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Implementation of Machine Learning Models for Predicting Internet Service Provider Customer Churn

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ABSTRACT

The telecommunications industry faces an extremely high level of competition, where the phenomenon of customer churn presents a significant challenge due to its impact on revenue decline and increased costs associated with acquiring new customers. This study aims to develop a churn prediction model using the Decision Tree algorithm and implement it in a web-based application to support customer retention strategies. The CRISP-DM methodology is employed, covering Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Experimental results show that the Decision Tree algorithm demonstrates strong performance in identifying non-churn customers, with a precision of 0.82, a recall of 0.91, and an F1-score of 0.86. However, its performance on the churn class remains limited, with a precision of 0.63, a recall of 0.44, and an F1-score of 0.52, highlighting the importance of addressing imbalanced data distribution to preserve existing data. The model underwent Learning Curve and Validation Curve analysis. The Learning Curve indicates a relatively stable model with a small gap, suggesting good generalization. The Validation Curve reveals that optimal performance is achieved at a moderate tree depth, avoiding the risk of overfitting at greater depths. Nevertheless, the main advantage of the Decision Tree is its interpretability, which highlights significant factors such as contract type, subscription duration, and additional services. The integration of the model into a web-based application also provides practical benefits through rapid churn risk monitoring, supporting the company's strategic decision-making.

Keywords: CRISP-DM; Decision Tree; ISP; Machine Learning; Prediction

INTRODUCTION

The telecommunications industry is one of the most dynamic, rapidly growing, and highly competitive sectors in today's digital era. The rapid advancement of information and communication technologies, along with rising customer expectations regarding service quality, compels telecom service providers to continuously innovate and maintain customer loyalty. In this context, customers have significant flexibility to switch from one provider to another due to various factors such as pricing, service quality, contract flexibility, or personal preferences.

The phenomenon of customers discontinuing their subscriptions to a service is commonly referred to as customer churn. Churn poses a major challenge for the telecommunications industry as it directly impacts revenue stability and increases operational costs, particularly in acquiring new customers (Rane et al., 2023). Studies indicate that the cost of acquiring new customers can be up to five times higher than retaining existing ones. Therefore, retaining current customers through effective retention strategies has become a critical business priority.

One viable strategy to reduce churn rates is the development of a predictive system that can identify customers likely to churn at an early stage. By identifying high-risk customers, companies can take timely and targeted actions—such as offering special deals, enhancing services, or launching personalized campaigns—to improve customer satisfaction and loyalty, thereby reducing the likelihood of actual churn.

In recent years, machine learning approaches have been increasingly adopted for churn prediction systems due to their ability to recognize complex patterns in historical customer data. Among the many available algorithms, the Decision Tree has become one of the most popular methods due to its high interpretability, its ability to handle both categorical and numerical data, and its efficiency in structuring decision logic that is easily understood by non-technical business users.

Based on this background, this study aims to develop a churn prediction model using the Decision Tree algorithm and implement it in a web-based application. The study focuses on customers of an Internet Service Provider (ISP) in Madiun City as a case study, ensuring that the resulting model is not only technically valid but also practically relevant

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in supporting customer retention strategies at the local level.

LITERATURE REVIEW

In the context of churn prediction, machine learning methods are widely adopted. They can recognize complex patterns in historical customer data. One of the most commonly used algorithms is the Decision Tree. This method is advantageous due to its interpretable structure. It supports both categorical and numerical data. Its clear, fast depiction of decision-making logic is noted by (Patil, 2024). Decision Trees offer stable and competitive predictive performance. The algorithm can identify customers at risk of churning with relatively high accuracy. It has inherent strengths and limitations. (Chang et al., 2024) reported an Area Under Curve (AUC) of 0.80 on a telecommunications customer dataset. (Zhou et al., 2023) showed that the recall of the Decision Tree reached nearly 90% for identifying actual churners.

(Bhatnagar & Srivastava, 2025) applied a Decision Tree model on customer data and achieved approximately 90% accuracy. In their systematic review, (Tebu & Izang, 2025) highlighted that Decision Tree remains among the most frequently used algorithms for churn analysis over the past decade. (Maan & Maan, 2023) noted that the interpretability of this model, alongside Random Forest and XGBoost, provides significant added value for understanding the problem being addressed.

