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Original Article

Revolutionizing Marketing Analytics: A Data-Driven Machine Learning Framework for Churn Prediction

Bhumeka Narra[1], Navya Vattikonda[2], Anuj Kumar Gupta[3], Dheeraj Varun Kumar Reddy Buddula[4], Hari Hara Sudheer Patchipulusu[5], Achuthananda Reddy Polu[6]
[1]Sr Software Developer, Statefarm.
[2] Business Intelligence Engineer, International Medical Group Inc.
[3] Oracle ERP Senior Business Analyst ,Genesis Alkali.
[4] Software Engineer, Anthem Inc.
[5] Software Engineer, Iheartmedia.
[6] SDE3, Microsoft.

***Abstract** - One of the biggest problems for big businesses is customer attrition. Since consumers are the primary source of income for businesses in the rental industry, they are specifically searching for strategies to keep them as clients. This study presents the data-driven machine learning technique for telecom sector churn prediction, addressing challenges of noisy, imbalanced, and high-dimensional data through a comprehensive preprocessing pipeline that includes noise removal, SMOTE-based balancing, feature selection, and outlier detection. In order to create predictive models using Decision Trees and Random Forest classifiers, the preprocessed data which consists of 3,333 customer records with attributes ranging from call metrics to charge information is separated into training and testing sets. When measured using measures like accuracy, precision, recall, F1-score, and ROC analysis, the Decision Tree model performed better than other models like ANN and SVM, achieving 88% accuracy, 83% precision, 93% recall, and 88% F1-score. These outcomes show how the approach may produce useful insights for improving customer retention and marketing strategy optimization in changing telecom contexts.*

***Keywords** - Customer Churn Prediction, Customer Retention, Marketing Analytics, Predictive Analytics, Telco-Customer-Churn dataset, Machine Learning.*

1. Introduction

Today's business environment makes customer satisfaction and retention the keys to success, thus making the analysis of customer behavior a fundamental source of market advantage. The telecommunication industry, which operates within an environment of swift expansion and aggressive market competition, maintains customer churn as its constant business challenge because customers sever relationships with provider services [1]. The act of customer turnover results in both revenue decrease and the waste of expenses spent on customer acquisition through advertising and concession programs alongside operational expenses.

The analysis of massive customer interaction data provides patterns and meaningful insights businesses can use for engaging with clients who show signs of disengagement. The acquired insights guide companies to deliver customized offers and enhanced service delivery, which both boost customer fulfillment levels and marketing cost-effectiveness.

The strategic requirement for organizations to predict customer churn extends beyond technical challenges, especially when operating with subscription-based business models[2]. Through accurate customer attrition identification, companies can create proactive strategies that lower customer turnover rates and bring substantial profits over extended periods. Error prediction capabilities of machine learning allow data analysis to proceed autonomously, which constitutes the analytical transformation that leads marketers to produce predictive models for decision-making. Machine learning describes the method of teaching digital computers to perform tasks that qualify as learning through animal or human behavior and cognitive processes [3]. An ML system gathers observations of its working environment to improve performance in the future [4].

1.1. Contribution of Study

The research analyzes a data-based machine learning system that aims to transform marketing analysis through customer churn forecasting. The research establishes advancements within its field through improved model efficiency and data-based customer retention decisions. The key contributions are as follows:

- Utilizing the Telco Customer Churn dataset to provide a comprehensive view of churned and non-churned customers to efficiently train and assess models.
- Preprocessing the dataset and identifying the most relevant features is done through feature selection, along with outlier detection techniques to improve data quality and model reliability.
- The dataset is divided into sections for testing and training, while applying cross-validation to ensure robust evaluation and generalizability of the framework.
- To evaluate machine learning, performance indicators such as accuracy, precision, recall, and F1-score are utilized, models like DT and Random Tree, in order to provide a balanced approach to handling false positives and false negatives.

