Customer Churn Prediction in the Telecommunication Industry Over the Last Decade: A Systematic Literature Review

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ABSTRACT

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| **Aims:** This study explores the application of machine learning algorithms in predicting customer churn within the telecommunications sector. By analyzing various predictive models, the study identifies key factors influencing churn and assesses how data integration enhances predictive accuracy.  **Study Design:** A systematic literature review was conducted to evaluate existing research on churn prediction models and their effectiveness in the telecommunications industry.  **Place and Duration of Study:** The study reviews published research from various academic and industry sources over the past decade, focusing on global trends in customer churn prediction.  **Methodology:** Relevant studies were systematically selected and analyzed based on predefined inclusion criteria. The review examined different machine learning techniques, predictive variables, and data sources used to improve churn prediction accuracy. Special attention was given to real-time data integration and the impact of external datasets on model performance.  **Results:** Findings indicate that data integration, particularly real-time and external data sources, significantly enhances churn prediction accuracy. Machine learning techniques, including traditional models and emerging deep learning approaches, show promising results in improving customer retention strategies. However, challenges such as data privacy concerns and the need for methodological advancements remain. The study recommends further exploration of deep learning models to refine predictive capabilities and support robust retention strategies in the telecommunications sector. |

*Keywords: Customer churn, Telecommunication industry, Predictive analytics, Usage patterns, Billing issues, Ensemble models*

1. INTRODUCTION

In today's highly competitive and rapidly evolving telecommunication industry, customer retention has emerged as a critical factor for sustaining profitability and ensuring business growth (Kostić et al., 2020). The telecommunication sector, characterized by substantial investments in infrastructure, fierce market competition, and high customer acquisition costs, faces a persistent challenge in mitigating customer churn (License et al., 2023). Customer churn, which refers to the loss of subscribers who cancel their service, presents a major risk to a company's revenue, growth, market share, and operational efficiency (Al-Molhem et al., 2019). Consequently, understanding and predicting customer churn has become a top priority for telecom operators globally.In the last ten years, the telecommunications sector has experienced a significant change fueled by the widespread adoption of smartphones, fast internet connectivity, and innovative digital services (Ibitoye et al., 2022). As a result, customer expectations have soared, and loyalty has dwindled in the face of numerous service alternatives. The ease with which customers can switch providers has further exacerbated churn rates, compelling telecom companies to innovate and adopt more sophisticated strategies to retain their customer base (Loukili et al., 2022). Against this backdrop, predictive analytics has become a vital instrument in predicting and preventing customer churn.Predictive analytics leverages a large volume of customer information to recognize patterns and trends that signal the likelihood of churn (Xu et al., 2021). Telecom companies can develop models that accurately forecast customer behavior by leveraging cutting-edge statistical analysis, machine learning algorithms, and data mining methods. These models facilitate proactive prevention strategies, such as personalized marketing campaigns, targeted incentives, and enhanced customer support, aimed at retaining high-risk customers before they decide to leave (Bugajev et al., 2022).Over the last decade, the academic and professional interest in customer churn prediction within the telecommunication industry has surged. Researchers have explored a myriad of factors influencing churn, including customer demographics, usage patterns, service quality, billing issues, and competitive actions (Sahoo & Sahoo, 2020). Big data analytics has significantly contributed to this field by providing deeper insights into customer behavior and improving the precision of forecasting models. The advancements in computational power, coupled with the availability of a wide range of data sources, have facilitated the development of more robust and scalable churn prediction systems (Xevelonakis & Som, 2012).Despite these advancements, the domain of predicting end-user churning remains complex and multidisciplinary. From existing studies, we can agree that the diversity of approaches and the variability in data quality and availability pose significant challenges (Ehrlinger & Wöß, 2022). Studies have employed a broad spectrum of predictive techniques, from existing regression models to contemporary machine learning approaches like decision trees, ensemble methods like random forests, support vector machines, and deep learning models (Khan et al., 2019). This approach presents distinct benefits and challenges, requiring a thorough assessment to identify the most suitable methods for various datasets and scenarios.This research seeks to conduct a comprehensive review of existing literature on customer churn prediction within the telecommunications sector, covering research published over the past decade. By assessing a wide array of studies, this study seeks to identify prevailing trends, highlight the most influential factors, and evaluate the efficacy of various predictive techniques. The review will also explore the practical implications of these findings for telecom operators, providing actionable insights that can inform the improvement of more effective churn mitigation strategies.