Other studies have also demonstrated the consistent performance of this method. (Kirdponpattara et al., 2024; Sullivan et al., 2024; Ultsch et al., 2024) suggested that the Decision Tree can serve as a baseline model before employing more complex algorithms. Studies by (Hendri et al., 2024; Ibrahim Adedeji Adeniran et al., 2024; Sam et al., 2024) supported the use of Decision Trees, albeit with varying accuracy levels. (Hasan et al., 2024) conducted a comparative analysis of several algorithms, including Decision Tree, and reaffirmed its reliability and interpretability across different churn prediction scenarios.

Although Decision Tree may not always be the top-performing algorithm when compared to more advanced models, its simplicity, explainability, and transparency remain key advantages. Unlike many previous studies, the dataset in this research is intentionally kept imbalanced to investigate the implications of using the full, real-world dataset without applying balancing techniques. As such, accuracy is not used as the main evaluation metric; instead, the study employs precision, recall, and F1-score to assess model performance.

Recent research trends also indicate the potential for real-world deployment of predictive models through web-based systems. This deployment and maintenance phase is commonly referred to as MLOps (Machine Learning Operations) (Shankar et al., 2024). One of the most practical and accessible ways to achieve this is through the use of the Flask framework, which has been proven effective in similar use cases (Gupta et al., 2023; Kotha et al., 2023; Orovwode et al., 2024), especially for churn prediction tasks (Ye, 2025). These studies highlight the benefits of Flask in terms of simplicity, speed, and API integration capabilities, making it a suitable choice for operationalizing machine learning models.

METHOD

This study uses the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach, which comprises six primary phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The CRISP-DM approach has also been applied to a similar case but with a different target object (Oetama, 2023). Each phase, as illustrated in Fig. 1, has been adapted to meet the specific needs of this study. It was selected due to its structured, industry-proven methodology, which ensures systematic progression through all critical phases while allowing flexibility for project-specific adaptations. Its widespread adoption further supports reproducibility, transparency, and comprehensive handling of both technical and business objectives in churn prediction.

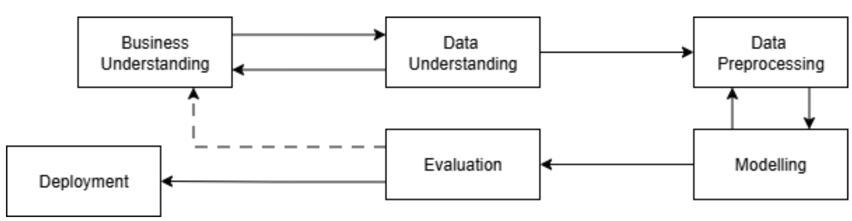

Fig. 1 Metode Cross Industry Standard Process for Data Mining (CRISP-DM)

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In the Business Understanding phase, the primary objective is to comprehend the business problem at hand, which is customer churn in the telecommunications industry. In this context, the goal of the study is to develop an accurate churn prediction model that can be integrated into a web-based platform to support the company's decision-making.

During the Data Understanding phase, an exploration of the telecommunications customer dataset is conducted. The dataset includes various features such as gender, senior citizen status, subscription length, service type, monthly charges, total charges, and churn status. The initial analysis aims to understand the data characteristics and detect any potential issues within the dataset.

The Data Preprocessing phase involves selecting relevant data, cleaning the data, normalizing text formats, and transforming categorical variables to match the input format required by the machine learning model. In this study, data selection is performed by choosing features relevant to the target variable (Churn) based on a literature review and preliminary correlation analysis. Columns that do not directly contribute to the model, such as customer ID, are removed from the dataset. Data cleansing ensures data quality by addressing missing values—for example, missing numerical values in attributes like TotalCharges are imputed using the median. Duplicate records are also identified and removed to prevent bias during model training. Data distribution for both numerical and categorical variables is examined using visualizations such as histograms, boxplots, and bar charts to identify significant imbalances or outliers. Label encoding is applied to convert categorical features into numerical form suitable for processing by the Decision Tree algorithm.

