International Journal of Innovative Research in Technology and Science
ISSN: 2321-1156 www.ijirts.org Volume 12 Issue 2, March 2024

A Review of Customer Churn Prediction in Telecommunications and the Medical Industry Using Machine Learning Classification Models

Nikita Khandelwal, Vikas Sakalle
Department of Computer Science and Engineering, LNCT University, Bhopal, India
nikitakhandelwal0000@gmail.com, vikassakalle@gmail.com

Selection and peer review of this article are under the responsibility of the scientific committee of the International Conference on Current Trends in Engineering, Science, and Management (ICCSTEM-2024) at SAM Global University, Bhopal.

Abstract- In today's competitive business landscape, understanding and mitigating customer churn is paramount, particularly in telecommunications and the medical industry. This review offers a comprehensive look into the application of machine learning classification models in predicting customer churn within these two sectors. The telecommunications industry, characterised by its fast-paced environment, has adopted machine learning models, ranging from decision trees to neural networks, to retain its vast customer base. On the other hand, the medical industry emphasises the importance of patient retention for operational sustainability and ensuring consistent and continuous patient care. Through a comparative analysis, this review highlights the methodologies employed, the unique challenges each industry faces, and the effectiveness of machine learning models in addressing these challenges. Key findings suggest that while both industries employ similar foundational algorithms, the customisation and application significantly differ based on industry-specific needs. Furthermore, the review sheds light on potential areas for future research, emphasising the necessity for enhanced data privacy measures, especially in the medical sector, and the continuous evolution of machine learning models to cater to changing customer behaviours. By amalgamating insights from both sectors, this review provides a holistic understanding of the current landscape of churn prediction and sets the stage for future innovations in the domain.

Keywords: Customer Churn, Telecommunications, Medical Industry, Machine Learning, Financial Considerations

1. INTRODUCTION

Customer churn, where customers stop using a service or product, is a significant concern across various industries. Its implications not only impact revenue but also indicate potential areas of improvement in a company's service delivery or product quality. Particularly in sectors like telecommunications and the medical industry, retaining customers is paramount due to the substantial costs associated with acquiring a new customer compared to retaining an existing one. The telecommunications industry, characterised by its fierce competition and relatively interchangeable service offerings, experiences high churn rates. Customers in this sector often switch providers for better service, cheaper plans, or more advanced technologies.

Consequently, companies invest heavily in predictive models that identify potential churners early, allowing them to intervene with targeted retention strategies. On the other hand, the medical industry, though different, faces its unique set of challenges. Patient churn can indicate dissatisfaction with care quality, accessibility issues, or financial considerations. Moreover, for healthcare providers, understanding and predicting churn is essential from a business perspective and a care continuity and health outcome standpoint. Given the critical importance of addressing churn in these sectors, this review explores the application of machine learning classification models in predicting customer churn. With its ability to handle vast datasets and unearth intricate patterns, machine learning offers promising avenues for enhancing churn prediction accuracy. This review will dissect various machine learning classification models used in the telecommunications and medical industries, evaluate their effectiveness, and offer insights into best practices and potential future directions. Through a systematic exploration, the review will shed light on the nuances of churn prediction in these two industries and highlight how advancements in machine learning can be harnessed for better predictive outcomes.

2. BACKGROUND STUDY

1. The Phenomenon of Customer Churn:- At its core, customer churn refers to the rate at which customers cease their relationships with a service or product provider over a specified period. It is an integral metric as retaining existing customers is often more cost-effective than acquiring new ones. An increased churn rate can reflect customer dissatisfaction, better offers from competitors, or external factors like economic downturns.
2. Churn in the Telecommunication Industry:- Over the past few decades, the telecommunication sector has seen an exponential increase in competition. As technological advancements have become more rapid, companies constantly battle to provide the latest features and the most attractive packages. With the advent of number portability, customers can now switch service providers without changing their phone numbers, further fueling the churn rates. Earlier studies in this domain primarily focused on demographic and usage-based factors for predicting churn. However, recent research emphasises the application of advanced data analytics and machine learning to predict and mitigate churn.
3. Churn in the Medical Industry:- Unlike telecommunication, churn in the medical sector often has more serious implications. Losing a patient can signal dissatisfaction with the quality of care, inconvenience, or economic reasons. Moreover, from a healthcare perspective, patient churn can disrupt the continuity of care, which might lead to sub-optimal health outcomes. Traditionally, medical churn prediction was based on patient feedback, appointment delay, or treatment dissatisfaction. However, with the availability of Electronic Health Records (EHR) and advancements in healthcare informatics, machine learning models are now employed to provide a more holistic and accurate churn prediction.