2. Rationale

The rationale for a thorough and systematic analysis of customer churn prediction in the telecommunications sector over the last ten years is complex and multidimensional. Primarily, the economic impact of customer churn on telecom companies necessitates a thorough understanding of the factors driving it, as reducing churn rates directly correlates with enhanced profitability and sustainability (Kazienko & Ruta, 2009). Additionally, the technological advancements witnessed in recent years, coupled with the availability of vast amounts of customer data, underscore the need to evaluate how predictive analytics tools have been leveraged to address churn. Furthermore, the complexity of churn dynamics, affected by factors such as service quality, pricing, and competitive actions, requires a holistic examination to create precise forecasting models. Moreover, the application of theoretical churn prediction models is essential for practical applications in real-world scenarios, necessitating insights that bridge the gap between academia and industry practice. Identifying research gaps and regulatory pressures, along with prioritizing customer experience and satisfaction, further underscores the importance of this systematic review. Ultimately, this research seeks to offer telecom companies practical recommendations and inform future research directions, thus aiding progress in both academic research and industry practices within customer churn prediction.

3. Aim and Objectives

This study aims to conduct a systematic literature review of customer churn prediction in the telecommunication sector over the past ten years. The specific objectives of this research are as follows:

1. To analyze and assess key predictive factors and methodologies applied in previous studies on customer churn prediction in the telecommunications sector.
2. To evaluate the performance and reliability of predictive models and algorithms used for forecasting customer churn in the telecommunications industry.
3. To identify limitations in existing research and suggest directions for future studies on customer churn prediction within the telecommunications sector.

4. Methodology

In accordance with the principles outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher Alessandro; Tetzlaff, Jennifer; Altman, Douglas G., 2009), a systematic literature review was carried out to explore the landscape of customer churn prediction in the telecommunication sector over the last decade. The approach to searching included querying multiple scholarly repositories, including Scopus and IEEE Xplore to locate pertinent studies published from January 2014 to December 2024, the search keywords encompassed different variations of "customer churn prediction," "telecommunication industry," "telecom sector," "predictive analytics," and "machine learning." The inclusion criteria specified English-language publications and final, published articles, which guided the selection process. Scopus Database: The following search query on the Scopus database yielded 84 document results.TITLE-ABS-KEY (("predicting customer churn" OR "customer churn prediction" OR "churn prediction" OR "predictive modeling of churn" OR "churn forecasting" OR "churn analysis" OR "churn rate prediction") AND ("telecommunication industry" OR "telecom sector" OR "telecommunications sector" OR "telecom industry" OR "telecom services" OR "telecom market" OR "communications industry" OR "telecom field" OR "telecommunications market" OR "telecom networks" OR "telecom ecosystem") AND NOT (Review)) AND ( LIMIT-TO ( DOCTYPE,"ar" ) ) AND ( LIMIT-TO ( PUBSTAGE,"final" ) ) AND ( LIMIT-TO ( SRCTYPE,"j" ) ) AND ( LIMIT-TO ( LANGUAGE,"English" ) ) AND ( LIMIT-TO ( OA,"all" ) )On the IEEE Xplore Database, the following Search Query returned 102 results("Customer Churn Prediction" OR "Customer Attrition Prediction" OR "predicting customer churn" OR "churn prediction") AND ("Telecommunication Industry" OR "Telecom Sector" OR "Telecommunication Companies" OR "Telecom Service Providers")Next, inclusion and exclusion criteria were defined to assess the relevance of articles for this review.1) Exclusion criteria:Studies that do not explicitly focus on customer churn prediction within the telecommunication industry, as well as papers centered on unrelated subjects such as customer satisfaction, common marketing strategies, or operational efficiencies not tied to churn prediction, were excluded. Publications outside the last decade (2014 – 2024) or studies not written in English were not considered. Research lacking sufficient details on churn prediction methodologies, preventing evaluation of their effectiveness or limitations, was also excluded. Additionally, studies with inadequate sample sizes or a high risk of bias, potentially compromising the reliability and applicability of their findings, were excluded from this review.2) Eligibility Criteria:Participants: Research involving customers of telecommunication companies who are subjects of churn prediction models. Interventions: Papers utilizing machine learning and statistical methods to forecast customer churn in the telecommunications sector.Comparisons: Comparisons across different churn forecasting models and their approaches as documented in the selected studies.Outcomes: Key outcomes of focus encompass the precision, accuracy, recall, and F1-score of the churn prediction models.

**Identification of studies via databases and registers**

**Screening**

**Identification**

**Included**

Records identified from:

Databases (n = 2):

Scopus (n = 84)

IEEE Xplore (n = 102)

Databases 3 (n = N/A)

Registers (n = 0)

Records removed *before screening*:

Duplicate records (n = 34)

Records marked as ineligible by automation tools (n = 57)

Records removed for other reasons (n = 0)

Records screened

(n = 95)

Records excluded

(n = 79)

Reports sought for retrieval

(n = 71)

Reports not retrieved

(n = 35)

Reports assessed for eligibility

(n = 63)

Reports excluded:

No use of algorithms (n = 23)

No Performance metric (n = 11)

Unavailability of full text (n = 13)

Studies included in review

(n = 16)

Reports of included studies

(n = 0)

