International Journal of Integrated Science and Technology (IJIST)
Vol.2, No.10, 2024: 907-918

Highly Accurate Customer Churn Prediction in the Telecommunications Industry Using MLP

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A R T I C L E I N F O

Keywords: Churn prediction, Telecommunication, MLP.

Received : 10, Agust
Revised : 12, September
Accepted: 18, Oktober

A B S T R A C T

Predicting customer Churn is of principal importance for many businesses, as it directly influences the continued utilization of company products by consumers and has a significant impact on company's financial health and sustainability. However, accurately forecasting customer attrition within the telecommunications sector presents considerable challenges. In response to this need, we propose a novel and highly accurate churn prediction model utilizing a Multilayer Perceptron (MLP) architecture. Our methodology begins with thorough data preprocessing, followed by the application of MLP to predict customer Churn. By employing the Synthetic Minority Over-sampling Technique (SMOTE) and iterative balancing, our proposed model has demonstrated an accuracy improvement of at least 5%, alongside a minimum 5% increase in the F1-score, when compared to existing state-of-the-art algorithms on the widely recognized Telco-Customer-Churn dataset. This research not only expands the opportunities for enhancing the interpretability of predictive models but also fosters a deeper understanding of Churn prediction mechanisms. Ultimately, these advancements contribute to the commercial sustainability and financial stability of telecommunications companies by facilitating more informed decision-making processes regarding customer retention strategies.

INTRODUCTION

Social media platforms have developed into effective tools for businesses to connect with their audiences, get their feedback, listen, and modify their products and services accordingly. The quick development of social media technology has ushered in a new era for companies to engage with their customer base, both existing and potential (Dai & Wang, 2021). The ever-growing number of mobile phone users has been interpreted in different ways in recent years, particularly in cities where the telecom market appears to have reached saturation. Exacerbating this dynamic of mobile telecom market saturation, the mobile communications industry has undergone a significant shift at the same time. A growing number of customers are actively switching their loyalty by moving their registered service from one competitor to another (Alboukaey et al., 2020). Nonetheless, as a result of the digital revolution, there is now intense rivalry among telecom service providers, who are vying to offer dependable communication services and seamless data coverage in both urban and rural locations. It is now urgently necessary to address the wide range of needs that customers have as a result of this evolution (Sridhar et al., 2020). Of course, an organization deals with two different kinds of customers: new customers and long-term ones. Not to be outdone, businesses have discovered that concentrating their marketing efforts on keeping current clients rather than continuously pursuing new ones is more economical and lucrative. Acknowledging the financial advantages of keeping current clients over attracting new ones (Lu et al., 2012), the business has purposefully changed its emphasis in marketing. In order to identify customers who are likely to leave or switch providers, network providers have therefore been actively involved in developing machine learning (ML) and deep learning (DL) models for Churn prediction.

To put it simply, a "Churner" is a customer who chooses to cancel their telecom service provider subscription and switch to a new one, thereby reducing the financial loss incurred by the company(Umayaparvathi & Iyakutti, 2012). This behavior carries significant consequences in the context of the telecommunications industry. Telecom companies experience Churn, which results in lost revenue from the departing customer as well as costs associated with acquiring new customers. Churn can have a major financial impact, not only could one customer leave, but there could also be a chain reaction as unhappy consumers tell others about you, causing more Churn. The cost of acquiring new customers to offset this Churn can be a considerable financial burden. Thus, reducing customer attrition is critical to telecom companies long-term viability and financial stability.

The manual Churn prediction knowledge base is complex due to numerous factors, and researchers from artificial intelligence (AI) solutions utilize fallout prediction automation and scalability. To find clients who have a high propensity to deviate, deviance prediction models have been developed (Rabbah et al., 2023; Spelmen & Porkodi, 2018). In the telecommunications industry, a variety of supervised machine learning algorithms (MLA), convolutional neural network

(CNN) models, and text mining algorithms are employed for deviation analysis(Beeharry & Tsokizep Fokone, 2022; Tariq et al., 2022). Researchers categorize the models into static and dynamic groups based on the features that the algorithms process (Alboukaey et al., 2020). One useful method for predicting client attrition is to use ML(Kumar & Logofatu, 2023), to extract static features from a customer representative of a telecom service in order to predict customer Churn.

In Figure 1, the customer Churn prediction process is visually depicted. The process starts with customer data, moves through Churn prediction, customer segmentation, strategy definition, and finally, actionable steps are taken to retain existing customers due to compnay revenue(Saha et al., 2024). Customer Churn prediction is a classification problem, where the goal is to predict which customers are likely to Churn before they leave. The target is binary: Churn (Yes) and Not Churn (No) for each customer. It is important to note that the proportions are often imbalanced, meaning a small percentage of customers are likely to Churn in a random sample. To process customer data and build a realistic model, it's necessary to consider a large number of attributes to account for all the factors that could influence Churn.