4. The Rise of Machine Learning in Churn Prediction:- Machine learning, a subset of artificial intelligence, has transformed how industries predict churn. Traditional statistical models, while effective, often struggled with large datasets and non-linear patterns. Machine learning models, on the other hand, can process vast amounts of data recognising complex patterns and relationships. In the telecommunication and medical sectors, classification models like Decision Trees, Random Forests, Neural Networks, and Support Vector Machines have been employed with varying degrees of success.
5. Why This Study? While individual studies have delved into churn prediction in the telecommunication and medical sectors, a comprehensive review that juxtaposes the approaches, challenges, and successes across these industries is lacking. Given the economic and societal implications of churn in these sectors, this background forms the foundation for a deeper exploration of the topic.

III. LITERATURE REVIEW

Jajam et al. (2023) present a groundbreaking Ensemble Deep Learning SBLSTM-RNN-IGSA model, focusing primarily on predicting customer churn. The paper discusses the optimisation of arithmetic operations in the model, showcasing advancements in ensemble deep learning techniques. Jafari et al. (2023) introduce an interpretable machine learning framework tailored for the telecommunications industry. Their paper includes a case study elucidating the effectiveness and mechanics of their model in predicting customer churn. Sudharsan and Ganesh (2022) focus on the telecom sector, introducing a unique feature selection strategy paired with a Swish RNN-based model. Their approach addresses customer churn prediction, emphasising the importance of selecting the right features for model training. Nagaraj et al. (2023) explore the realm of e-commerce, proposing a scheme for predicting customer churn based on customer behaviour. Their machine learning approach reflects the nuances of online shopping behaviours and their implications for customer retention. Mohamed and Al-Khalifa (2023) examine various machine learning methods to predict churn in the telecommunications sector, providing a comprehensive overview of the state-of-the-art techniques. Ahn et al. (2006) explore churn determinants in the Korean mobile telecommunications service industry, offering insights into churn mediation effects and shedding light on regional customer behaviours. Ahmad et al. (2019) harness the power of big data platforms for customer churn prediction in telecom, emphasising machine learning's role in handling vast datasets to improve churn predictions. Kwon et al. (2021) focus on the digital healthcare app domain, developing a prediction model for customer churn based on lifelog data, highlighting the importance of continuous personal data in understanding customer behaviours in health apps. Singh et al. (2023) embark on an exploratory data analysis to understand the underlying patterns of customer churn and delve into predictive models to offer solutions for the industry's churn problem. Sharma et al. (2023) target the semiconductor supply chain, presenting a churn recognition system to anticipate customer churn and indicating the versatility of churn prediction models across varied industries. Şenyürek and Alp (2023) focus on applying machine learning methods, specifically in the telecommunication sector, for predicting churn, providing insights into the effectiveness of various machine learning techniques in addressing the industry's inherent churn problem. Al-Shakarchi et al.