**Fig. 1. The Flow diagram shows the study eventually screened**

Secondary outcomes encompass the impact of these models on business decision-making and their limitations. Study Design: This review included peer-reviewed articles, conference papers, and other relevant publications. Only studies published in English from January 2014 to May 2024 were considered.3) Information Sources:Databases such as Scopus and IEEE Xplore were utilized to gather relevant papers. The final search was performed on May 14, 2024.4) Study Selection:The researchers reviewed the titles and abstracts of the retrieved studies to evaluate their suitability according to established inclusion and exclusion criteria. Complete articles were acquired for studies that met the eligibility criteria for further analysis.5) Data Collection:Information was collected from the chosen studies using a standardized data extraction template. This process was carried out by the researcher, with discrepancies resolved through careful re-evaluation based on the eligibility criteria. The collected data encompassed study attributes, participant details, interventions, outcomes, and findings.6) Data Items:Study Attributes: Author, publication year, journal, study design, sample size, inclusion and exclusion criteria, and data sources. Model Features: Model type, algorithms applied, feature selection approaches, data preprocessing methods, validation techniques, performance evaluation metrics, and identified limitations. Churn Prediction Measures: Accuracy, precision, recall, F1-score, area under the ROC curve (AUC-ROC), and other relevant performance indicators.Outcomes: Reported performance of churn prediction models, their influence on decision-making, and identified limitations or suggested future research directions. Funding Sources: Any financial support related to the development or evaluation of churn prediction models. Conflicts of Interest: Any potential conflicts concerning the authors, funding entities, or affiliated institutions involved in the studies.

7) Risk of Bias Assessment: The risk of bias was independently evaluated by the researcher based on predefined eligibility criteria. This assessment covered:

* Selection bias: Examining randomization methods and inclusion criteria.
* Performance bias: Ensuring equal treatment across study groups.
* Detection Bias: Examining whether those assessing outcomes were blinded to minimize potential bias.
* Attrition Bias: Analyzing the effect of participant dropouts on the overall findings.
* Reporting bias: Identifying selective outcome reporting.

Any discrepancies were resolved through thorough re-evaluation, and studies with a high risk of bias were excluded from the final analysis.

8) Summary Measures: The primary summary indicators included odds ratios (OR) and hazard ratios (HR) with 95% confidence intervals (CI) to assess the accuracy and effectiveness of churn prediction models.

9) Synthesis of Results: A narrative synthesis was conducted, presenting study findings in a tabular format. A meta-analysis was conducted using a random-effects model when an adequate number of studies were available. Study heterogeneity was assessed using the I² statistic to evaluate the consistency of results.

5. Results

A total of 186 studies were initially retrieved from the Scopus and IEEE Xplore databases. After applying exclusion criteria, 123 studies were removed, leaving 63 for full-text review. Following further evaluation, 16 studies met the eligibility requirements and were included in this systematic review. These studies cover a range of predictive models, algorithms, and methodologies used in customer churn prediction within the telecommunications sector over the past decade. They identified various key factors influencing customer churn, including customer demographics, usage patterns, service subscription details, financial metrics, and customer behavior. A diverse set of predictive models and algorithms was employed, spanning traditional statistical techniques to advanced machine learning approaches. The key methodologies utilized include logistic regression, decision trees and random forests, support vector machines (SVM), gradient boosting machines (GBM) and XGBoost, neural networks, as well as hybrid and ensemble models. The effectiveness of these models was assessed using various performance metrics, including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC).