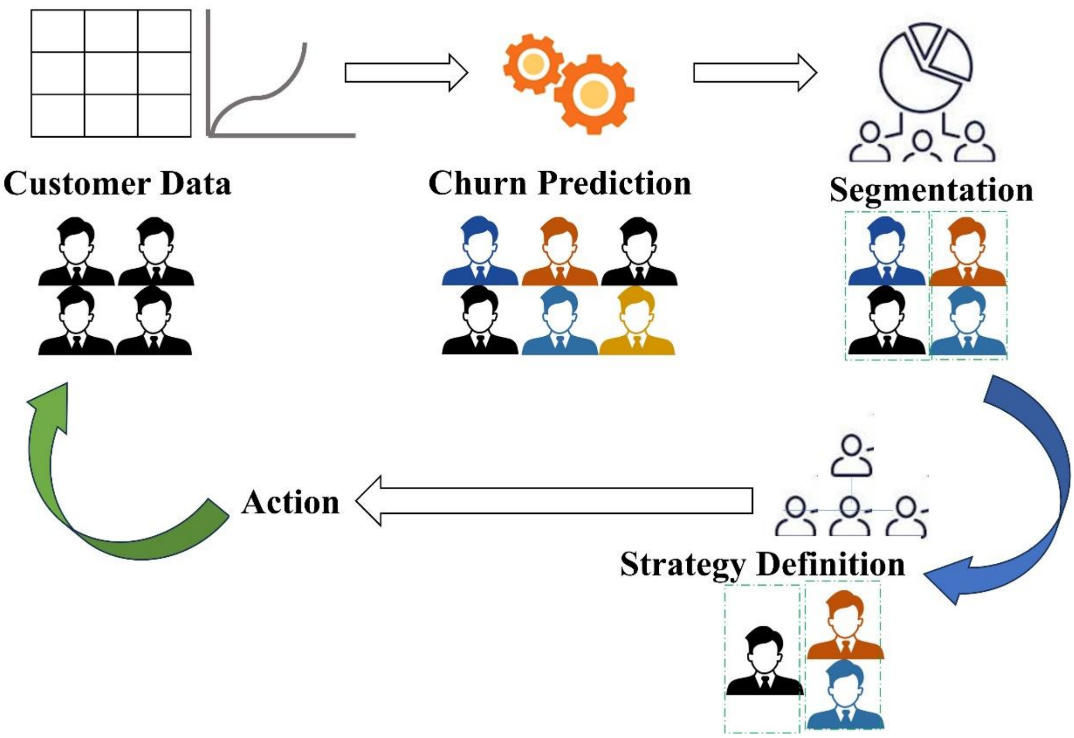


Figure 1: Churn prediction model

Telecommunication is a highly competitive industry (Sikri et al., 2024), so in the telecommunications industry, where social media technology is evolving, challenges like market saturation, meeting diverse customer needs, and the economic need for customer retention converge. Understanding and reducing customer Churn is essential for the sustainability and profitability of network service providers in this constantly changing landscape. To address the problem of highly imbalanced datasets, we applied the Synthetic Minority Over-sampling Technique (SMOTE) to balance the classes in the dataset related to telecommunication customer Churn. After that, we used Tukey's Fences (TF) to detect outliers in the dataset, and finally, we used the Multilayer Perceptron (MLP) algorithm for Churn classification, achieving 92% accuracy while also optimizing the model's execution time.

In data science literature, an outlier or anomaly refers to a data point that significantly deviates from the rest of the dataset. Diverse methodologies, including filtering, Independent Component Analysis (ICA), and Principal Component Analysis (PCA) (Han et al., 2022; Hyvärinen et al., 2001; Khalid et al., 2014), are employed to feature engineering. To address this concern, we propose a highly accurate customer Churn prediction method for the telecommunications industry using MLP. Additionally, by applying the TF algorithm, our model aims to enhance the overall accuracy and reliability of customer Churn prediction. Our contributions are as follows:

- Explainable Model: Providing insights into the importance of feature engineering and model optimization for Churn prediction.
- Elevating Churn prediction with MLP: We introduce an academic breakthrough by seamlessly integrating MLP into Churn prediction, promising substantial improvements. the proposed approach significantly enhances prediction accuracy, achieving 92% on the Telco-Customer-Churn dataset.
- Improving prediction accuracy by proper feature engineering: To address DL interpretability issues, we use the TF algorithm for outlier detection. TF enhances transparency, making DL more understandable and trustworthy for prediction experts.

The rest of the article is organized as follows. In Section 2, we review related work on the topic. Section 3 presents our method in the research. Subsequently, in Section 4, the obtained results and analysis. Finally, Section 5 concludes the paper and outlines directions for future work.

RELETED WORK

Researchers have proposed a number of methods, including DL and ML, to predict customer attrition in the telecommunications industry. Induja et al. (Induja & Eswaramurthy, 2016) introduced a kernelized extreme ML method. in order to classify patterns of customer attrition in the telecom industry. A naïve bayes classifier (NBC) was used to analyze customer turnover behavior based on four criteria; Customer unhappiness, switching cost, service utilization, and customer status. The data was preprocessed using an expectation maximization (EM) clustering approach. When the characteristics to predict client attrition were measured using the Bat and Kernel Extreme Learning Machine (KELM) algorithms, the method produced an 83% area under the curve (AUC) score. XGBoost, random forest(RF), and K-nearest neighbor (KNN) were used in (Pamina et al., 2019) to forecast customer Churn; XGBoost achieved the highest accuracy of 79.8%. NB and RF worked for (Lejeune, 2001). Their results showed that RF outperformed NB with an accuracy of 71.99%. They also found that the lack of processing in the experiments caused the dataset to be out of balance. Adhikary et al. (Adhikary & Gupta, 2021) compared more than 100 classifiers for customer Churn prediction problems and discovered that integrated RF using the bagging algorithm produced the best accuracy of 73.04%, while regularized RF outperformed all other classifiers by 67.20% in terms of AUC. Vijaya et al. (Vijaya & Sivasankar, 2019)used particle swarm optimization (PSO) in combination with feature selection and simulated annealing (FSSA) to predict customer attrition. PSO-FSSA turned out to be the most successful, achieving 94.08% accuracy and a 96.06% F1 score.