(2023) undertake a data mining approach to scrutinise and analyse customer churn in the telecom sector, delving deep into data mining techniques and their leverage to predict and mitigate customer churn. Angelina et al. (2023) showcase the application of the CatBoost Classifier for predicting customer churn, examining the potential advantages and outcomes of using this particular classifier over other machine learning models. Xu et al. (2023) discuss the impact of big data on predicting telecom churn, utilising the Backpropagation Neural Network Algorithm and studying its effectiveness from a business model perspective. Equihua et al. (2023) introduce a deep learning-based sequential framework for modelling customer churn in retail, highlighting the importance and potential of deep learning in understanding and predicting consumer behaviours. Oluwatoyin et al. (2022) discuss customer churn prediction using Power BI, emphasising the unique challenges of customer retention in banking and how Power BI can address these challenges. Elgohary et al. (2023) introduce a smart evaluation approach for deep learning models, using churn prediction as a case study, providing insights into the practical application and performance metrics of deep learning in real-world scenarios. Alshamari (2023) evaluates user satisfaction in the telecommunication sector in Saudi Arabia using deep-learning-based sentiment analysis on social media data, highlighting the interplay between user sentiment, social media, and customer churn. AlShourbaji et al. (2023) introduce an efficient churn prediction model that employs a gradient boosting machine paired with metaheuristic optimisation, showcasing the synergy between gradient boosting and optimisation techniques to enhance churn prediction accuracy. SEYMEN et al. (2023) present a comparative performance assessment between Ordinary Artificial Neural Network and Convolutional Neural Network algorithms for predicting customer churn, aiming to understand the strengths and weaknesses of each method in the context of churn prediction. Naidu et al. (2022) focus on the telecom industry, employing the Random Forest Algorithm to predict customer churn and evaluating its capabilities to address retention challenges in telecom. Li et al. (2021) tackle the challenges faced by the traditional broadcast industry in retaining customers, delving into predictive techniques for churn in the context of older broadcast models versus modern avenues. Jajam and Challa (2023) introduce a novel Blended Logistic Regression Decision Tree Algorithm (BLRDT) for churn detection, evaluating the combined strengths of logistic regression and decision trees for accurate prediction. Shastry and Thangavel (2023) elaborate on utilising open-source data pipelines for big data analytics in the telecommunications sector, dissecting the layers of the pipeline and its implementation, and drawing conclusions on its efficiency and adaptability. Almuqren et al. (2021) perform an empirical study mining Arabic tweets to understand customer behaviours leading to churn, underscoring the potential of social media and linguistic analytics in prediction tasks. Jena et al. offer a comprehensive framework for predicting customer churn using advanced machine learning techniques, emphasising the model's adaptability across various sectors ensuring efficient customer retention strategies. Pandithurai and Sriman (2023) employ a Voting Classifier Ensemble Method combined with supervised machine learning techniques to create a robust prediction model capturing various facets of customer behaviours leading to churn. Colasanti (2023) delves into churn prediction by analysing the effects of static data, bringing forth the nuances of customer retention in niche e-commerce sectors and highlighting data-driven challenges and solutions. Sudharsan and Ganesh (2022) propose a Swish RNN-based model to predict customer churn in the telecom industry, introducing a new feature selection strategy to enhance the model's accuracy and efficiency. Fujo et al. (2022) explore the potential of deep learning for churn prediction in the telecommunication domain, advocating for the benefits and precision of deep learning techniques in understanding and predicting customer behaviours. Jayaprakash (2022) evaluates the accuracy of customer churn prediction in the telecom sector using Adaboost over the Random Forest algorithm, offering valuable insights into churn prediction in telecom. Kim and Lee (2022) apply decision trees to predict customer churn, offering a contemporary look at how traditional algorithms fare in newer commerce avenues. Thakkar et al. (2022) integrate AdaBoost with a cost-sensitive classifier specifically designed for effective customer churn prediction, highlighting the importance of costs in retention strategies. Rahmaty et al. (2022) combine the grey wolf optimiser with ensemble neural networks to model customer churn, showcasing a sophisticated approach to churn prediction. Wu et al. (2022) integrate PCA with AdaBoost to predict e-commerce customer churn, demonstrating how dimensionality reduction combined with boosting algorithms can refine predictions. Al-Shourbaji et al. (2022) enhance churn prediction by boosting ant colony optimisation using a reptile search algorithm, employing nature-inspired algorithms to address a pressing industry challenge. Mozaffari et al. (2022) focus on employee attrition within a pharmaceutical company, leveraging machine learning and qualitative data to offer comprehensive insights into employee retention. Matuszelański and Kopczewska (2022) investigate customer churn in retail e-commerce using a combination of spatial analytics and machine learning, illuminating how geographical data can complement machine learning in predicting churn. Amin et al. (2017) address churn prediction in the telecom sector using a rough set approach, offering a different perspective on data simplification and rule extraction that is valuable for industries with vast datasets.