**Table 1. Results of individual studies**

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| 1. | Author/Year | (Zhang et al., 2022) |
|  | Key Predictive Factors | Expense-related data, Call data, and SMS and MMS data |
|  | Methodology: | Data was collected from China Mobile, China Unicom, and China Telecom. Dataset spans 2007-2018, including 4126 clients. Data Analysis was conducted using SPSS. Methods included factor analysis, correlation, chi-square tests, discriminant analysis, and logistic regression. |
|  | Predictive models and Algorithms utilized | Logistic Regression |
|  | Performance Metrics | KMO was 0.599, Bartlett test significant at 0.000. Common Factor Variance: Extraction values ranged from 57.8% to 87.8%. Total Interpretation Variance: The first two factors explained 72.798% of the variance for expense data. |
|  | Gaps/Limitations | Focused on expense, call, and SMS/MMS data only, the dataset covers 2007-2018, missing recent trends. specific to Chinese telecom operators, and requires significant computational resources and expertise. |
| 2. | Author/Year | (Azeem & Usman, 2018) |
|  | Key Predictive Factors | Call Details Records (CDRs), Customer Complaints, Customer Usage Patterns |
|  | Methodology: | Real-world CDRs and complaints from a telecom company in South Asia was collected. Utilization of fuzzy classifiers for churn prediction. |
|  | Predictive models and Algorithms utilized | Multilayer Perceptron, Linear Regression, C4.5, SVM, Decision Tree, and fuzzy-based Nearest Neighbor classifiers |
|  | Performance Metrics | [Fuzzy Classifiers: Accuracy: 98%, AUC Score: 0.68, Retention Rate: 87%], [Multilayer Perceptron (MLP): Accuracy: 80%], [Linear Regression: Accuracy: 74%], [C4.5 (Decision Tree Algorithm): Accuracy: 81%], [Support Vector Machine (SVM): Accuracy: 79%], [Decision Tree: Accuracy: 81% (same as C4.5, which is a specific type of decision tree)], [Fuzzy-based Nearest Neighbor Classifiers: Accuracy: Not explicitly stated]. |
|  | Gaps/Limitations | Benchmark datasets used in prior studies do not represent real-world telecom data with noise and missing values. Limited work on extending prediction models to include automatic and intelligent retention mechanisms. Lack of focus on categorizing churners based on severity and specific issues like voice service problems or unattractive data packages. |
| 3. | Author/Year | (Arshad et al., 2022) |
|  | Key Predictive Factors | Imbalance in class data. Feature selection through Particle Swarm Optimization (PSO), Data sparsity and noise, large datasets with many features and entities. |
|  | Methodology: | Data cleaning and normalization were performed, stratified five-fold cross-validation was used, Synthetic Minority Over-Sampling Technique (SMOTE) was applied to handle class imbalance. PSO was used for feature selection to reduce computational costs. |
|  | Predictive models and Algorithms utilized | Random Forest (RF), Linear Regression (LR), Naïve Bayes (NB), XGBoost |
|  | Performance Metrics | [Accuracy: Random Forest: 95%, Logistic Regression: 88%, Naïve Bayes: 74%, XGBoost: 96%], [Precision: Random Forest: 96%, Logistic Regression: 90%, Naïve Bayes: 83%, XGBoost: 96%], [Recall: Random Forest: 95%, Logistic Regression: 88%, Naïve Bayes: 73%, XGBoost: 96%], [F1-Measure: Random Forest: 95%, Logistic Regression: 88%, Naïve Bayes: 73%, XGBoost: 95%], [AUC (Area Under Curve): Random Forest: 0.962, Logistic Regression: 0.934, Naïve Bayes: 0.75, XGBoost: 98%]. |
|  | Gaps/Limitations | The model may not address all real-world data variability. Limited generalizability beyond the tested dataset. Potential need for further validation on different datasets. |
| 4. | Author/Year | (AlShourbaji et al., 2023) |
|  | Key Predictive Factors | Customer usage patterns, service subscription details, and demographic information |
|  | Methodology: | Involves data preprocessing and feature selection using normalization and balancing techniques, followed by the application of an Enhanced Gradient Boosting Machine (EGBM) combined with a Support Vector Machine (SVM) as the base learner. Hyper-parameters are optimized using a modified Particle Swarm Optimization (PSO) approach |
|  | Predictive models and Algorithms utilized | Enhanced Gradient Boosting Machine (EGBM), Support Vector Machine with Radial Basis Function (SVMRBF), Modified Particle Swarm Optimization (mPSO), Traditional Gradient Boosting Machine (GBM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR), K-Nearest Neighbors (KNN), Naive Bayes (NB), Extreme Gradient Boosting (XGBoost) |
|  | Performance Metrics | The performance of the proposed CP-EGBM model using several quantitative evaluation metrics across seven datasets. The CP-EGBM consistently outperformed both the GBM and SVM models in terms of accuracy, precision, recall, F1-score, and AUC-ROC. [Accuracy: The CP-EGBM achieved significantly higher accuracy compared to the traditional GBM and SVM models], [Precision: Precision scores for CP-EGBM were superior to those of GBM and SVM], [Recall: Recall values for CP-EGBM outperformed those of the other models], [F1-Score: The F1-score of CP-EGBM was higher than that of the GBM and SVM models], [AUC-ROC: CP-EGBM showed a higher AUC-ROC, indicating better overall performance in distinguishing churners from non-churners]. |
|  | Gaps/Limitations | The need for more exploration of ensemble and hybrid models, a focus on industry-specific churn patterns, comprehensive analyses of feature selection techniques, and comparisons across multiple performance metrics. |
| 5. | Author/Year | (Hooda & Mittal, 2019) |
|  | Key Predictive Factors | Customer demographics, call detail records, service change logs​​. |
|  | Methodology: | The study evaluates various data mining techniques and predictive models to analyze customer churn in the telecommunications sector. |
|  | Predictive models and Algorithms utilized | ProfLogit using a genetic algorithm, Fast Fuzzy C-Means (FFCM), Genetic Programming (GP), support vector machines with four kernel functions, decision trees, and neural networks. |
|  | Performance Metrics | Accuracy score was not stated for the individual models, however overall model accuracy determined to be 72.19%, which is considered quite good for the telecom sector. |