In the Exploratory Data Analysis (EDA) stage, exploratory analyses are conducted to identify patterns and correlations among variables as well as visual relationships between features and the target variable (Churn). The results of this analysis inform decisions regarding feature selection and model design. The dataset is split into training and testing subsets with an 80:20 ratio. Stratified sampling is employed to ensure that the proportion of the Churn class remains balanced in both subsets. Although Decision Trees are not sensitive to feature scaling, feature scaling is still performed to maintain preprocessing consistency and facilitate comparisons with other models in the future.

The Decision Tree model is constructed using the scikit-learn library, initially with default parameters to establish a baseline model. Subsequently, hyperparameter tuning is conducted to find the optimal combination of parameters such as max_depth, min_samples_split, and criterion using Grid Search and cross-validation techniques.

Model evaluation is conducted by measuring the accuracy, precision, recall, and F1-score metrics. Accuracy quantifies the overall proportion of correct predictions, whereas precision and recall evaluate the trade-off between correctly identifying positive instances and minimizing misclassifications. The F1-score, as the harmonic mean of precision and recall, provides a balanced assessment of performance, while ROC-AUC measures the model's discriminative ability between positive and negative classes. Special emphasis is placed on recall to effectively capture customers who are likely to churn. A confusion matrix is utilized to assess the model's performance in distinguishing between churn and non-churn customers in greater detail. If the evaluation results do not meet expectations, improvements can be made starting from the Business Understanding phase, including preprocessing and tuning adjustments. All these stages are designed to be systematically replicable and enable seamless integration into a Python-based web application system using frameworks such as Flask during the Deployment phase.

RESULT

The results of this study are presented based on the CRISP-DM framework, which includes the phases of Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. In the Business Understanding phase, the main issue addressed is the high churn rate among telecommunications customers. The study aims to develop a churn prediction model using the Decision Tree algorithm that can assist the company in identifying high-risk customers and provide a predictive system in the form of a web-based application.

Table 1
Business Understanding of the Data Obtained

No	Feature	Value	Description
1	customerID		Unique ID for each customer
2	gender	Male, Female	Customer's gender
3	SeniorCitizen	1, 0	Whether the customer is a senior citizen (retiree) or not
4	Partner	Yes, No	Whether the customer has a partner
5	Dependents	Yes, No	Whether the customer has dependents
6	tenure	Yes, No	Duration of subscription in months
7	PhoneService	Yes, No	Whether the customer has phone service

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8	MultipleLines	Yes, No, No phone service	Whether the customer has multiple phone lines
9	InternetService	DSL, Fiber optic, No	Type of internet service used by the customer
10	OnlineSecurity	Yes, No, No internet service	Whether the customer has online security service
11	OnlineBackup	Yes, No, No internet service	Whether the customer has online backup service
12	DeviceProtection	Yes, No, No internet service	Whether the customer has device protection service
13	TechSupport	Yes, No, No internet service	Whether the customer has technical support service
14	StreamingTV	Yes, No, No internet service	Whether the customer has TV streaming service
15	StreamingMovies	Yes, No, No internet service	Whether the customer has movie streaming service
16	Contract	Month-to-month, One year, Two year	Customer's contract type
17	PaperlessBilling	Yes, No	Whether the customer uses paperless billing
18	PaymentMethod	Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic)	Payment method used by the customer
19	MonthlyCharges		Monthly fee paid by the customer
20	TotalCharges		Total amount paid by the customer during the subscription
21	Churn	Yes, No	Whether the customer unsubscribed

The Data Understanding phase involved analyzing the telecommunications customer dataset. The target variable is Churn, consisting of two classes: "Yes" for customers who discontinued their subscriptions and "No" for those who remained subscribed. Initial analysis revealed an imbalanced class distribution, with non-churn customers dominating over churn customers, as illustrated in Fig. 2.