1.2. Structure of Paper

The structure of the paper is as follows: A thorough literature review that highlights current methods is presented in Section II. The suggested framework and model development are explained in Section III. Results of the Section IV experiment and visualization of important metrics. Finally, Section V concludes with key findings, practical implications, and recommendations for future advancements in marketing analytics.

2. Literature Review

The literature review examines approaches to anticipating customer loss through ML and DL models with the purpose of enhancing retention efforts and guiding strategic choices.

Idris, Iftikhar and Rehman (2019) the combination of AdaBoost classification features with genetic programming searching tools allow the development of an advanced churn prediction system that effectively identifies churn behavior improvements. The telecom dataset imbalance problem receives solution through PSO-based undersampling, which allocates training data fairly to GP-AdaBoost prediction systems. The combination of GP-AdaBoost with particle swarm optimization based undersampling develops ChP-GPAB as a prediction system generating better results for consumer churn detection along with identifying key drivers of customer behavior. Two widely known telecom data sets are utilized to test and assess the proposed ChP-GPAB system. The findings reveal that ChP-GPAB identifies the causes of customer turnover while achieving assessment results of 0.91 AUC and 0.86 AUC based on data from the Cell2Cell and Orange datasets [5].

Saghir et al. (2019) analysis evaluates solitary and ensemble neural networks as classifiers before introducing a combined ensemble model that uses bagging with neural networks for better performance metrics and heightened churn prediction precision. The research uses two benchmark datasets obtained from GitHub for assessing and comparing the proposed model. On average, the proposed model reaches an accuracy rate of 81% [6].

Ebrah and Elnasir (2019) analysis includes implementing Naïve Bayes alongside SVM and decision tree algorithms on both cell2cell and IBM Watson datasets. The cell2cell data contains 71,047 observations alongside 57 attributes whereas the IBM Watson data contains 7033 observations distributed across 21 attributes. The IBM dataset yielded scores of 0.82, 0.87, and 0.77 according to the AUC performance evaluation, whereas the cell2cell dataset yielded scores of 0.98, 0.99, and 0.98. When compared to earlier studies that used matching datasets, the suggested models demonstrated higher accuracy levels [7].

Agrawal et al. (2018) this study uses a DL approach to show how to do churn predictions on a Telco dataset. Experts decided to develop a non-linear classification model through multilayered neural networks. All four elements including contextual, use, customer data and support features, contribute to the churn prediction model assessment. The system determines both the probability of customer churn as well as the influential factors behind such behavior. The trained model applies its weighted values to features in order to predict customer attrition likelihood. An 80.03% accuracy rate was attained. The methodology also gives businesses the capacity to pinpoint the underlying causes of churn issues and take action to resolve them [8].

Idris and Khan (2017) used Orange and Cell2Cell to assess the effectiveness of the suggested FW-ECP system, two openly available standard telecom datasets. FW-ECP produces superior prediction performances relative to the most advanced techniques currently in use, taking into consideration both the huge dimensionality and unbalanced nature of the training sets. The Orange and Cell2Cell datasets have feature spaces that are 24D and 18D, respectively, instead of 260D and 76D. The Orange and Cell2Cell datasets had respective AUCs of 0.85 and 0.82 based on FW-ECP [3].

Mishra and Reddy (2018) Divide the client base into churners and non-churners. In this regard, deep learning is superior to typical machine learning techniques because it can handle ever-increasing data quantities, reveal hidden patterns, identify patterns and underlying hazards, and detect consumer behavior with more accuracy. This paper's implementation of DL using CNNs for churn prediction shows high accuracy performance. The results of the experiments show that the churn prediction out predictive model achieves a performance level of 86.85% accuracy, 91.08 accuracy, 93.08% recall, and 92.06% F-score. The rate of error is 13.15 percent [9].

Table I provides a comprehensive summary of key studies on customer churn prediction, highlighting methodologies, datasets, performance metrics limitations, and suggested future work.