The study by Rabbah and colleagues (Rabbah et al., 2023) focuses on predicting customer attrition in the telecommunications sector. Using ML, a multilayer stacking network comprising eight selected models was built. Its accuracy exceeded that of individual base models by 80.1%. This illustrates the effectiveness of the recommended approach in enhancing telecom providers' Churn prediction. Kumar and others (Kumar & Logofatu, 2023), in order to forecast customer attrition in the telecom industry, this study compared several well-liked supervised MLA, such as decision trees (DT), Boosting, Bagging, Stacking, and Voting. Their model received the highest accuracy score of 83.4% when compared to other models in the literature. However, prior research did not consider outlier detection in order to create a simple and effective model with high accuracy for forecasting telecom Churn in a short amount of time. This paper presents a proper method for predicting customer Churn in the telecom industry by appropriate feature engineering with MLP algorithm.

METHOD

The three components of the suggested methodology are with feature engineering includes; data preprocessing, classification, and evaluation.

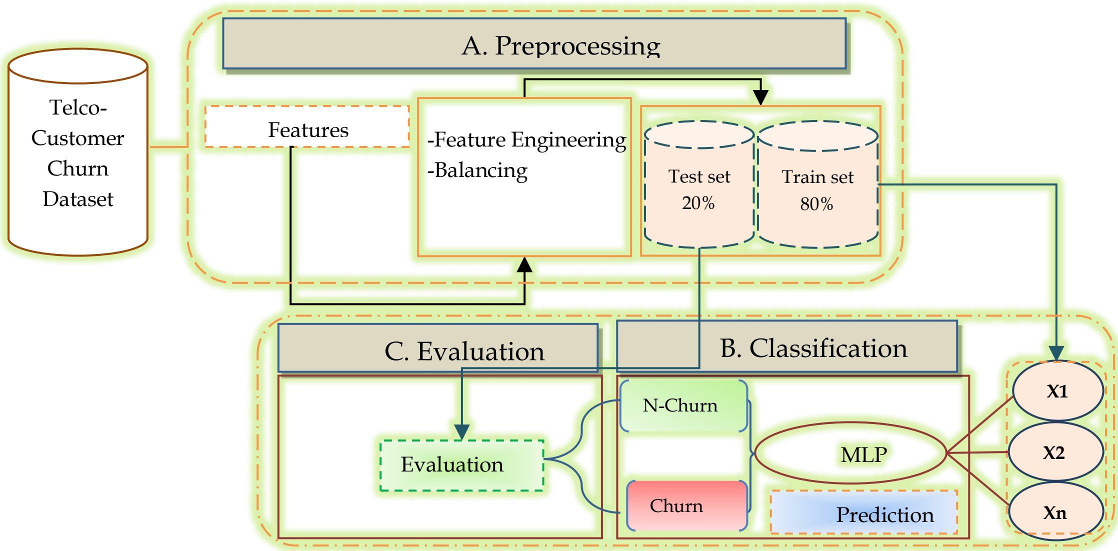


Figure 2: Structure model

To get ready for the next stage, we first performed feature engineering. In the second section, we considered all of the dataset's columns—aside from "gender"—and concluded that while some features are useful for telecom companies, others are not. Ultimately, we suggested using TF for outlier detection during this stage to improve the prediction result. Since Churn prediction is a binary classification problem, we used the MLP algorithm in the third section to classify the Churn and non-Churn (Kumar & Logofatu, 2023). In the end, the trained models are tested and assessed taking into account the AUC as well as additional evaluation parameters (Accuracy, Precession, Recall, and F1-Score). As a result, Figure 2 displays our model.

DATASET

The dataset[1] comprises a substantial 7043 data points, as presented in Table 1. Each data point provides distinct insights into the behaviour and characteristics of our customers, serving as the foundation for our research. One of the main variables in our Churn analysis is the "Churn" column, which identifies customers who have chosen to cancel their subscription in the last month. Additionally, the "Services" section provides useful details regarding the range of services that specific clients have selected, such as phone services, multiple lines, internet access, online security, online backup, device protection, tech support, and streaming TV and movies.

Num. Co	Columns	No. Instance	Data Type
1	customerID	7043	object
2	gender	7043	object
3	SeniorCitizen	7043	int64
4	Partner	7043	object
5	Dependents	7043	object
6	tenure	7043	int64
7	PhoneService	7043	object
8	MultipleLines	7043	object
9	InternetService	7043	object
10	OnlineSecurity	7043	object
11	OnlineBackup	7043	object
12	DeviceProtection	7043	object
13	TechSupport	7043	object
14	StreamingTV	7043	object
15	StreamingMovies	7043	object
16	Contract	7043	object
17	PaperlessBilling	7043	object
18	PaymentMethod	7043	object
19	MonthlyCharges	7043	float64
20	TotalCharges	7043	object
21	Churn	7043	Object
Total		287,943	

Figure 3: Dataset information

[1] https://www.kaggle.com/datasets/blastchar/telco-customer-Churn

DATASET BALANCING

Feature engineering is an essential element of data preparation, especially when dealing with imbalanced datasets. The ability of the model to accurately represent the classification performance is strongly influenced by balancing, which is a crucial component of accurate classification. Because cases from the minority class are frequently not accurately classified, this is especially important (Spelmen & Porkodi, 2018). During the first stage of preprocessing, we carefully divided the features into two groups: numeric and categorical columns. This was done according to the data types of each group. This stage lays the groundwork for the changes that come after. One of the most significant problems we faced was the extremely unbalanced dataset, as Figure 4 could be located. There are two classes in the dataset: "Yes" and "No." Here, 'Yes' indicates Churn-containing cases, whereas 'No' indicates Churn-free cases. The imbalance is clearly visible, highlighting the necessity of taking corrective action. We used the synthetic minority over-sampling method (SMOTE) to correct the imbalance. As shown in Figure 5, this technique entails oversampling the minority class ('Yes') in order to generate a more balanced distribution. In order to overcome the issue of class imbalance and enable better model training and classification performance, the 'Yes' class is oversampled.