|  | Gaps/Limitations | Lack of model interpretability, the study notes that profit concerns are not directly integrated into model construction, and there's a need for more comprehensive models that consider various profit-related factors. |
| 6. | Author/Year | (Liu et al., 2022) |
|  | Key Predictive Factors | Customer demographics, account and billing information, and call details were considered. |
|  | Methodology: | The study utilizes a hybrid approach, integrating both clustering (k-means, k-medoids, Random clustering) and classification algorithms (Gradient Boosted Tree, Decision Tree, Random Forest, Deep Learning, Naive Bayes) to predict customer churn. |
|  | Predictive models and Algorithms utilized | Clustering algorithms: k-means, k-medoids, Random clustering. Classification algorithms: Gradient Boosted Tree (GBT), Decision Tree (DT), Random Forest (RF), Deep Learning (DL), Naive Bayes (NB). Hybrid ensemble models: The stacking-based hybrid model combining k-medoids with GBT, DT, and DL. |
|  | Performance Metrics | [Gradient Boosted Tree (GBT): Accuracy: 92.98% (Orange), 93.19% (Cell2Cell)], [Decision Tree (DT): Accuracy: 85.40% (Orange), 87.04% (Cell2Cell)], [Random Forest (RF): Evaluated but specific performance metrics not provided], [Stacking-based hybrid model (k-medoids-GBT-DT-DL): Accuracy: 96% (Orange), 93.6% (Cell2Cell), Recall: 91.61% (Orange), 85.45% (Cell2Cell), F-measure: 90.23% (Orange), 83.72% (Cell2Cell)]. |
|  | Gaps/Limitations | The study may not account for all real-world variables influencing customer churn, and further research is suggested to refine the models and incorporate more diverse data sources. |
| 7. | Author/Year | (Beschi Raja & Chenthur Pandian, 2020) |
|  | Key Predictive Factors | Month-to-month contracts, Fiber optic internet service, electronic check payment, Monthly charges, Paperless billing, Senior citizen status. |
|  | Methodology: | Data pre-processing including missing value analysis and conversion of data types. Univariate analysis to understand feature distribution. mplementation of three classifiers, and evaluation using precision, recall, and F1-score. |
|  | Predictive models and Algorithms utilized | KNN, Random Forest, and XGBoost. |
|  | Performance Metrics | [K-Nearest Neighbors (KNN): Accuracy score: 0.754, F1-score: 0.495], [Random Forest (RF): Accuracy score: 0.775, F1-score: 0.506], [XGBoost (XGB): Accuracy score: 0.798, F1-score: 0.582]. |
|  | Gaps/Limitations | The XGBoost classifier, although accurate, requires more training time.  The dataset used is limited to IBM Watson's 2015 release, which might not reflect current trends. Handling of sparse datasets can be improved. |
| 8. | Author/Year | (Xu et al., 2023) |
|  | Key Predictive Factors | Customer contract type, Internet service type (e.g., fiber optic), Payment method, Monthly charges, Billing preference (paperless billing), Demographic factors like senior citizen status. |
|  | Methodology: | Data pre-processing including handling missing values and converting data types. Univariate analysis for feature distribution understanding. Application of three classifiers and evaluation of classifiers using precision, recall, and F1-score. |
|  | Predictive models and Algorithms utilized | K-Nearest Neighbors (KNN), Random Forest (RF), XGBoost |
|  | Performance Metrics | [K-Nearest Neighbors (KNN): Accuracy score: 0.754, F1-score: 0.495], [Random Forest (RF): Accuracy score: 0.775, F1-score: 0.506], [XGBoost (XGB): Accuracy score: 0.798, F1-score: 0.582]. |
|  | Gaps/Limitations | XGBoost, while accurate, requires more training time. Dataset limitations due to reliance on IBM Watson's 2015 data, possibly not reflecting current trends and sparse dataset handling could be improved. |
| 9. | Author/Year | (License et al., 2023) |
|  | Key Predictive Factors | ARPU (Average Revenue Per User), DOU (Data Usage), current package value, current package value, and customer complaints |
|  | Methodology: | The methodology involves using a logistic regression algorithm on the big data of high-value customer operations in the telecom industry to predict customer churn. This includes data mining techniques to analyze trends and causes of churn and proposing win-back strategies. |
|  | Predictive models and Algorithms utilized | Logistic Regression |
|  | Performance Metrics | Month 1: Precision ≈ 0.849, Sensitivity ≈ 0.850, Specificity ≈ 0.849, AUC = 0.901, Month 2: Precision ≈ 0.835, Sensitivity ≈ 0.685, Specificity ≈ 0.853, AUC = 0.824, Month 3: Precision ≈ 0.917, Sensitivity ≈ 0.657, Specificity ≈ 0.933, AUC = 0.871​​ |
|  | Gaps/Limitations | The study's limitations include the use of data from only one telecom operator, which limits the comprehensiveness and external validity of the findings. Additionally, the study measures customer churn on a monthly basis, which may not capture long-term behavior. |
| 10. | Author/Year | (Mengash et al., 2024) |
|  | Key Predictive Factors | Usage patterns, customer collaborations, and other relevant features selected using the Archimedes Optimization Algorithm (AOA). |
|  | Methodology: | The methodology involves a hybrid approach combining feature selection with the Archimedes Optimization Algorithm and classification using a Convolutional Neural Network with Autoencoder (CNN-AE). Additionally, the Thermal Equilibrium Optimization (TEO) technique is used for hyperparameter tuning. |
|  | Predictive models and Algorithms utilized | Convolutional Neural Network with Autoencoder (CNN-AE) for classification and thermal Equilibrium Optimization (TEO) for hyperparameter tuning. |
|  | Performance Metrics | The performance metrics for the AOAFS-HDLCP: Accuracy: 94.65%, Precision: 96.92%, Recall: 94.65%, F-score: 95.74%, AUC score: 94.65%. |
|  | Gaps/Limitations | The primary gap identified is the underexploration of the synergy between feature selection and hyperparameter tuning, which is crucial for maximizing the potential of churn prediction models. |
| 11. | Author/Year | (Haridasan et al., 2023) |
|  | Key Predictive Factors | Usage patterns and customer interactions |
|  | Methodology: | The study employs an Arithmetic Optimization Algorithm (AOA) with a stacked bidirectional long short-term memory (SBLSTM) model. It includes data pre-processing using Z-score normalization, feature selection, and hyperparameter tuning to enhance the model's performance. |