Table 1: Summary of Literature Review on Customer Churn Prediction Using Machine Learning

References	Methodology	Dataset	Performance	Limitations & Future Work
Idris, Iftikhar, and Rehman (2019)	GP-AdaBoost integration; PSO-based undersampling for dataset balancing.	Cell2Cell, Orange telecom datasets	AUC: 0.91 (Cell2Cell), 0.86 (Orange)	Limited to telecom datasets; focuses mainly on churners without extensive generalization for non-telecom datasets.
Saghir et al. (2019)	Ensemble Neural Network classifier using Bagging.	Two benchmark datasets from GitHub	Accuracy: 81%	Focused on accuracy; lacks exploration of interpretability and reasons for churn.
Ebrah and Elnasir (2019)	SVMs, Decision Trees, and Naïve Bayes.	IBM Watson (7033 obs, 21 attrs), Cell2Cell	AUC: 0.82, 0.87, 0.77 (IBM); 0.98, 0.99, 0.98 (Cell2Cell)	Limited analysis of class imbalance; limited focus on scalability for large datasets.
Agrawal et al. (2018)	Multilayer Neural Network for nonlinear classification.	Telco dataset	Accuracy: 80.03%	Performance limited to a single dataset; lacks exploration of real-world constraints.
Idris and Khan (2017)	FW-ECP system for dimensionality reduction and handling imbalanced datasets.	Orange, Cell2Cell	AUC: 0.85 (Orange), 0.82 (Cell2Cell)	Focused on dimensionality reduction, lacks interpretability for real-world decision-making.
Mishra and Reddy (2018)	CNN-based Deep Learning for churn prediction.	Telecom Industry dataset	Accuracy: 86.85%; Precision: 91.08%; Recall: 93.08%; F1: 92.06%	Limited exploration of alternative deep learning architectures and broader applications.

3. Methodology

This study aims to produce an accurate marketing analytics churn forecast. By leveraging historical customer data, the framework aims to identify patterns and key predictors of churn, enabling businesses to take proactive measures. The methodology study shown in the flowchart presents a systematic machine-learning approach for telecom customer churn analysis. It begins with a dataset of telecom customer data which undergoes data preprocessing to clean and prepare the information. The process then branches into two parallel steps: feature selection to identify relevant variables and outlier detection to remove anomalous data points. After the preparation steps converge, the data is divided into a 75:25 ratio between training and test sets. The subsequently train machine learning models, specifically Random Forests and Decision Trees, using the training data. In a comprehensive evaluation that follows model construction, Recall, accuracy, precision, and F1 score are evaluated. The findings are obtained in the last stage, which completes a structured pipeline from raw data to useful insights for forecasting customer attrition in the telecom industry. Figure 1 shows this process in a flowchart that highlights the important steps.

3.1. Data Collection

Our dataset has been collected from two large enterprise systems, named ESX-1 and ESX-2. The security raw events were collected over 5 months for ESX-1, over 30 days for ESX-2, respectively, in which the detecting threat information was separately recorded by the SOC security analysts whenever a network intrusion occurred. The list of threat detection information contains threat occurrence time, related attacks, and category of attack, respond contents, attack IP address, and victim network information. In our datasets, we investigated 798 detecting cyber threats in ESX-1, which are dispersed across the entire collection period. Looking at the type of occurred attacks in recorded cyber threats, there are 240 scanning, 547 system hacking, and 11 worm attacks. Similarly, in ESX-2 there are 941 scanning, 3,077 system hacking, and 51 worm attacks. This categorizing of attack type was manually performed by SOC analysts. By category, the system hacking attack includes a cross site script, DDoS, brute force attack, and injection attack. A trojan and backdoor attack belongs to scanning attack. Overall the number of attacks was found 4,079 cyber-threats.