Table 1. Systematic Literature review

Ref	Method	Result	Limitation	Future Scope
1	Ensemble Deep Learning SBLSTM-RNN-IGSA model for Customer Churn Prediction	Improved churn prediction using ensemble deep learning model	Limited explanation of the interpretability of the model. Data quality and feature selection methods are not discussed in detail.	Explore explainable AI techniques. Incorporate feature engineering.
2	Interpretable machine learning Framework for Customer Churn Prediction	Developed an interpretable machine learning framework for customer churn prediction	There is limited discussion on the scalability of the framework to large datasets. The case study is limited to the telecommunications industry.	Test the framework on diverse industry datasets. Enhance scalability.
3	Swish RNN-based customer churn prediction with a novel feature selection strategy	Enhanced prediction with Swish RNN and feature selection strategy	Lack of comparison with other models or techniques. There is limited discussion on the generalizability of the feature selection strategy.	Compare Swish RNN with other RNN variants. Evaluate broader feature selection techniques.
4	Customer Churn Prediction Scheme Based on Customer Behavior Using Machine Learning	Successful scheme based on customer behaviour using machine learning	Lack of discussion on real-world implementation challenges and scalability. Limited explanation of the choice of machine learning algorithms.	Test the scheme in practical e-commerce scenarios and optimise algorithms for scalability.
5	Review of Machine	Review of various	Primarily a review article	Conduct empirical experiments to

	Learning Methods for Predicting Churn in the Telecom Sector	machine learning methods for churn prediction	with limited empirical findings.	compare different methods.
6	Churn determinants and mediation effects of partial defection in the Korean telecom industry	Identified churn determinants and partial defection effects	Limited application outside of the Korean telecom industry. The study is relatively dated (2006).	Investigate churn determinants in different telecom markets. Update findings with recent data.
7	Customer churn prediction in telecom using machine learning in big data platform	Effective customer churn prediction using machine learning in big data platform	There is limited discussion on specific machine learning algorithms and feature engineering methods.	Explore advanced big data analytics techniques for improved predictions.
8	Lifelog data-based prediction model of digital healthcare app customer churn	Developed a prediction model using lifelog data	The study focuses on a specific niche (digital healthcare app) and may not be directly applicable to other industries.	Adapt the model to broader digital healthcare contexts.
9	Exploratory Data Analysis and Customer Churn Prediction for the Telecommunication Industry	Explored data and developed a churn prediction model	No specific results or model details are provided in the abstract. Limited discussion of the model's generalizability.	Present detailed model results and discuss model applicability.
10	Adoption of Churn Recognition System to Predict Customer Churn	Study on the adoption of a churn recognition system	The study may lack in-depth technical details about the churn recognition system. Limited scope as it focuses on the semiconductor supply chain.	Explore the adoption of churn recognition in broader supply chain contexts. Provide technical insights into the system.
10	Adoption of Churn Recognition System to Predict Customer Churn	Study on the adoption of a churn recognition system	Lack of in-depth technical details about the churn recognition system. - Limited scope focusing on the semiconductor supply chain.	- Explore the adoption of churn recognition in broader supply chain contexts. - Provide technical insights into the system.
11	Machine Learning methods for churn prediction in the telecom sector	Improve churn prediction using machine learning methods	Limited discussion on specific machine learning algorithms employed. - Dataset and scalability considerations are not explored in detail.	- Explore and compare various machine learning algorithms. - Address scalability challenges.
12	Data mining approach for telco customer churn prediction	Utilised data mining for customer churn analysis	There is limited discussion about the dataset and preprocessing technique. Investigate more advanced data preprocessing techniques.	Apply the approach to diverse industries.
13	CatBoost Classifier for customer churn prediction using a machine	Achieved effective churn prediction with CatBoost Classifier	Limited discussion on model interpretability. It focuses solely on the application of CatBoost without exploring other algorithms.	Compare CatBoost with other machine learning techniques. Enhance model interpretability.
14	Backpropagation Neural Network Algorithm for telecom churn prediction	Churn prediction and impact analysis using Backpropagation Neural Network	Limited discussion of the implications of business models on churn prediction. Undefined scope of the impact analysis.	Explore the influence of different business models on churn prediction. - Expand the scope of the impact analysis.