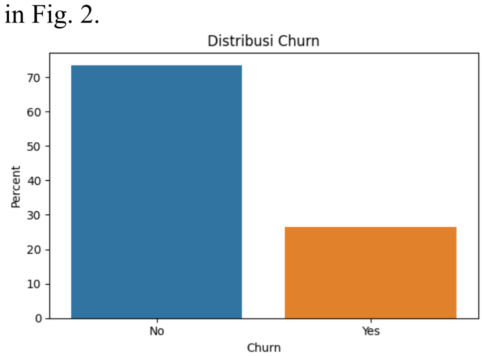

Fig. 2 The observed churn data distribution

In the Data Preparation phase, feature selection removed irrelevant attributes such as customerID, while missing values in TotalCharges were handled with median imputation. Data distribution was examined visually using histograms, boxplots, and bar charts (see Fig. 2), and the dataset was confirmed to contain no duplicates. Categorical variables were converted to numerical form through label encoding, supporting further analysis. This analysis revealed that tenure and contract type significantly contribute to customer churn status, as shown in Table 2.

Table 2
Pearson Correlation of the Feature

No	Feature	Correlation	No	Feature	Correlation
1	Churn	1,000,000	11	TechSupport	-0.282492
2	gender	-0.008612	12	OnlineSecurity	-0.289309
3	StreamingTV	-0.036581	13	tenure	-0.352229
4	StreamingMovies	-0.038492	14	Contract	-0.396713
5	InternetService	-0.047291	15	PhoneService	0.011942
6	Partner	-0.150448	16	MultipleLines	0.038037
7	Dependents	-0.164221	17	PaymentMethod	0.107062
8	DeviceProtection	-0.178134	18	SeniorCitizen	0.150889
9	OnlineBackup	-0.195525	19	PaperlessBilling	0.191825
10	TotalCharges	-0.199037	20	MonthlyCharges	0.193356

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Correlation analysis showed that the variables used exhibit varying degrees of association with churn. Some variables demonstrated a positive correlation, indicating that higher values of these variables are associated with a greater likelihood of customers churning. For example, MonthlyCharges had a correlation coefficient of 0.193, and PaperlessBilling showed a correlation coefficient of 0.192, suggesting that customers with higher monthly charges and those who use paperless billing are more prone to churn. Conversely, some variables had a negative correlation with churn, meaning they contribute to enhancing customer loyalty. Variables such as contract duration, with a correlation of -0.397, and tenure, with -0.352, affirm that the longer a customer has been subscribed and the longer the chosen contract duration, the lower the likelihood of churn. Additional support services, such as OnlineSecurity and TechSupport, also exhibited fairly significant negative correlations of -0.289 and -0.282, respectively, indicating that customers with these support services tend to be more loyal.

On the other hand, some variables showed almost no influence on churn, such as gender (-0.009), PhoneService (0.012), and MultipleLines (0.038), suggesting their contribution to churn prediction is relatively minor. Overall, although the strength of these correlations ranges from weak to moderate, this pattern provides important insights that cost factors, contract type, subscription length, and the use of additional services are key indicators for understanding customer churn behavior in the telecommunications industry. The dataset was then split into training and testing subsets at an 80:20 ratio using stratified sampling.

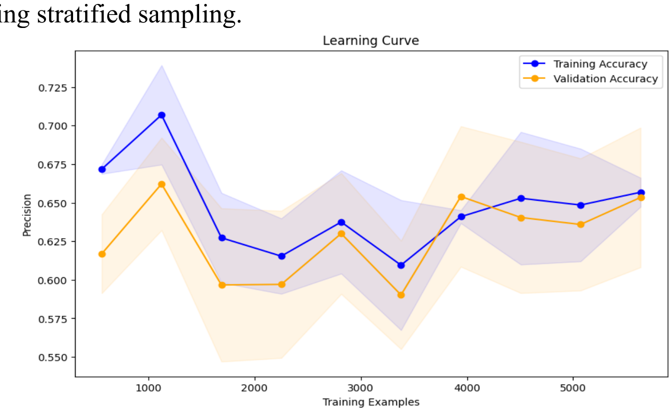

Fig. 3 Hyperparameter Tuning using Learning Curve

In the modeling phase, the Decision Tree algorithm was chosen due to its simple tree structure, ease of interpretation, and ability to handle both categorical and numerical variables simultaneously. An initial model was built using default parameters to establish a baseline performance before optimization. Subsequently, hyperparameter tuning was conducted to improve model performance and prevent overfitting. The parameters tested included max_depth to limit the depth of the tree, min_samples_split to specify the minimum number of samples required to split a node, and criterion (Gini and Entropy) to evaluate the quality of the splits. The tuning process employed Grid Search with cross-validation, allowing the selection of the best parameters based on the average performance on the training data.