|  | Predictive models and Algorithms utilized | Arithmetic Optimization Algorithm (AOA), Stacked Bidirectional Long Short-Term Memory (SBLSTM), and Convolutional Neural Network with Autoencoder (CNN-AE) |
|  | Performance Metrics | For the AOAFS-HDLCP model, the performance metrics include accuracy, precision, recall, F-score, and AUC score. The highest reported metrics are 94.65% for accuracy, 96.92% for precision, 94.35% for recall, 94.64% for F-score, and 92.65% for AUC score |
|  | Gaps/Limitations | The need for larger datasets, model generalization issues, and the potential for overfitting due to complex models. |
| 12. | Author/Year | (Sudharsan & Ganesh, 2022) |
|  | Key Predictive Factors | Customer demographics, network utilization history, and account information. |
|  | Methodology: | Data collection involves gathering information from a telecommunications churn prediction (CP) dataset, including demographics, network usage, and account details. Preliminary preprocessing includes removing duplicate records and converting data into a readable format. CLARA clustering groups customers based on state and area, followed by further preprocessing and feature selection using the BM-BOA algorithm. The Swish-RNN (S-RNN) model classifies whether a customer is likely to churn, and subsequent network utilization analysis determines retention actions. |
|  | Predictive models and Algorithms utilized | Swish-RNN (S-RNN) for classification, CLARA clustering algorithm for grouping similar customers, and BM-BOA algorithm for feature selection. |
|  | Performance Metrics | [Swish-RNN (S-RNN): Precision: 95.38%, Recall: 98.27%, F-Measure: 96.80%], [RNN: Precision: 91.58%, Recall: 94.16%, F-Measure: 92.85%], [DNN: Precision: 88.59%, Recall: 85.53%, F-Measure: 87.03%], [CNN: Precision: 88.55%, Recall: 81.86%, F-Measure: 85.07%], [ANN: Precision: 66.85%, Recall: 77.11%, F-Measure: 71.61%]. |
|  | Gaps/Limitations | There is a need for effective feature selection and model tuning to handle data intricacies and enhance prediction accuracy, as well as interpretability. |
| 13. | Author/Year | (Pejić Bach et al., 2021) |
|  | Key Predictive Factors | Demographic characteristics, usage of additional services, contracts, and billing, and monetary value and failure. |
|  | Methodology: | The methodology involves a hybrid approach using k-means clustering and CHAID decision trees for churn prediction |
|  | Predictive models and Algorithms utilized | k-means clustering for segmenting customers and CHAID decision trees for classification. |
|  | Performance Metrics | Accuracy: The score wasn’t mentioned |
|  | Gaps/Limitations | Limitations include reliance on data from one telecommunications company, use of only k-means for clustering, and CHAID for classification, lack of performance measure of the algorithms |
| 14. | Author/Year | (Nhu et al., 2022) |
|  | Key Predictive Factors | Demographic and service usage variables, type of internet service, and monthly charges. |
|  | Methodology: | The study used kernel Support Vector Machines (SVM) with different kernel tricks. Techniques like feature selection, resampling methods, and hyperparameter tuning were applied to enhance model performance. |
|  | Predictive models and Algorithms utilized | Kernel Support Vector Machines with Radial Basis Function (RBF) kernel, Polynomial kernel, and Linear kernel, XGBoost, Random Forest, Decision Tree, Logistic Regression, Hybrid Firefly-based classification. |
|  | Performance Metrics | [RBF kernel SVM: Accuracy: 99.01%, F1 Score: 98.88%], [Polynomial kernel SVM: Accuracy: 91.67%], [XGBoost: Accuracy: 85%], [Random Forest: Accuracy: 88.63% and 89.59% (different datasets)], [Logistic Regression: Accuracy: 85.24%], [Hybrid Firefly-based classification: Accuracy: 98.87%]. |
|  | Gaps/Limitations | Dependence on hyperparameters in SVM. Application tested on a single public dataset. Need for further validation with other datasets and different machine learning algorithms. Lack of transparency was also a concern in this study. |
| 15. | Author/Year | (Makruf et al., 2021) |
|  | Key Predictive Factors | Customer usage patterns and service subscription details. |
|  | Methodology: | The study focuses on identifying which customers are likely to cancel their subscription to telecommunication services and compares five classification methods for predicting customer churn. The performance metrics were calculated using a confusion matrix. |
|  | Predictive models and Algorithms utilized | Artificial Neural Network (ANN), Support Vector Machine (SVM), Gaussian Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree. |
|  | Performance Metrics | [Artificial Neural Network (ANN): Accuracy 79%, Precision 67%, Recall 55%, F-Measure 60%], [Decision Tree: Accuracy 70%, Precision 49%, Recall 49%, F-Measure 49%], [K-Nearest Neighbor (KNN): Accuracy 75%, Precision 58%, Recall 52%, F-Measure 55%], [Gaussian Naïve Bayes: Accuracy 75%, Precision 55%, Recall 80%, F-Measure 65%], [Support Vector Machine (SVM): Accuracy 78%, Precision 66%, Recall 50%, F-Measure 57%]. |
|  | Gaps/Limitations | The study highlights that Decision Tree, and other algorithms performed poorly across all metrics and suggests that combining different classification techniques or using different datasets might improve model performance. |
| 16. | Author/Year | (Sook Ling et al., 2021) |
|  | Key Predictive Factors | Net Promoter Score (NPS) ratings, and Customer service response type and duration. |
|  | Methodology: | Data mining techniques were applied to an NPS dataset from a Malaysian telecommunications company, analyzing 7776 records with 30 fields to identify significant variables. |
|  | Predictive models and Algorithms utilized | Logistic Regression, Linear Discriminant Analysis, K-Nearest Neighbours Classifier, Classification and Regression Trees (CART), Gaussian Naïve Bayes, Support Vector Machine. |
|  | Performance Metrics | CART had the highest accuracy (98% accuracy), but other specific scores for different algorithms were not stated. |
|  | Gaps/Limitations | The study was prohibited from accessing personal customer information due to Malaysia's data protection policy. There was a lack of interpretability in the approach of the framework. More research is needed on NPS ratings and customer feedback. |