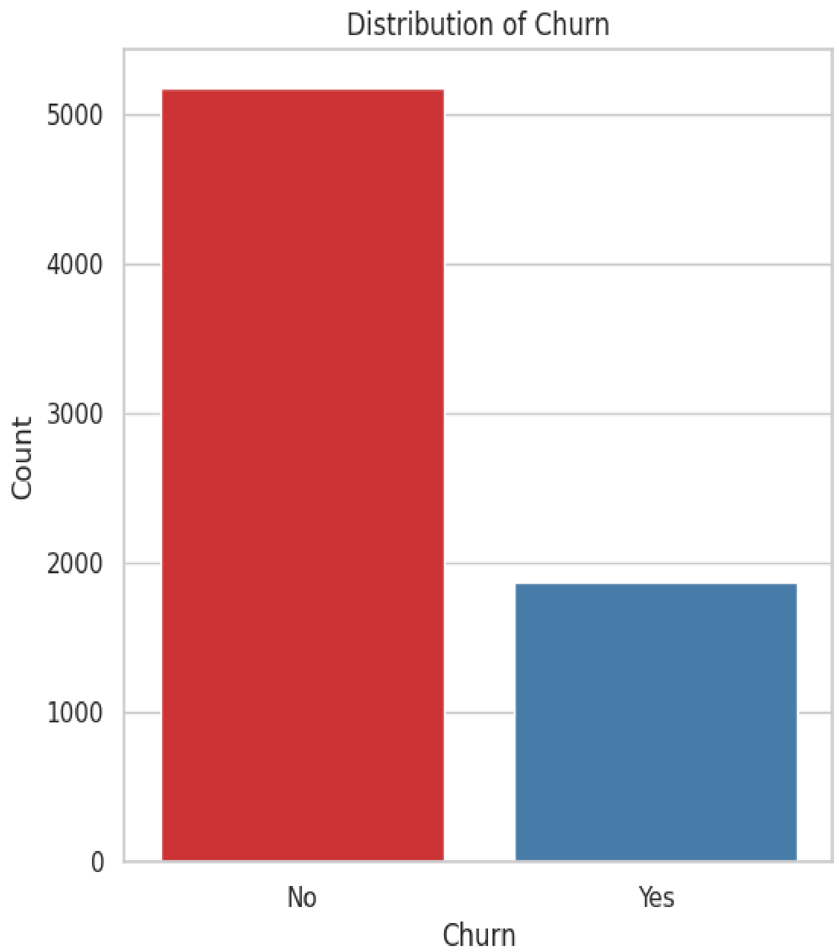


Figure 4: Dataset instance before balancing

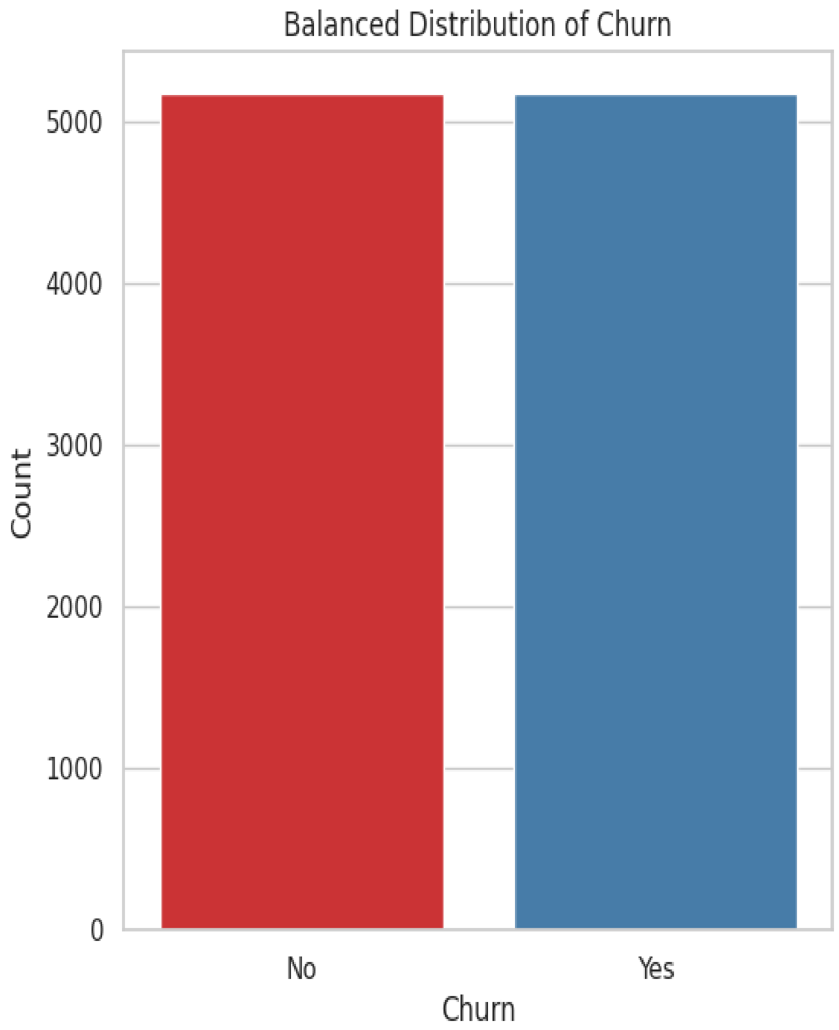


Figure 5: Dataset instance after balancing

FEATURE SELECTION

A crucial component of improving ML models' overall performance is feature selection(Hall, 1999), which mainly aids in preventing overfitting, optimizing computing effectiveness, and boosting generalization. By selecting and keeping only the most pertinent features, the technique helps to reduce the influence of noise and extraneous data in the dataset. After examining a dataset with 21 attributes in the context of a particular example, the "gender" column was removed. This choice was based on the knowledge that, in the context of Churn prediction, the "gender" attribute was marginally significant. By carefully selecting features, ML models can improve their interpretability, accuracy, and resource efficiency, making them suitable for use in practical settings.