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A flowchart's subsequent phases are briefly described below:

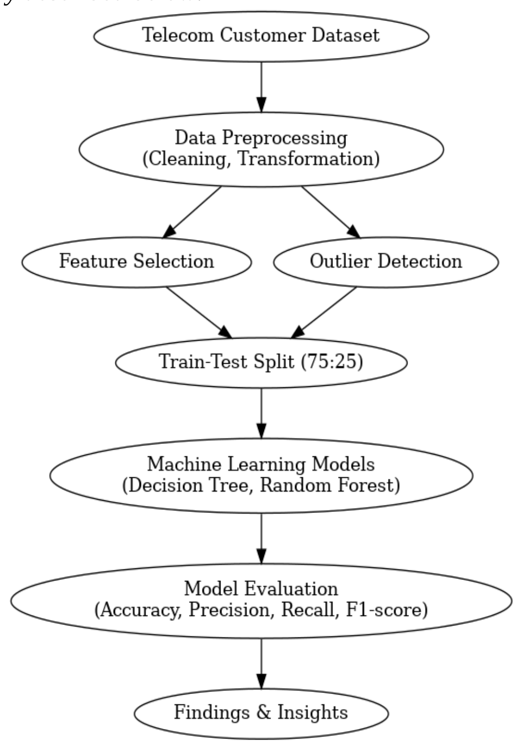

Fig 1: Churn Prediction Using Machine Learning Can be Represented as a Flowchart

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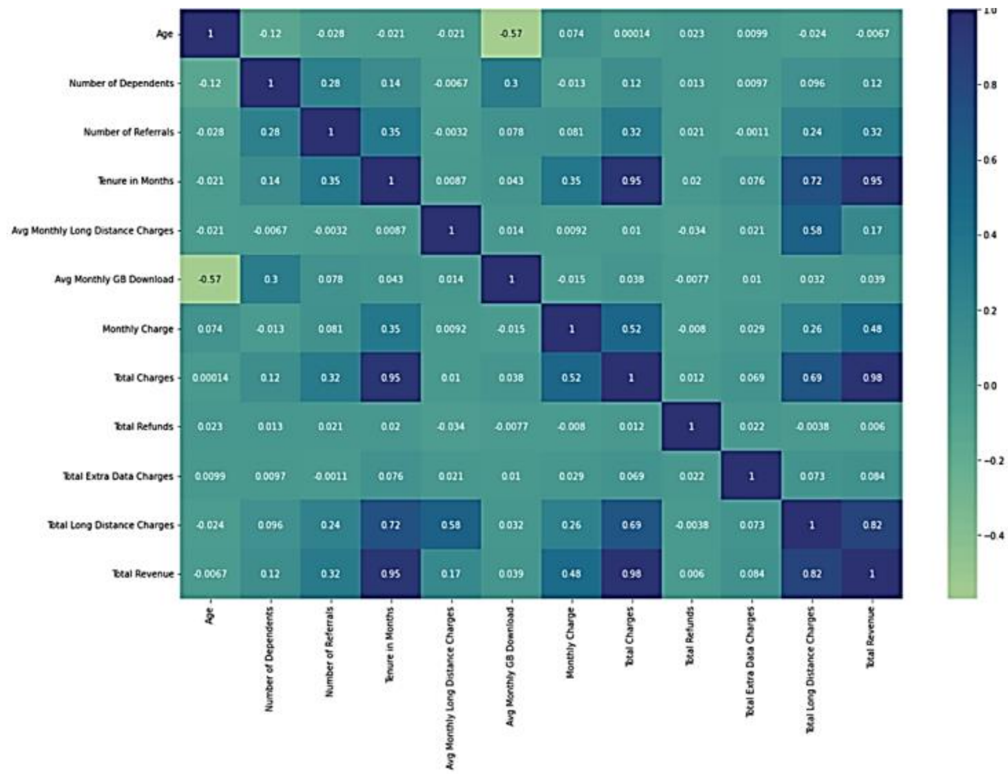