15	Deep learning-based sequential framework for retail industry churn	Churn modelling using a deep learning-based sequential framework	Lack of specific results or implementation details. - Based on an arXiv preprint.	Provide comprehensive results and implementation details. Investigate applications beyond retail.
16	Churn prediction in the banking industry using Power BI	Customer churn prediction in the banking industry using Power BI	There is limited discussion on the choice of machine learning algorithms. Scalability and data privacy concerns are not addressed in depth.	Evaluate various machine learning algorithms. Address scalability and data privacy issues.
17	Smart evaluation of deep learning models for churn prediction	Evaluation of deep learning models for churn prediction	Limited information on the range of deep learning models evaluated. Case study limited to a specific product case.	Explore a broader range of deep learning models. Apply the evaluation to different industry cases.
18	Sentiment analysis for user satisfaction in Saudi Arabia's telecom sector	Sentiment analysis for user satisfaction in the Saudi Arabian telecom sector	It focuses on sentiment analysis rather than churn prediction. Limited discussion of the impact on churn prediction.	Investigate the relationship between sentiment analysis and churn prediction. Extend the study to other regions.
19	Churn prediction using gradient boosting machine and metaheuristic optimisation	Efficient churn prediction using gradient boosting machine	There is limited discussion on the choice of optimisation techniques and their impact. Scalability considerations are not addressed in detail.	Explore optimisation techniques and scalability enhancements.
20	Comparative performance assessment of ordinary artificial neural network and CNN in churn prediction	Comparison of artificial neural network and CNN for churn prediction	There is limited discussion on the specific performance metrics used for assessment. Only two types of models are compared.	Compare a wider range of machine learning algorithms. Define comprehensive performance metrics.
21	Churn prediction in telecoms using Random Forest algorithm	Churn prediction using the Random Forest algorithm	There is limited discussion on the specifics of Random Forest parameter tuning. Scalability challenges are not explored in depth.	Investigate parameter tuning for Random Forest. Address scalability concerns.
22	Customer churn prediction in the traditional broadcast industry	Churn prediction in the traditional broadcast industry	The study focuses on a specific industry, which may limit its generalizability. Specific model details may not be provided.	Explore applications beyond the broadcast industry. Provide detailed model information.
23	Churn detection for insurance data using Blended Logistic Regression Decision Tree Algorithm (BLRDT)	Churn detection using BLRDT algorithm	There is limited discussion on the dataset used and model performance metrics. The study focuses on a specific industry (insurance).	Apply BLRDT to different datasets and industries. Define comprehensive performance metrics.
24	Telco big data analytics using an open-source data pipeline	Telco big data analytics using an open-source data pipeline	The study may lack in-depth technical details about the data pipeline. Limited scope as it focuses on data pipeline implementation.	Provide technical insights into the data pipeline. Explore broader applications beyond telco.
25	Arabic Twitter mining for customer churn prediction	Prediction of customer churn behaviour using Arabic Twitter mining	There is limited discussion of the application outside of Twitter data. Limited exploration of other social media platforms.	Extend the analysis to other social media platforms. Investigate diverse data sources.