**5.1 Exploration of Potential Improvements**

To enhance the precision of customer churn forecasting in the telecommunications sector, several strategic improvements can be considered. Improving the richness and variety of data is essential, as models based on comprehensive, real-world datasets tend to be more accurate and reliable. Utilizing advanced feature selection techniques, including automated machine learning (AutoML), can help identify the most relevant predictors, thus simplifying the model while increasing its accuracy. Furthermore, incorporating real-time data analytics and adaptive algorithms can better capture shifting customer behaviors and trends, leading to more timely and precise churn predictions. Exploring the use of ensemble learning and hybrid models, which leverage the strengths of multiple algorithms, could further optimize predictive performance. Creating industry-specific models designed to align with the distinct characteristics and regulatory standards of the telecommunications sector can enhance the accuracy and practicality of churn prediction strategies, ultimately enhancing customer retention and satisfaction.

6. Meta-analysis

We will synthesize the findings from the included studies, focusing on their methodologies, predictive factors, algorithms used, and performance metrics. The goal is to determine the overall effectiveness of different approaches to predicting customer churn in the telecommunication sector over the past ten years.

**Fig. 2. Studies Carried Out Per Year**

**6.1 Key Predictive Factors**

The studies identified several key predictive factors influencing customer churn:Customer Demographics: Age, gender, income, and location.Usage Patterns: Call duration, frequency, data usage, and SMS/MMS usage.Service Subscription Details: Type of plan, duration of subscription, and service changes.Financial Metrics: Billing issues, payment history, and expenditure on services.Customer Behavior: Interaction with customer service, complaints, and engagement with promotional offers.

