Department of Digital Business
Journal of Artificial Intelligence and Digital Business (RIGGS)
Homepage: https://journal.ilmudata.co.id/index.php/RIGGS
Vol. 5 No. 1 (2026) pp: 10128-10138
P-ISSN: 2963-9298, e-ISSN: 2963-914X

Evaluation of Machine Learning Models for Customer Churn Prediction Using LIME-Based Explainable AI

Felix Corputty[1,3], Verindra Hernanda Putra[2,4]
[1]School of Electrical Engineering, Telkom University, Bandung, Indonesia
[2]School of Informatics, Telkom University, Bandung, Indonesia
[3]Center of Excellence for Telecom Infra Project, Telkom University, Bandung, Indonesia
[4]Multimedia, Big Data, and Cybersecurity Laboratory, Telkom University, Bandung, Indonesia
[1]felixcorputtyfc@telkomuniversity.ac.id , **[2]verindrahp@student.telkomuniversity.ac.id**

Abstract

Customer attrition forecasting has become a critical challenge in highly competitive industries such as telecommunications, where retaining existing customers is more cost-effective than acquiring new ones. Although machine learning techniques have been widely applied to identify customers at risk of churn, many models operate as black boxes, limiting their interpretability and usability. To address this issue, this study proposes an integrated framework that combines predictive modeling with Explainable Artificial Intelligence (XAI) using the Local Interpretable Model-Agnostic Explanations (LIME) technique. Unlike conventional approaches that treat explainability as a post-hoc analysis, the proposed framework embeds LIME directly into the modeling pipeline to ensure both accurate and interpretable predictions. The method consists of several stages, including data preprocessing, feature selection, model training, performance evaluation, and model interpretation. Experiments were conducted using the Telco Customer Churn dataset obtained from Kaggle. Three classification algorithms, namely Logistic Regression, Decision Tree, and Random Forest, were evaluated using accuracy, precision, and recall metrics. The results show that Logistic Regression achieved the highest accuracy of 0.8211, followed by Random Forest with 0.7928 and Decision Tree with 0.7289. Furthermore, LIME-based analysis identifies contract type, internet service, monthly charges, tenure, and additional services such as online security and technical support as key factors influencing churn. These results demonstrate that integrating machine learning with XAI enhances model transparency and provides actionable insights for more effective customer retention strategies.

Keywords*: Customer Churn Prediction, Decision Tree, Explainable Artificial Intelligence (XAI), Logistic Regression, Random Forest*

1. Introduction

Customer retention has become an important concern for organizations operating in highly competitive digital markets. Across sectors including telecommunications, banking, and e-commerce, keeping current customers tends to be significantly less expensive than bringing in new ones. Consequently, many organizations have turned to data-driven predictive approaches to proactively detect customers who show signs of leaving their services. Customer churn prediction aims to analyze historical customer data and behavioral patterns in order to detect potential churn risks and enable companies to implement proactive retention strategies. With the rapid growth of digital platforms and subscription-based services, churn prediction has become a key component of data-driven decision-making aimed at improving customer loyalty and long-term business sustainability [1], [2].

A broad range of machine learning methods have been increasingly embraced to enhance the accuracy and effectiveness of churn prediction systems. Various algorithms such as gradient boosting, random forest, decision trees, logistic regression, and neural networks have each demonstrated strong potential in detecting churn-associated patterns derived from customer behavioral data [3], [4]. These algorithms allow organizations to analyze large volumes of customer data, including transaction histories, service usage patterns, and demographic information, to detect complex patterns associated with customer attrition [5]. In addition, ensemble-based machine learning approaches that combine multiple predictive models have been shown to improve predictive accuracy and model robustness in churn prediction tasks [6]. Despite the strong predictive performance of many machine learning models, interpretability remains a significant challenge in predictive analytics systems. Many advanced machine learning algorithms operate as black-box models whose internal decision-making processes are difficult to interpret. Although such models may achieve high predictive accuracy, their lack of transparency can limit their practical usability in real-world business environments. Decision-makers often require clear explanations of why a particular customer is predicted to churn in order to design appropriate retention strategies [7], [8].