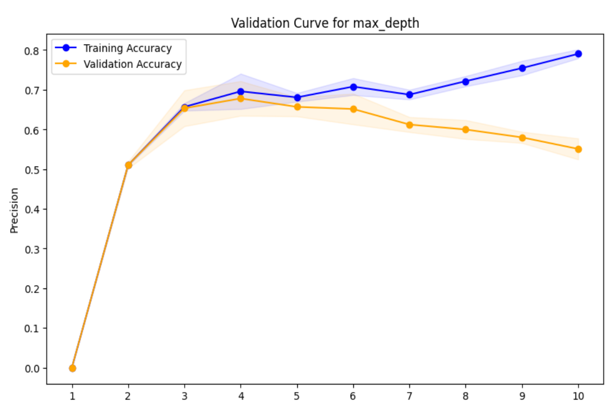

Fig. 4 Hyperparameter Tuning using Validation Curve

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The precision results for the training and testing data, relative to the dataset size, can be observed from the blue and orange lines in Figs. 3 and 4, respectively. It can be concluded that the closer the precision values between the training and testing data, the better the model's fit to the data. The recommended max_depth value is the one where there is a strong overlap between the training and testing data precision. In this case, max_depth values of 3 or 4 are considered. The preferred choice is the one with higher accuracy and a smaller standard deviation within the overlapping range.

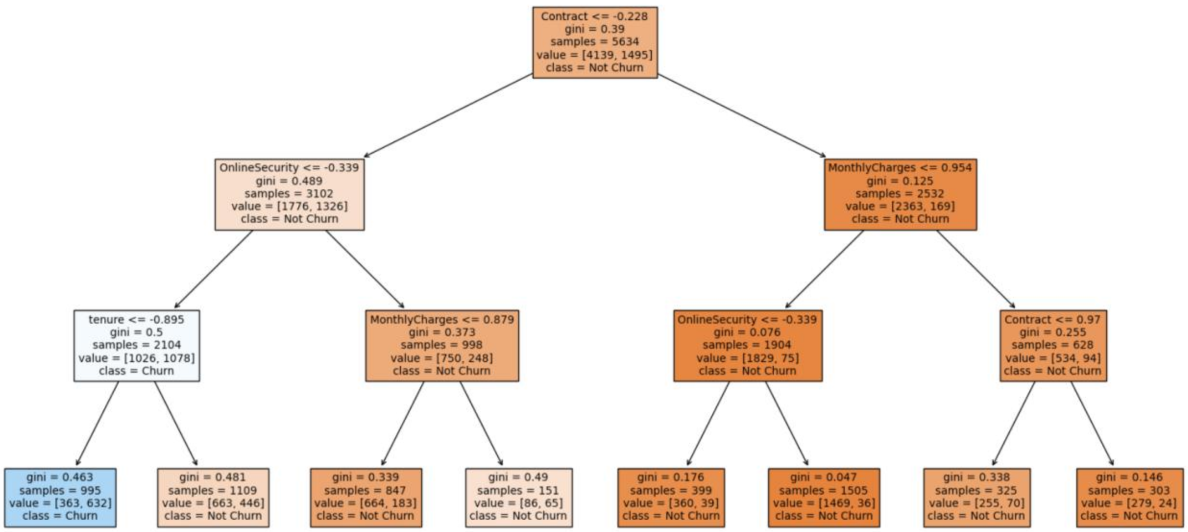

Fig. 5 Decision Tree Model Visualization

The modeling results are visualized in Fig. 5. In the decision tree, elements such as Feature Name, Gini, Samples, Value, and Class play a crucial role in illustrating the characteristics of each node. The Feature Name indicates the feature used to make a decision at a given node. If the feature's value is less than or equal to a certain threshold, the sample proceeds to the left node; otherwise, it moves to the right node. Gini measures the impurity of the node, where a lower Gini value indicates higher purity (i.e., the node is dominated by a single class), while values approaching 0.5 suggest a more balanced distribution between the classes (e.g., Churn and Not Churn). Samples represent the total number of samples that reach the node, providing an overview of the population size at that decision point. Value details the number of samples belonging to each class (Churn and Not Churn) at the node. Finally, Class refers to the most frequently occurring class at that node, which becomes the model's prediction for any sample reaching that point. All of these elements work together to inform the decision-making process at each node within the decision tree.