CORRELATION HEATMAP OF NUMERICAL FEATURES IN CHURN ANALYSIS

Correlation heatmap of numerical features in customer Churn analysis. The correlation heatmap visually in Figure 2 4 represents the relationships between numerical features in the dataset. Each square in the heatmap corresponds to the correlation coefficient between two features, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation). The color intensity and direction of the color (blue for negative, red for positive) indicate the strength and type of correlation. In this heatmap, several notable correlations can be observed. For instance, there is a strong positive correlation between total day minutes and total day charge, which is expected as these features are directly related. Additionally, a moderate negative correlation exists between total day minutes and total eve minutes, suggesting that customers who use more day minutes tend to use fewer evening minutes. Further analysis of these correlations can provide valuable insights into customer usage patterns and potential Churn factors.

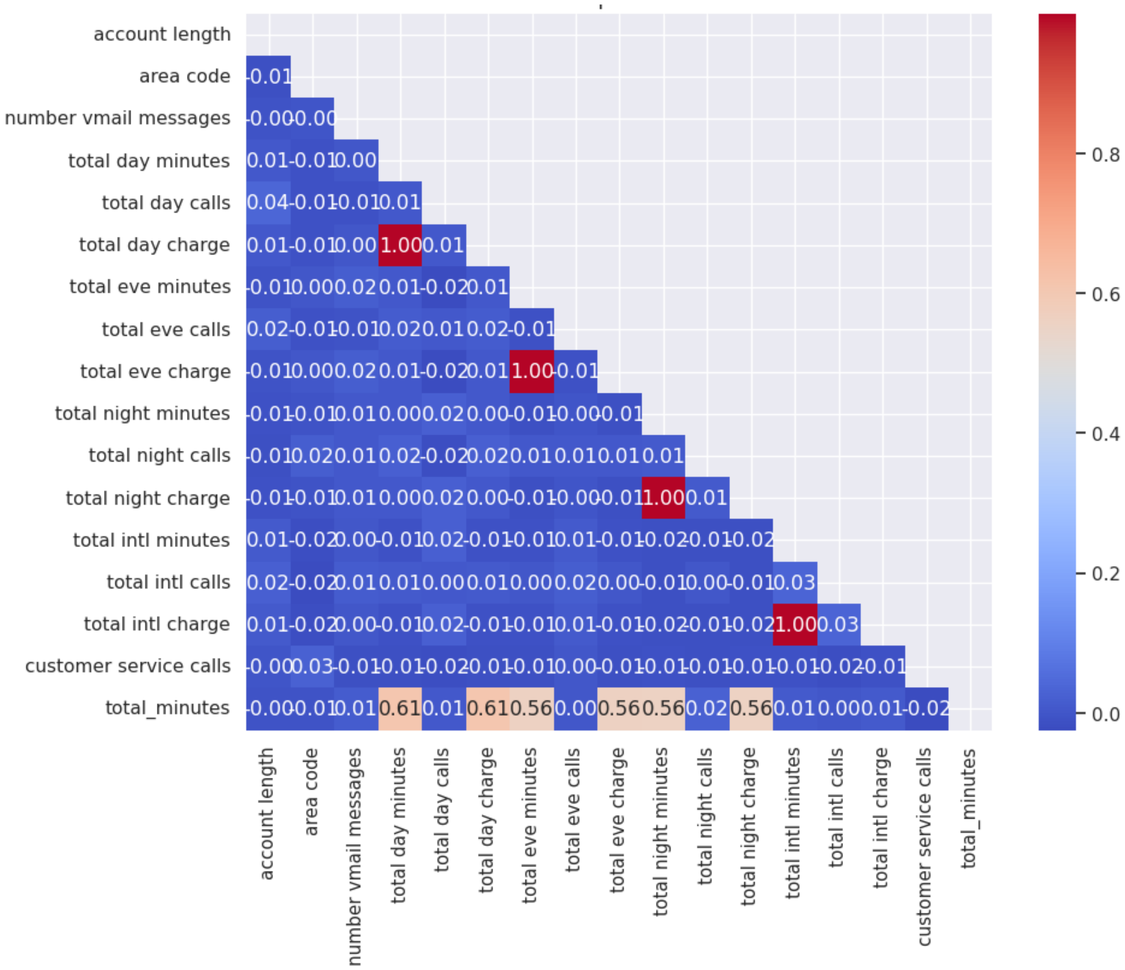
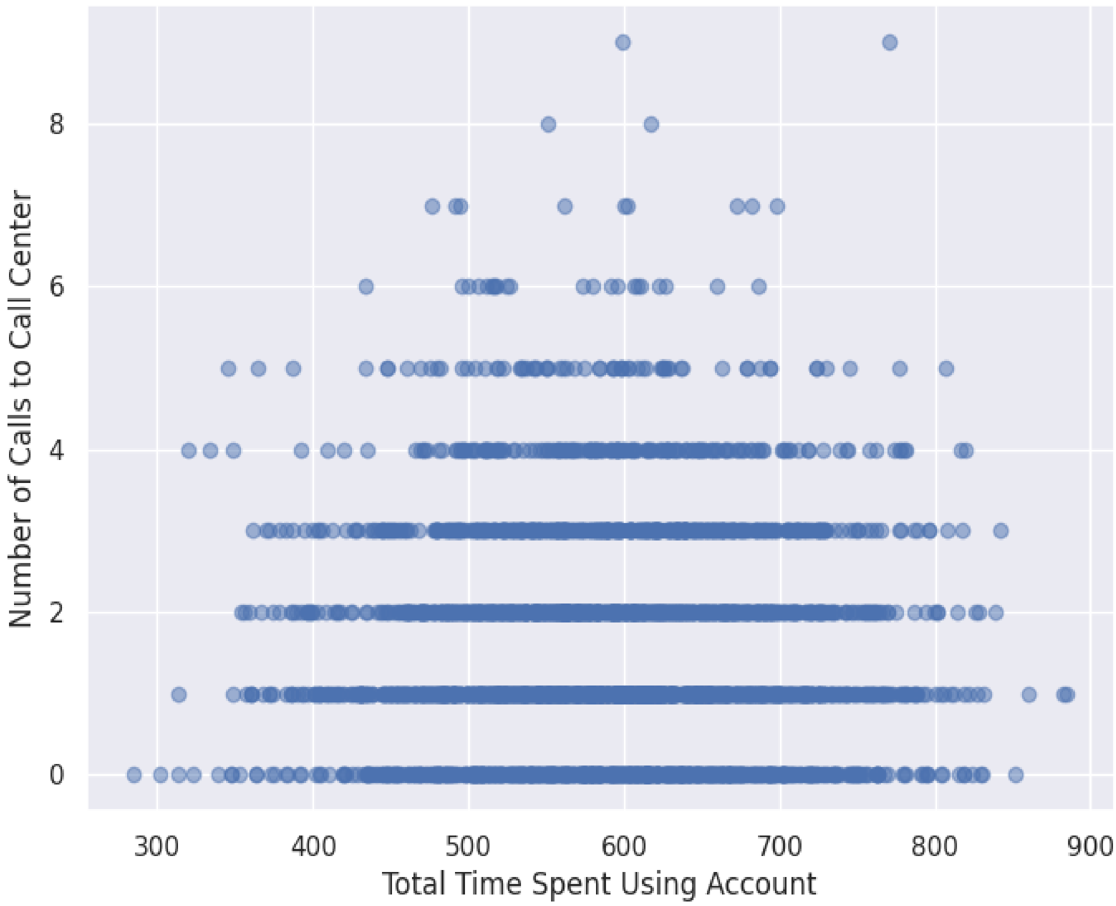


