voting Classifier, and LSTM	LSTM outperformed standard classifiers by capturing time-based customer behavior patterns; achieved strong precision and recall	89%	Future work could involve expanding datasets and integrating explainable AI for churn reasoning
Azhar, Saikhu & Buliali (2025)	Ensemble machine learning for churn prediction	Used XGBoost and LightGBM with SMOTE-ENN and GridSearchCV for hyperparameter tuning	SMOTE-ENN handled imbalance; optimized XGBoost and LightGBM achieved superior predictive accuracy	96.49% (XGBoost) / 96.32% (LightGBM)	May explore deep learning integration and cross-domain validation to enhance robustness

Toprak, Berfin Mercan & Osmanca (2025)	Comparative churn prediction on multiple telecom datasets	Evaluated 16 ML models on IBM Telco, Orange Telecom, and Maven Analytic datasets	Linear Discriminant (IBM), Gradient Boosting (Orange), and Linear Regression (Maven) gave best results	80% (IBM), 94% (Orange), 99% (Maven)	Model generalization may vary across datasets; future work could employ transfer learning
Haroon P. S. et al. (2024)	Early churn prediction in telecom data	One-hot encoding for preprocessing, TSA for feature selection, SVM-IRF for classification	TSA-SVM-IRF achieved superior performance compared to GWO-ENN and S-RNN	96.82%	Could test on larger datasets and explore hybrid deep models for further improvement
Verma (2024)	Churn prediction for telecom corporations	Implemented DT, RF, and KNN models	RF performed best among the three with higher accuracy in churn forecasting	82% (RF)	Suggests inclusion of ensemble deep learning models for enhanced accuracy
Aravinda et al. (2024)	Telecom customer churn using clustering and SVM	Used Adaptive k-means clustering for class balancing and SVM for classification	Proposed method improved classification generalization and handled high-dimensional data	95.70%	Needs optimization for precision and recall imbalance; explore neural-based SVM extensions
H. M. et al. (2023)	Combined customer segmentation and churn prediction	Employed ML classifiers with SMOTE for balancing	Gradient Boosting Classifier achieved best performance at 95.13% accuracy	95.13%	Future work could explore ensemble deep learning models and real-time churn monitoring systems

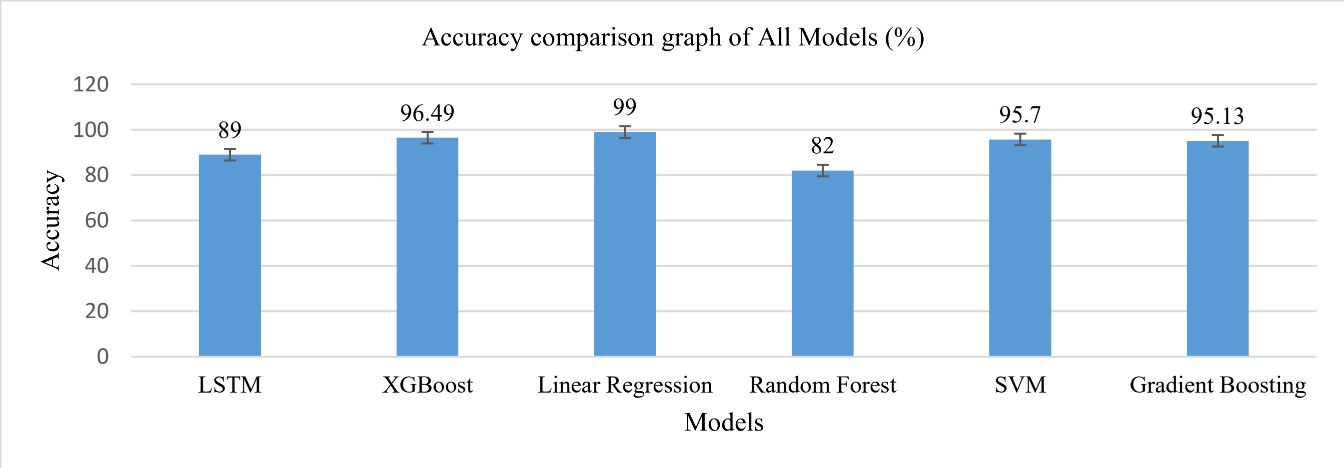

Fig. 3. Accuracy Comparison Graph of All Models for literature study

Figure 3 of the Accuracy Comparison Graph of All Models (%) for the literature study bar chart compares the six machine learning algorithms —LSTM, XGBoost, Linear Regression, Random Forest, SVM, and Gradient Boosting — based on their classification accuracy percentage. After Gradient Boosting (95.13%), Linear Regression (96.49%), and Support Vector Machines (SVM) (95.7%), Linear Regression (99%) was the most accurate model. The Random Forest model achieved the lowest effectiveness, with an accuracy of 82%, in comparison to the LSTM model's 89%. The error bars on each column indicate the uncertainty in the accuracy score for each model.

VI. Conclusion And Future Work

The predictive analytics framework for predicting telecom customer churn is at the heart of the digital transformation in the telecom company. By combining machine learning and deep learning technology with enormous amounts of consumer data, service providers may find clients who are at danger, develop targeted marketing efforts, and come up with good ways to keep customers. By transforming raw behavioural and transactional data into valuable insights, these models optimize operations, reduce acquisition costs, and strengthen customer relationships. Ensembler-based and neural network-based methods, such as XGBoost, LSTM, and hybrid learning architectures, have rendered predictions much more accurate and interpretable. This allows telecom firms to address churn issues in real time and in a dynamic manner. However, several issues persist, including data imbalance, feature interpretability, and the scalability of telecom systems, which are not always uniform. Also, ensuring AI-driven decision-making is fair, private, and open is becoming increasingly critical.

Future studies should focus on developing churn prediction models that are more interpretable, responsive, and actionable in real-time, leveraging a wide range of data sources, including social media sentiment, usage history, and support interactions. Integrating ML, DL, and RL into a hybrid model may significantly improve the accuracy of churn predictions. Additionally, edge computing, federated learning, and sophisticated data augmentation methods can help create scalable implementations that preserve data privacy.

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