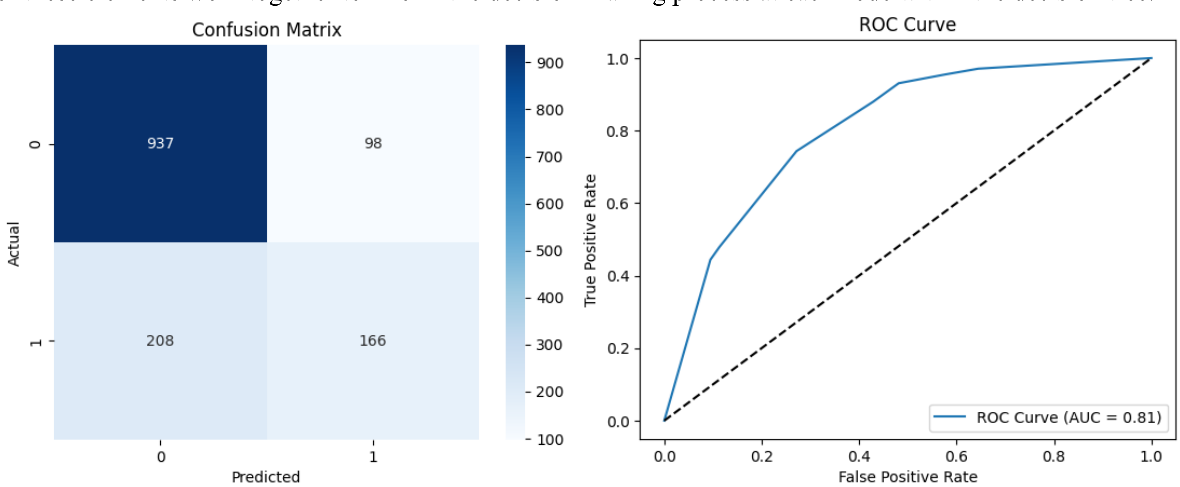

Fig. 6 Confusion Matrix & ROC AUC Curve

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Model performance was evaluated using **accuracy**, **precision**, **recall**, **F1-score**, and **ROC-AUC** metrics. These evaluation metrics were selected because they provide complementary perspectives on model performance, particularly under class-imbalanced conditions common in churn prediction. Accuracy provides a general overview, while precision and recall emphasize the correctness and sensitivity of churn prediction. Precision and recall are especially important in this context, as misclassifying actual churners (false negatives) can lead to potential revenue loss. These metrics were computed based on the confusion matrix shown in Fig. 6. Due to the imbalanced nature of the churn data, accuracy was de-emphasized in favor of precision, recall, and F1-score, which offer a more informative view of model performance.

The model achieved a precision of 0.82 and a recall of 0.91 for customers who did not churn, resulting in an F1-score of 0.86, indicating strong performance in identifying non-churn customers. Conversely, performance on the churn class was relatively lower, with a precision of 0.63, a recall of 0.44, and an F1-score of 0.52, suggesting that the model was only able to correctly identify a limited portion of customers who actually discontinued their subscriptions. This imbalance highlights an opportunity for improvement through resampling or threshold optimization to enhance churn detection. The curve in Fig. 6 shows that the ROC curve lies above the diagonal line and that the AUC value is close to 1, confirming that the model performs effectively in distinguishing between positive and negative classes.

After the model was successfully developed, it was subsequently implemented into a simple web-based form. The primary objective of this implementation is to enable non-technical users to perform predictions. The resulting interface is shown in Fig. 7. The form consists of 20 input fields corresponding to the features used in the previously developed model. Users are required to fill in or select values for each of these fields. Upon clicking the "Predict" button, the prediction result is displayed below the button. There are two possible outcomes: "Customer is likely to stay" or "Customer is likely to churn."