Figure 6: Correlation heatmap of numerical features in Telecom-dataset

TIME SPENT VS. NUMBER OF CALLS TO CALL CENTER

Relationship between time spent and number of calls to call-Center. The scatter plot Figure 3 5 illustrates the relationship between the total time spent using an account and the number of calls made to the call centre. Each dot represents a customer, with its position on the graph indicating their total time spent and corresponding number of calls. From the plot, it can be observed that there is a general trend of customers who spend more time using their accounts making fewer calls to the call-Center. This might suggest that customers who are more engaged with the service or have a better understanding of its features require less support. However, there are also outliers, indicating that some customers may have specific needs or issues that require frequent contact with the call-Center, regardless of their overall usage time. Further analysis could



delve into the reasons behind these outliers and explore potential improvements to the service or support processes.

Figure 7: Relationship between time spent and number of calls to call center.

RESULTS AND DISCUSSION

We used Python language in the Colab environment to implement the proposed method. Table I shows the experimental environment which shows more details about the tools that we used.

Table I: Experimental environment

Environment	Value
Operating system	Windows 11
CPU / GPU	Google Colab
Memory	8 GB
Language	Python
Software development environment	Numpy, Pandas, Sklearn, Imblearn, etc.

The evaluation metrics consist of the following definitions: accuracy, precision, recall, and F1-measure. Accuracy is the right ratio of correctly classified samples to the total number of samples that were tested Equation (1). Precision is the accurate ratio of the number of positive samples that have been classified to the total number of positive samples for a given class Equation (2). Recall is the equation Equation (3). shows the accurate ratio of detected positive samples to the total number of positive samples in the testing set for a particular class. The last parameter for the evluation is F1-Score weighted average of recall and precision for every class or the entire classifier is known as the F1-measure Equation (4).

$$"Accurcy" = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$"Precision" = \frac{TP}{TP+FP} \tag{2}$$

$$"Recall" = \frac{TP}{TP+FN} \tag{3}$$

$$"F1-measure" = \frac{2*Precision*Recall}{Precision+Recall} \tag{4}$$

For a specific class, True Positive (TP) signifies the count of correctly identified positive samples, True Negative (TN) indicates the count of accurately recognized negative samples, False Positive (FP) represents the count of negative samples mistakenly classified as positive and False Negative (FN) signifies the count of positive samples erroneously categorized as negative.

EVALUATION

In this subsection, we evaluate the suggested method's performance with an emphasis on Churn prediction, utilizing the "Telco-Customer-Churn" dataset, which is detailed in Figure 3. In order to properly assess the suggested approach, we separated the dataset into two subsets: a training set that included 80% of the data and a different test set that included the remaining 20%. This section makes sure that our model gains knowledge from a substantial amount of the data, but it also keeps a separate set aside for testing to determine how well it can generalize. Three images make up Figure 8's visual depiction of the suggested MLP performance in the Churn classification;

ROC Curve: The model's ability to distinguish between Churning and non-Churning customers is strong, with an AUC of 0.98.