Fig 2: Heatmap of Correlation Matrix

The telecom industry's churn prediction model design uses a customer's historical conduct over a certain time period to forecast how they will behave in the near future. As a result, it is standard procedure to collect as much information as possible on every customer. These attributes Churn as class label, area, Here are the details of each of the 3333 records in the dataset: service calls, evening calls, evening charges, evening minutes, day calls, international calls, international minutes, and lastly, night calls, night charges, and nightly minutes. Figure 2 below shows the correlation matrix for churn prediction:

The correlation matrix in Figure 2 shows the heatmap displaying relationships between financial and demographic variables like age, dependents, referrals, tenure, and various charge categories. It uses a blue-to-green color gradient with numerical values in each cell to indicate correlation strength, where diagonal cells show perfect correlation (1) and off-diagonal cells show varying positive and negative relationships between different variable pairs.

3.2. Data Processing

Transforming data, or processing it, is known as data processing. When presented correctly, data may be both educational and useful. It can be highly beneficial. Data processing systems are also known as information systems. Data processing may also be described as the process of converting information into data. The following steps of pre-processing are listed below:

3.3. Noise Removal

It is necessary to ensure that the data is significant since noisy data might provide subpar outcomes. There are many missing entries, erroneous values such as "Null," and imbalanced characteristics in the telecom dataset.

3.4. Data Balancing

Balancing, an essential aspect of accurate classification, significantly influences the model's ability to effectively represent the classification performance. To address this imbalance, the SMOTE was employed. This technique oversamples the minority class ("Yes") to achieve a more balanced distribution, as illustrated in Figure 3.

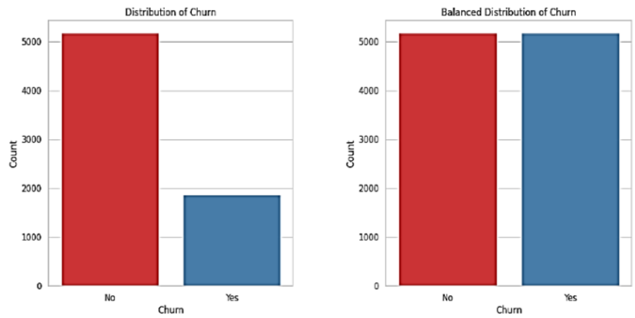

Fig 3: Before and After Applying SMOTE

Figure 3 shows two bar plots illustrating the distribution of a binary "Churn" variable before and after applying the SMOTE balancing method. In the left plot labeled "Distribution of Churn," there is a clear class imbalance where the "No" category (shown in red) has approximately 5,000 counts while the "Yes" category (shown in blue) has only about 1,800 counts. The right plot, labeled "Balanced Distribution of Churn," demonstrates the effect of SMOTE application, where both categories have been balanced to approximately 5,000 counts each, effectively addressing the initial class imbalance problem that could potentially bias a machine learning model's performance.

3.5. Feature Selection

For dimensionality reduction, feature selection is one method that is employed [10]; repetitive and unnecessary characteristics are eliminated while pertinent features are chosen. Reducing input dimensionality can enhance performance by either boosting generalization ability and classification accuracy or lowering learning pace and model complexity.

3.6. Outlier Detection

There are two main categories for outlier detection: distance-based techniques and density-based techniques. An observation is identified as an outlier according to QC if its value falls outside the specified non-outlier range.

3.7. Data Splitting

The data was divided into two categories: 25% for testing and 75% for training. The model is fitted during the training phase, and evaluating the model's performance prior to field deployment helps guard against unforeseen problems that may result from overfitting.