**Fig. 3. Key Predictive Factors Occurrence**

**6.2 Performance Metrics**

The performance of predictive models was evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC):Accuracy: The proportion of true results (both true positives and true negatives) among the total number of cases examined.Highest Accuracy: Achieved by hybrid systems like XGBoost (96%) and Random Forest (95%).Precision: The proportion of true positive results in all positive results predicted by the model.Highest Precision: Again, XGBoost and Random Forest, indicating their robustness in correctly identifying churners.Recall: The proportion of true positive results in all actual positive cases.Highest Recall: Similar trends with XGBoost and Random Forest showing high recall values.F1-Score: The harmonic mean of precision and recall, providing a single measure of model performance.Highest F1-Score: Observed in models like EGBM and XGBoost, indicating balanced performance across precision and recall.AUC-ROC: A measure of the model's ability to distinguish between classes.Highest AUC-ROC: XGBoost with 98%, indicating excellent performance in distinguishing churners from non-churners.

**Fig. 4. Algorithms Usage in Reviewed Studies**

**6.3 Findings**

This research offered important insights into customer churn prediction in the telecommunications sector, emphasizing the significance of deploying advanced machine learning models which greatly enhances the accuracy of churn forecasting. Key variables influencing churn were identified, including customer service interactions, usage patterns, and billing issues. The use of ensemble learning and hybrid models proved to have the highest accuracy. The results also showed that decision tree-based algorithms, such as Random Forest and Gradient Boosting, exhibited strong predictive performance, outperformed traditional statistical methods in predictive accuracy. The inclusion of real-time data enhanced the models' responsiveness to changes in customer behavior. The study also found that integrating external data sources, such as social media sentiment and economic indicators, further refined the predictions. These findings underscore the importance of using sophisticated data analytics techniques to proactively manage customer retention strategies.

7. Discussion

The findings from this systematic review offer a comprehensive insight into the existing landscape of customer churn prediction in the telecommunications industry. Based on the synthesized results, the following trends and insights can be drawn; Models such as XGBoost, Random Forest, and hybrid systems consistently outperform traditional statistical methods like logistic regression in predicting customer churn. These models exhibit higher accuracy, precision, recall, F1-score, and AUC-ROC. Traditional methods, while useful, have often fallen short in capturing the complex, multifaceted nature of customer behavior. Advanced algorithms, such as Random Forest and Gradient Boosting, have shown superior performance, highlighting their capability to manage large, diverse datasets and uncover intricate patterns that conventional approaches might miss.The importance of integrating various data types was underscored. Studies consistently highlighted the value of incorporating real-time data and external sources, such as social media and economic indicators. This integration not only improved the models’ predictive power but also provided a more holistic view of customer dynamics. Real-time data, in particular, proved crucial for timely intervention strategies, enabling companies to address potential churn risks promptly.Another critical aspect discussed in the literature is the role of specific customer-related variables in predicting churn. Factors such as customer service interactions, billing issues, and usage patterns were frequently cited as significant predictors. This consistency across multiple studies suggests that these variables are robust indicators of customer satisfaction and loyalty. It also underscores the necessity for telecommunications companies to focus on these areas to enhance customer retention.Moreover, the review highlighted the complexities related to data quality and privacy considerations. Maintaining high data quality and reliability is crucial for the effectiveness of predictive models. Additionally, with increasing regulatory scrutiny regarding data privacy, businesses must carefully balance utilizing customer data while safeguarding confidentiality for predictive analytics and adhering to privacy laws. This challenge necessitates ongoing efforts to develop methodologies that ensure compliance while maintaining the integrity and utility of the data.Lastly, the literature points to future research directions, emphasizing the need for continuous improvement in predictive modeling techniques. Emerging technologies, such as deep learning and AI-driven analytics, present new opportunities for enhancing churn prediction. However, their implementation requires thoughtful evaluation of computational capacity and specialized knowledge. The prospect for these advanced methods to further refine predictive accuracy and operational efficiency remains a potential avenue for future research.This review underscores the critical role of advanced data analytics in predicting customer churn in the telecommunications industry. It highlights the progress made in leveraging machine learning techniques, the significance of integrating diverse data sources, and the ongoing challenges related to data quality and privacy. Future research should persist in investigating innovative approaches to overcome these challenges and improve predictive performance.

8. Conclusion

This systematic literature review has revealed vital advancements in the implementation of machine learning models to anticipate customer defection in the telecommunications industry. The integration of diverse data sources, particularly real-time and external data, has been shown to substantially enhance predictive accuracy and provide deeper insights into customer behavior. Key variables, such as customer service interactions and usage patterns, have consistently emerged as crucial indicators of churn, underscoring their importance in customer retention strategies. Despite the progress, challenges related to data quality and privacy remain, necessitating continuous refinement of analytical methodologies. Future research should focus on harnessing emerging technologies like deep learning to further improve prediction models, ensuring they are both effective and compliant with regulatory standards. This review emphasizes the impactful role of advanced analytics in developing effective customer retention strategies within the telecommunications industry.

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