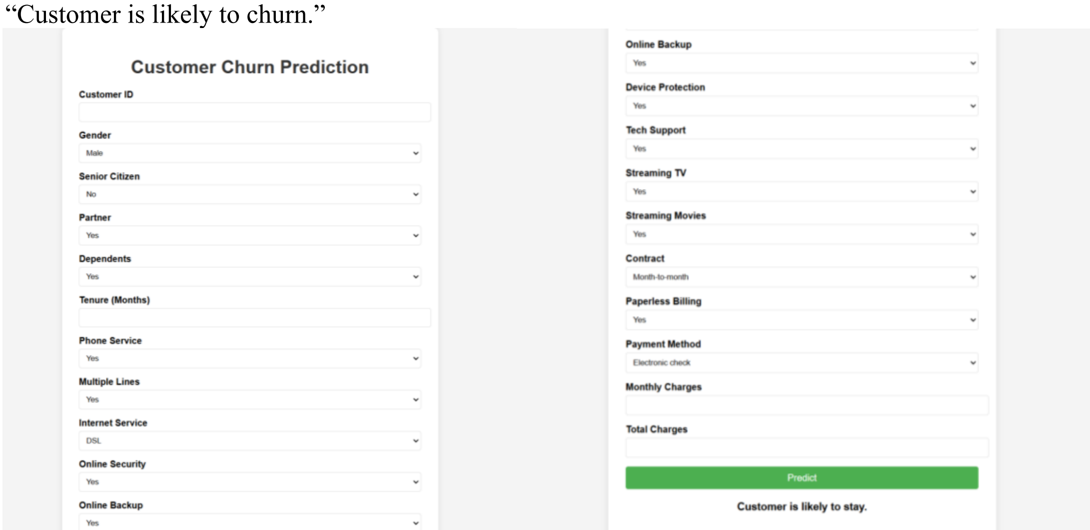

Fig. 7 Web Based Model Implementation

DISCUSSIONS

The results of this study demonstrate that the Decision Tree algorithm is capable of delivering satisfactory performance in predicting customer churn in the telecommunications industry, particularly in identifying customers who are unlikely to churn. This is evidenced by the high precision and recall values for the non-churn class, at 0.82 and 0.91, respectively, resulting in an F1-score of 0.86. This performance aligns with previous studies that highlight the advantages of Decision Trees in classifying data with relatively simple structures and offering high interpretability (Bhatnagar & Srivastava, 2025; Maan & Maan, 2023; Patil, 2024).

However, the model's performance on the churn class still shows limitations, with a recall of only 0.44 and an F1-score of 0.52. This issue can be attributed to data imbalance, where the number of churned customers is significantly lower than that of non-churned customers. Such an imbalance causes the model to become biased toward the majority class, thereby reducing its ability to effectively identify actual churners. This highlights the importance of addressing data imbalance to avoid similar issues in future models.

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The interpretability of Decision Trees provides additional value. The resulting tree structure effectively highlights the most influential factors contributing to churn, including contract type, tenure, and additional services such as online security and technical support. This information has significant practical implications for telecommunications companies, as it can serve as a basis for designing more targeted customer retention strategies. For instance, customers with short-term contracts and high monthly charges could be prioritized for loyalty programs or special offers.

From an implementation perspective, integrating the model into a web-based application presents opportunities for easier monitoring of churn risk. The user-friendly nature of the web interface also supports a practical approach that is well-suited for business use. This enables marketing and customer service teams to take prompt preventive actions toward customers identified as high-risk.

CONCLUSION

This study developed a customer churn prediction model for the telecommunications industry using the Decision Tree algorithm. The model was implemented into a web-based application. Evaluation results show that the Decision Tree identifies non-churn customers effectively, achieving a precision of 0.82, a recall of 0.91, and an F1-score of 0.86. However, performance on the churn class remains a concern, highlighting the need to address data imbalance in future work. Overall, the model achieves solid results, as shown by the ROC curve and AUC values. Despite its limitations, the model's interpretability offers significant added value, as it reveals key factors influencing churn, including contract type, tenure, and additional services. The integration of the model into a web-based application is also a noteworthy contribution, as it enables companies to monitor churn risk in a more systematic manner and supports more proactive customer retention strategies. In conclusion, this study offers a predictive solution and a practical, real-world approach. It supports data-driven decision-making in the telecommunications industry.

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