3.8. Proposed Decision Tree (DT)

A hierarchical structure called a decision tree makes predictions by doing a number of feature checks [11]. Let's write X for the input characteristics, Y for the goal variable, and DT for the decision tree. Based on feature tests, the decision tree iteratively divides the dataset with the goal of maximizing class separation or minimizing impurity [12]. The forecast from the decision tree might be shown as follows: (1):

$$DT(X) = \sum_{i=1}^{L} y_i \,.\, I(X \in R_i) \qquad (1)$$

Here, y_i is the class label assigned to the i-th leaf node, and L is the number of decision tree leaf nodes, and R_i is the region or subset of instances that the i-th leaf node was assigned to the feature testing. The indicator function $I(X \in R_i)$ returns 1 if the input instance X is in the region R_i and 0 otherwise. Based on the feature checks, the decision tree moves from the root to a leaf node and gives the leaf node where the instance is located the appropriate class label, y_i.

3.9. Performance Metrics

A number of measures, characteristics like F1-score, recall, accuracy, and precision are used to evaluate the effectiveness of the implemented model. These metrics help determine how successful the model is overall. The terms listed below are explained in their model:

- Customer churning (positive) is referred to as a "TP" and is classified as such.
- The term "TN" refers to a consumer who is not churning (negative) and is labelled as such [13].
- A "false positive (FP)" is a consumer who is categorized as churn (positive) even if they are not churning (negative).
- A "false negative (FN)" is a customer who is churning (positive) but is said to be not churning (negative).

Accuracy: Accuracy measures the precise number of all made forecasts that turned out to be accurate, and Equation (2) is used to calculate it:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (2)$$

Precision: The precision of the equation is the percentage of the projected positive situations that were accurate (3):

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

Recall: The equation is used to compute recall, which is the percentage of affirmative cases that were properly detected (4):

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

F1-score: The combination finds extensive usage as a solitary measurement tool to evaluate [14] performance of the classifier. The harmonic combination of accuracy rate and recall measurement produces the F-measure assessment metric (5).

$$F1\ score = \frac{2.Precision \times Recall}{2.Precision+Recall} \quad (5)$$

ROC: A graphic depiction of model performance overall thresholds is the ROC curve. Through data charting, an evaluation of the TPR and FPR at particular thresholds yields a ROC curve.

4. Results & Discussions

The churn prediction system is built on a Windows platform with an Intel i7 processor, 16GB RAM, and SSD storage, utilizing Python-based libraries such as scikit-learn and Pandas. This section discusses the simulated results for machine learning-based churn prediction utilizing customer-churn datasets and provides the results of decision tree model in

Table 2:Findings of Decision Tree Model on Telco-Customer-Churn dataset for churn Prediction