Confusion Matrix: Out of 1668 Churning customers, 699 are correctly predicted (true positives), and 42 are false negatives. For non-Churning customers, 843 are correctly predicted (true negatives), and 84 are false positives.

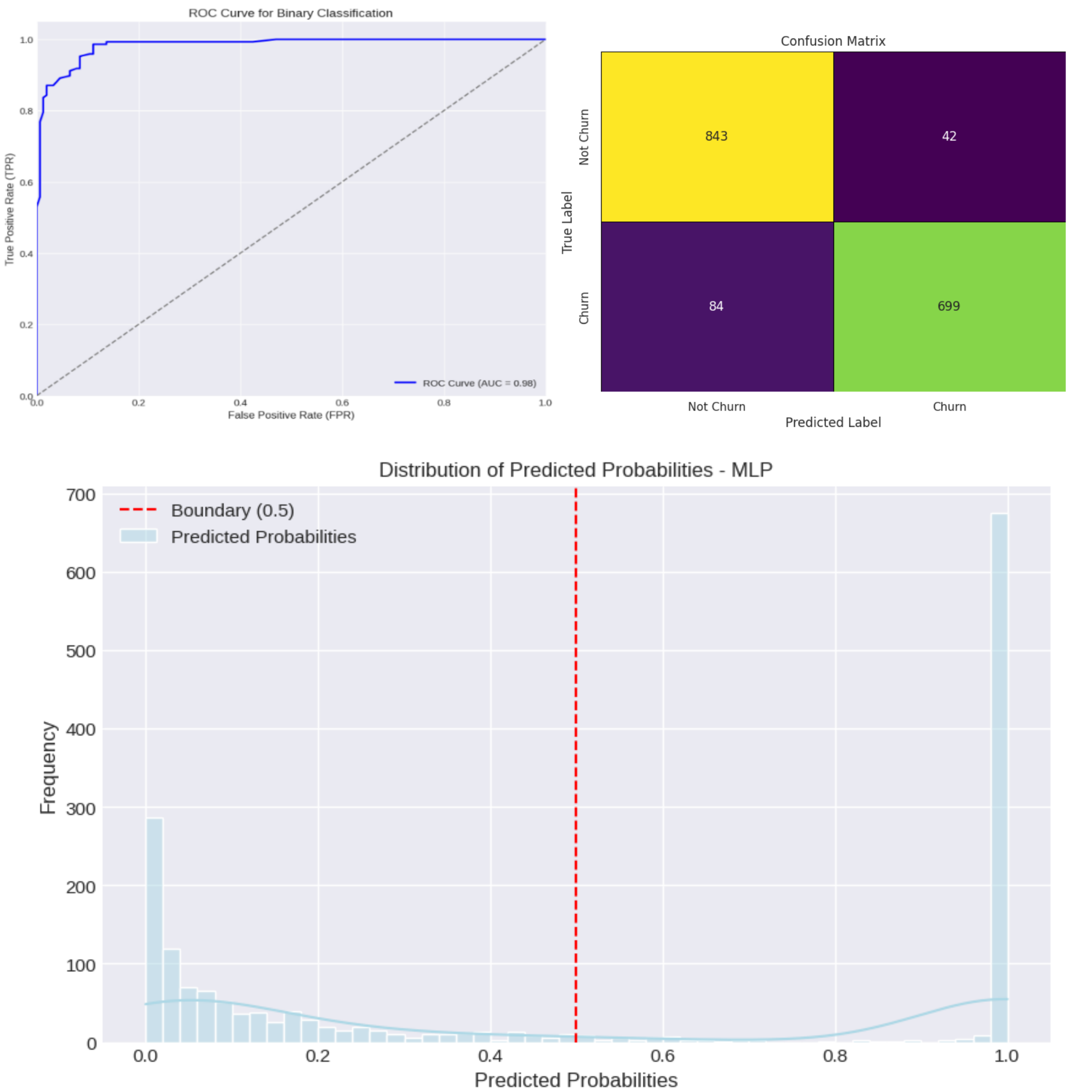


Figure 8: Churn classification performance

Predicted Probabilities: The predicted probabilities show that Churning customers generally have higher probabilities compared to non-Churning customers.

All three images in Figure 8 demonstrate strong model performance in predicting customer Churn. The high AUC, low number of incorrect predictions in the confusion matrix, and distinct probability distributions for the two groups highlight the model's high accuracy. A comparative analysis was also conducted to evaluate the effectiveness of our proposed MLP with the balanced dataset for predicting Churn.

We compared our model's results with previous cutting-edge techniques in the field. Figure 9 shows a detailed comparison of precision, recall, accuracy, and F1-score. Our approach significantly outperforms previous state-of-the-art methods across all metrics, highlighting its effectiveness in Churn prediction using the "Telco-Customer-Churn" dataset. The model achieves high accuracy, recall, precision, and F1-score, along with minimal loss and short training time, confirming its superior performance.

DISCUSSION

We go into great detail about the results we got and how they affect the Churn prediction domain in this section. Our suggested method has shown outstanding results in Churn prediction using the "Telco-Customer-Churn" dataset. Notably, our approach outperforms previous methods in all important metrics, even though previous methods have produced noteworthy results.