26	Advanced customer churn prediction using machine learning	Framework for advanced customer churn prediction using machine learning	There is limited discussion on the specifics of the machine learning algorithms used. Scalability and data privacy concerns are not addressed.	Explore a variety of machine learning algorithms. Address scalability and data privacy issues.
27	Telecom churn prediction using voting classifier ensemble method	Churn prediction using a voting classifier ensemble method	Limited explanation of the ensemble method components. Scalability considerations are not discussed in detail.	Provide detailed insights into the ensemble method. Address scalability challenges.
28	Customer churn prediction in slow fashion e-commerce context	Churn prediction in a slow fashion e-commerce context	It focuses on a niche (slow fashion e-commerce), limiting generalizability. Specific model details may not be provided.	Explore applications beyond slow fashion e-commerce. Provide detailed model information.
29	Customer churn prediction in the telecom industry using deep learning	Churn prediction in the telecom industry using deep learning	There is limited discussion on specific deep learning algorithms and model interpretability. Scalability considerations are not explored.	Investigate various deep learning algorithms. Enhance model interpretability. Address scalability concerns.
30	Churn prediction using Power BI for the banking industry	Customer churn prediction using Power BI for the banking industry	There is limited discussion on the choice of machine learning algorithms. Scalability and data privacy concerns are not addressed in depth.	Evaluate various machine learning algorithms. Address scalability and data privacy issues.
31	AdaBoost with cost-sensitive classifier for customer churn prediction	Churn prediction using AdaBoost with a cost-sensitive classifier	There is limited discussion on the choice of cost-sensitive classifier and its impact. Scalability considerations are not discussed.	Explore different cost-sensitive classifiers. Address scalability challenges.
32	Decision tree application in influencer commerce for customer churn prediction	Application of decision trees in influencer commerce for churn prediction	Limited discussion on the choice of decision tree parameters. Scalability challenges are not explored in depth.	Investigate decision tree parameter tuning. Address scalability concerns.
33	AdaBoost with cost-enabled cost-sensitive classifier for churn prediction	Improved customer churn prediction using cost-sensitive AdaBoost	There is limited discussion on the choice of cost-sensitive classifier and its impact. Scalability considerations are not discussed.	Explore different cost-sensitive classifiers. Address scalability challenges.
34	Grey wolf optimiser and ensemble neural networks for customer churn modelling	Enhanced churn modelling through grey wolf optimiser and ensemble neural networks	There is limited discussion on the specifics of the ensemble neural networks and their impact. Scalability challenges are not explored.	Investigate ensemble neural network configurations. Address scalability concerns.
35	PCA-AdaBoost model for E-commerce customer churn prediction	Improved prediction using the PCA-AdaBoost model for E-commerce churn	Limited discussion on the PCA dimensionality reduction technique. Specific performance metrics may not be provided.	Explore advanced dimensionality reduction techniques. Define comprehensive performance metrics.
36	Ant colony optimisation with reptile search algorithm for churn prediction	Enhanced churn prediction using ant colony optimisation and reptile search	Limited explanation of the ant colony optimisation parameters. Scalability considerations are not discussed in depth.	Investigate parameter tuning for ant colony optimisation. Address scalability concerns.

37	Accuracy Measure of Customer Churn Prediction in the Telecom Industry Using Adaboost over Decision Tree Algorithm	Improved accuracy in telecom industry churn prediction using Adaboost with Decision Tree	There is a Limited discussion on the choice of Decision Tree parameters. Scalability challenges are not explored.	Investigate Decision Tree parameter tuning. Address scalability concerns.
38	Customer churn prediction for web browsers	Customer churn prediction for web browsers	Limited details on the specific web browser data and model performance metrics exist. Scalability considerations are not addressed.	Provide insights into the web browser data and define performance metrics. Address scalability concerns.
39	Employee attrition prediction in a pharmaceutical company using machine learning approach and qualitative data	Employee attrition prediction using machine learning and qualitative data	There is limited discussion on the impact of qualitative data on prediction. Scalability and data privacy concerns have not been explored.	Explore the influence of qualitative data on prediction. Address scalability and data privacy issues.
40	Customer Churn in Retail E-Commerce Business: Spatial and Machine Learning Approach	Churn prediction in retail e-commerce using spatial and machine learning	There is limited discussion on the choice of spatial features and model scalability. Specific model details may not be provided.	Explore advanced spatial features and scalability enhancements. Provide detailed model information.
41	Customer churn prediction in telecom using the rough set approach	Churn prediction in telecom using a rough set approach	There is limited discussion on the specific rough set parameters and their impact. Scalability considerations are not discussed.	Investigate parameter tuning for a rough set approach. Address scalability challenges.

IV. RESEARCH GAP

The research gap in churn prediction encompasses several key areas that warrant further exploration and analysis. Firstly, there is a tendency for reviews to predominantly discuss traditional machine learning models such as Decision Trees, Support Vector Machines, and Logistic Regression, potentially overlooking the potential benefits of exploring deep learning models or hybrid approaches in this context. Additionally, while cross-industry comparisons between the telecommunication and medical sectors offer valuable insights, reviews often fail to adequately explore how results and challenges differ between these industries, leaving a gap in understanding. Moreover, limited attention is given to the unique data challenges in these industries, including data collection, cleaning, and preprocessing issues. Ethical and privacy concerns, particularly pertinent in the medical field due to regulations like GDPR and HIPAA, also deserve more extensive discussion within churn prediction literature. Temporal dynamics, such as seasonal variations and market fluctuations, are another overlooked area despite their potential impact on churn predictions.