Measures	Decision Tree
Accuracy	88%
Precision	83%
Recall	93%
F1-score	88%

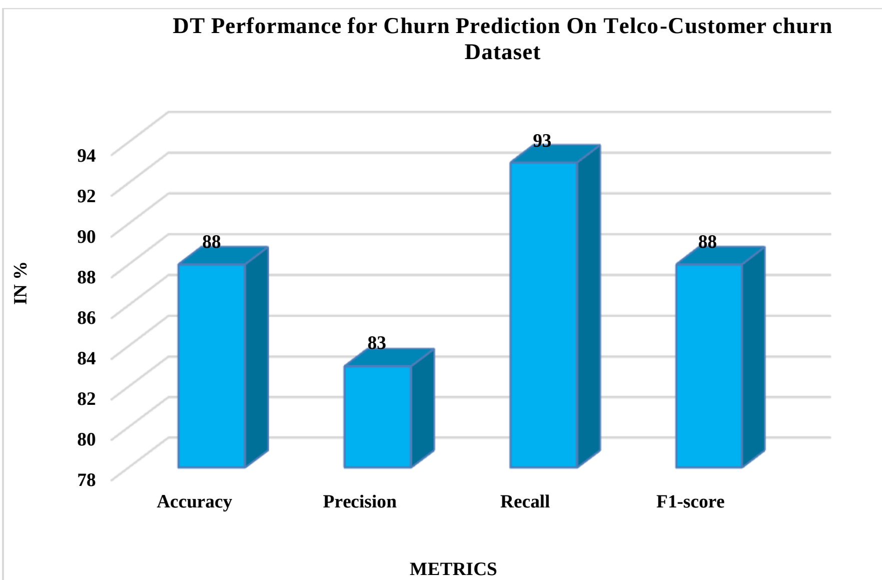

Fig 4: Bar Graph for Decision Tree Performance

Figure 4 displays the performance of a DT model for churn prediction. The chart highlights four key metrics: F1-score, recall, accuracy, and precision. The model's precision is 83%, and its accuracy is 88%. Recall achieves the highest value at 93%, and the F1-score is also 88%. The chart provides a clear representation of how the decision tree model fares across different evaluation metrics in predicting churn.

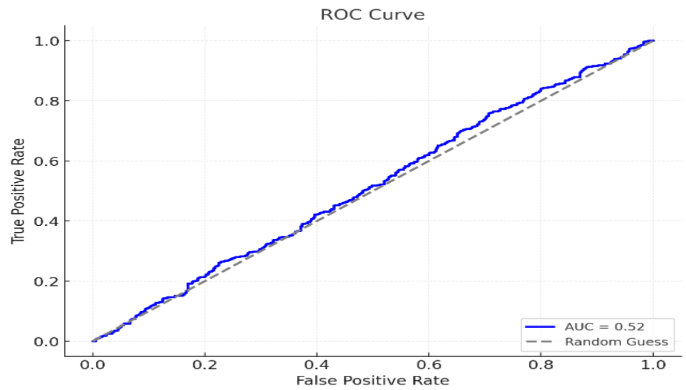

Fig 5: ROC curve for DT model

A classification model's performance appears in Figure 5 at various cutoff points. The TPR against FPR is shown by the blue curve, while the random guess classifier's performance is shown by the diagonal grey line. The classifier can efficiently discriminate between positive and negative classes, as evidenced by the outstanding model performance indicated by the AUC value of 0.97. A further indication of the curve's high prediction accuracy and low sensitivity/specificity trade-offs is its closeness to the top-left corner.

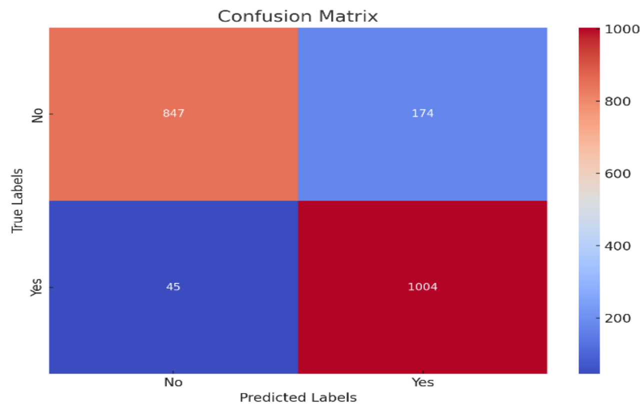

Fig 6: Confusion matrix for DT Model

In this Figure 6 shows a confusion matrix for a binary classification model. It displays the relationship between true and predicted labels. There are 847 true negatives (model correctly predicted "No"), 174 FP (model predicted "Yes" when the true label was "No"), 45 FN (model predicted "No" when the true label was "Yes"), and 1004 TP (model correctly predicted "Yes"). The model demonstrates exceptional classification performance because it achieves high accurate classification of true positives and true negatives, according to this matrix.