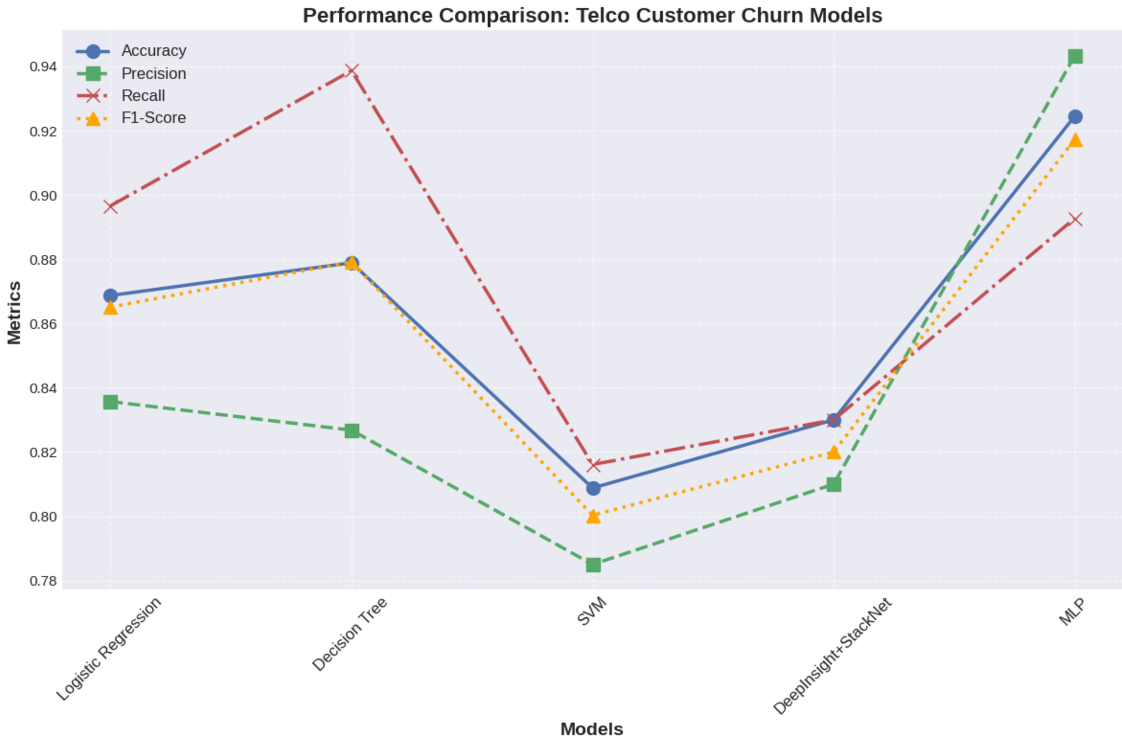


Figure 9: Our work vs state-of-the-art and other models

As illustrated in Figure 9, earlier scholarly research has suggested a number of methods for Churn prediction in telecoms using the "Telco-Customer-Churn" dataset. Nevertheless, unlike our study, past investigations have typically not produced an ideal and extremely precise model. By presenting a novel strategy with a potent classification model through MLP with proper feature engineering, we hope to close this particular research gap. This method aims to advance the field of Churn prediction by improving the overall efficacy and accuracy of Churn prediction. We evaluated our suggested model's performance to the most recent related work as well as basic ML methods including logistic regression (LR), DT, and support vector machines (SVM). The average of every assessment parameter is used to assess the performance of the machine learning models:

- LR: F1-score (86%), Accuracy (87%), Precision (83%), and Recall (89%).
- DT: F1-score (88%), Accuracy (88%), Precision (83%), and Recall (93%).
- SVM: F1-score (82%), Accuracy (81%), Precision (78%), and Recall (82%).

We also contrasted our results with those of fresh scholarly investigations. With the help of a Deep-BP-ANN model, Fujo et al. (Fujo et al., 2022) were able to forecast Churn with 88% accuracy.

Our proposed method performs competitively when compared to previous researched works, especially in the recall parameter (89%). It uses the TF algorithm for outlier detection in the dataset and carefully engineers features to help with accurate model classification. This suggests that the capacity to recognize genuine Churn cases—customers who discontinue their services—is good. Although the DT obtained a slightly greater recall near (93%). Its lesser precision (94%) however, suggests a greater possibility of false positives (classifying non-Churning clients as having a high probability of Churning). This demonstrates the significance of our method, which concentrates on the most pertinent data for Churn prediction using feature engineering and the MLP algorithm to identify intricate linkages within the data. Consequently, the balanced performance and simplicity of our model, demonstrated in its excellent F1-score (92%) across all evaluation criteria, underscores its efficacy in Churn prediction for telecommunication companies where eliminating both false positives and false negatives is key.is essential.

CONCLUSION

The study offers a thorough examination of Churn prediction in the telecom sector, highlighting the value of client retention and the application of deep learning algorithms (DLA)—specifically, the MLP algorithm—for Churn prediction, due to non-complexity. The dataset was thoroughly analysed in our study, including feature selection, data preprocessing, and classification using the MLP algorithm. the precision, recall, accuracy, and F1-score as well as the usefulness of the suggested strategy in forecasting customer Churn were highlighted in the results. The paper's approach earned a remarkable 92% accuracy rate in a comparative analysis with current academic studies, and other models, greatly exceeding previous state-of-the-art techniques. The remarkable precision, recall, F1-score, and high accuracy highlight the MLP algorithm's potential for precisely identifying clients who are at risk of Churning. The results corroborate the hypothesis that the suggested approach has potential for successful Churn prediction in the telecom sector, enhancing the long-term viability and financial stability of telecom firms. The comprehensive examination of the study and its enhanced effectiveness in comparison to current methods validate the possibility of utilizing (DLA), particularly the MLP algorithm, for effective Churn prediction in the telecommunications industry.

Subsequent efforts ought to concentrate on refining models to enhance the efficacy of Churn prediction and extending the MLP methodology to diverse datasets. Furthermore, improving the interpretability of DLA will guarantee more transparency and understanding in Churn forecasts, enabling telecom firms to make better decisions.

CODE AND DATA

Code and datasets used in this study are available upon request.

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