Furthermore, the significance of domain-specific feature engineering in improving model efficiency is often underestimated, highlighting a gap in research focus. The need for interpretable models, especially in high-stakes domains like healthcare, is apparent, yet reviews often lack discussion. Integration with other operational systems, deployment challenges, and real-time prediction capabilities are additional areas where gaps exist. The economic implications of churn prediction, including direct and indirect costs, are not deeply explored, nor are the potential cultural and geographical variations that may influence churn behaviour and prediction models. Finally, beyond traditional evaluation metrics, there is a need to consider other measures such as F1-score, AUC-ROC, or economic cost functions in the context of churn prediction, which are often overlooked in existing literature. Addressing these gaps can significantly enhance the effectiveness and applicability of churn prediction models across various industries.

V. ADVANTAGE

The advantages of conducting a comprehensive review of churn prediction techniques are manifold. Firstly, such a review offers stakeholders a holistic overview of the current landscape of churn prediction methodologies, providing a broad perspective on the field's progression and the methodologies currently in use. By examining the telecommunication and medical industries, readers can glean cross-industry insights, identifying unique challenges and opportunities in each domain and potentially transferring best practices between industries. Moreover, the review facilitates algorithm comparison, enabling companies to discern which machine learning models perform best in specific scenarios and guiding implementation decisions. Additionally, identifying best practices, ranging from data preprocessing to model evaluation, can streamline churn prediction by highlighting proven methodologies across multiple studies. Consolidating resources into a single review saves stakeholders time and effort by presenting a consolidated view of the field and providing a benchmark against which businesses can compare their methodologies and results.

Furthermore, the review can offer valuable data insights, shedding light on the data types most valuable for churn prediction and guiding data collection and feature engineering efforts. The review stimulates innovation and guides future research endeavours and industry applications by highlighting emerging trends and identifying research gaps. Moreover, by differentiating between industry-specific challenges faced by the telecommunication and medical sectors, the review can lead to better-targeted solutions. Importantly, by promoting collaboration between machine learning experts, telecommunication specialists, and medical professionals, the review fosters interdisciplinary efforts, potentially leading to novel insights and approaches. Finally, a well-conducted review, particularly if peer-reviewed, enhances the summarised findings' trustworthiness, ensuring that businesses and researchers base their decisions and further research on robust evidence. Overall, such a review plays a pivotal role in advancing the field of churn prediction, facilitating informed decision-making, promoting collaboration, and stimulating innovation.

VI. CONCLUSION

The dynamic landscape of customer churn prediction has witnessed a tremendous evolution over the years, and its implications are particularly significant in the telecommunication and medical sectors. As demonstrated in this review, machine learning classification models have emerged as pivotal tools in offering precise, actionable insights that allow businesses to make informed decisions and enhance customer retention. The high competition and rapid technological advancements in the telecommunication industry underscore the need for efficient churn prediction. Applying advanced machine learning models, from decision trees to deep learning, has proven to significantly enhance the accuracy and robustness of churn prediction, allowing businesses to implement timely interventions. Conversely, with its unique challenges, the medical industry demands a slightly different approach. The stakes are higher, as patient churn can directly affect health outcomes. Machine learning models here predict churn and give insights into underlying reasons, helping medical institutions improve care quality and patient satisfaction. Cross-industry comparisons reveal fascinating insights. While the nature of customer relationships and data differs between telecommunication and medical sectors, the foundational methodologies and algorithms often overlap, demonstrating the versatility and adaptability of machine learning techniques.

Nevertheless, as with all technological applications, challenges persist. Data privacy concerns, especially in the medical sector, the necessity for interpretable models, and the ever-evolving nature of customer behaviours necessitate continuous research and adaptation. In closing, the field of customer churn prediction, bolstered by machine learning, is a testament to the confluence of technology and business strategy. As we move forward, researchers and industry professionals must collaborate, innovate, and refine these models, ensuring they remain relevant, efficient, and effective in a world where customer retention is just as vital as acquiring a new one.

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