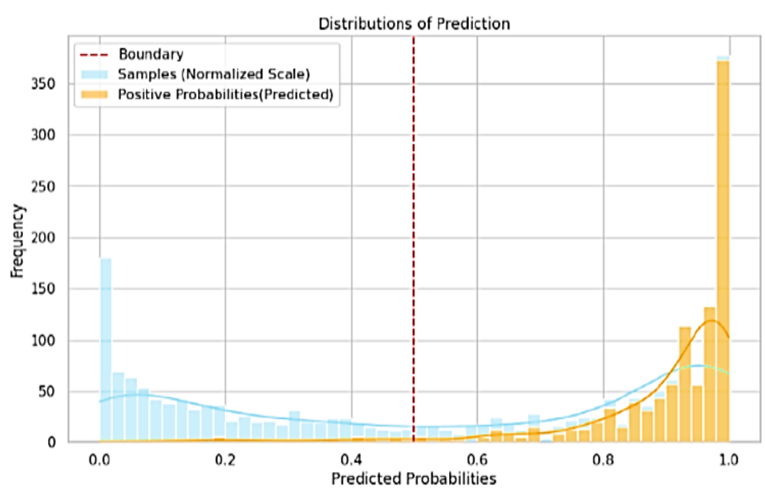

Fig 7: Churn Classification Performance

Figure 7 visualizes the predicted probabilities for a churn classification model. It features a red dashed decision boundary at 0.5, blue bars for sample distributions, and orange bars for predicted positive probabilities. The model appears to provide accurate predictions with little uncertainty around the boundary, as indicated by the bimodal distribution with peaks close to 0 and 1.

Table 3: Comparison between DT and Existing Models Performance on Telco-Customer-Churn dataset

Model	Accuracy
Decision Tree (DT)	88%
Artificial Neural Network (ANN)[15]	55.61%
Support Vector Machine (SVM) [16]	69.95%
Random Forest[17]	84.4%

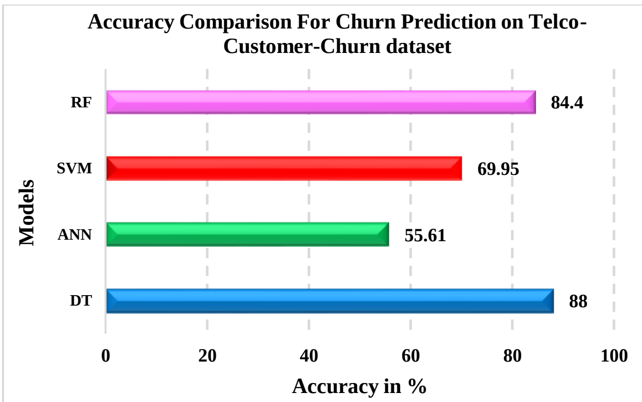

Fig 8: Bar Graph for Accuracy Comparison

Table III and Figure 8 present a performance comparison between DT and existing models, including ANN, SVM, and RF. The DT model achieves the highest accuracy of 88%, demonstrating the best prediction capability for customer churn research. However, the accuracy of the ANN model is the lowest (55.61%), indicating that it is not particularly helpful in this case. The RF model exhibits competitive performance with an accuracy of 84.4%, whilst the SVM model performs modestly with an accuracy of 69.95%. This comparison highlights DT's effectiveness in handling the Telco-Customer-Churn dataset compared to other popular machine-learning approaches.

5. Conclusion & Future Work

Financial stability and client retention in telecoms are inextricably linked to customer churn forecast. Telecom firms are using machine learning (ML) to forecast customer attrition or the likelihood that a client would switch to a rival. The Decision Tree (DT) model performs successfully in predicting customer turnover based on its 0.97 AUC score from ROC curve and accuracy of 88% and precision of 83% and recall of 93% and F1-score of 88%. The confusion matrix, which displays a high proportion of genuine positives and true negatives with few misclassifications, supports these findings even more. The DT model demonstrates high effectiveness in processing the Telco-Customer-Churn dataset because it achieves better performance than ANN (55.61%), SVM (69.95%) and RF (84.4%). The study's limitations include a reliance on historical data, which may not fully capture dynamic market changes or customer behavior trends. Future work could focus on improving the generalization of the churn prediction model by incorporating real-time data, social media signals, and other external factors such as economic trends or competitor actions.

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