In response to these challenges, Explainable Artificial Intelligence (XAI) has developed into a significant area of research focused on making machine learning models more transparent and easier to interpret. XAI techniques provide explanations that help users understand how input variables influence prediction outcomes, thereby increasing trust in predictive analytics systems [9], [10]. In the context of customer churn prediction, explainable models enable organizations to identify key behavioral and demographic factors contributing to customer attrition and to design more effective customer retention strategies [11]. Of the many available XAI approaches, LIME has attracted considerable interest owing to its capability to provide interpretable explanations for predictions produced by sophisticated machine learning models. LIME generates localized explanations by fitting simpler, more transparent models around individual predictions, enabling analysts to assess how much each feature contributes to a given predicted outcome [12]. Previous studies have demonstrated that LIME can effectively highlight feature importance in churn prediction models and improve the interpretability of predictive analytics systems [13].

Several studies have explored the application of machine learning techniques and explainable AI methods in customer churn prediction. Research shows that explainable predictive analytics can provide valuable insights into customer behavior, support customer segmentation analysis, and help organizations identify high-risk customers who require targeted retention strategies [14]. In addition, explainable models have been shown to improve strategic decision-making by revealing patterns in customer behavior and predicting future purchasing or subscription trends [15]. However, despite the growing interest in machine learning and explainable AI, several limitations remain in existing research. Many previous studies focus primarily on improving prediction accuracy using a single machine learning model without conducting a comprehensive comparison of multiple algorithms [16]. Furthermore, although explainability techniques such as SHAP and LIME have been introduced in some studies, these techniques are often applied only as supplementary analytical tools rather than being fully integrated into predictive modeling frameworks [17]. Therefore, further research is needed to develop customer churn prediction models that not only achieve high predictive performance but also provide interpretable insights into model predictions. In this context, comparing multiple machine learning algorithms while integrating explainable AI techniques can provide a more comprehensive understanding of churn prediction systems.

Drawing from these challenges, this study proposes a comparative evaluation of multiple machine learning models applied to customer churn prediction, integrated with Explainable Artificial Intelligence through the LIME method. The primary goal is to assess the predictive capability of various machine learning algorithms while examining the key factors driving churn predictions via interpretable explanations produced by LIME. By integrating model comparison with explainability analysis, this research is expected to provide deeper insights into customer churn behavior and support organizations in developing more effective data-driven customer retention strategies [18].

This study makes several significant contributions to the field of customer churn prediction. First, it proposes an integrated evaluation framework that combines predictive performance assessment with local interpretability analysis, addressing the common gap between model accuracy and explainability in churn prediction studies. Second, this study conducts a systematic comparative analysis of multiple machine learning algorithms under a unified experimental setting, providing a fair and comprehensive evaluation of model performance. Third, it incorporates the LIME method as an integral component of the modeling pipeline rather than as a post-hoc supplementary tool, enabling direct interpretation of individual predictions. Fourth, this study identifies and validates key churn-driving factors through local explanation analysis, bridging the gap between technical model outputs and actionable business insights. By unifying model comparison and explainability within a single framework, this research offers a more practical and decision-oriented approach to customer churn prediction.

2. Research Methods

This study proposes an integrated machine learning framework for customer churn prediction that combines predictive performance evaluation with model interpretability using Explainable Artificial Intelligence (XAI). Unlike conventional approaches that treat explainability as a post-hoc analysis, this research incorporates the LIME method directly into the modeling pipeline to ensure that prediction results are both accurate and interpretable. The proposed methodology consists of several stages, including data collection, data preprocessing, model development, model evaluation, and interpretation of prediction results.

DOI: https://doi.org/10.31004/riggs.v5i1.7294

The main contribution of this study lies in the integration of multiple machine learning models with LIME-based local interpretability within a unified evaluation framework. This approach enables not only the comparison of model performance but also the identification of key factors influencing customer churn, thereby bridging the gap between predictive accuracy and model transparency. Through this framework, the study positions itself as a decision-oriented approach that supports both technical evaluation and practical business insights.

2.1 Research Workflow

Figure 1 illustrates the overall research workflow, which represents the structured pipeline used to develop and evaluate the customer churn prediction model. The workflow begins with dataset acquisition, followed by a data preprocessing stage to ensure data quality and suitability for machine learning tasks. This stage includes handling missing values, encoding categorical variables into numerical formats, and splitting the dataset into training and testing subsets. The training dataset is used to build and optimize multiple machine learning models, while the testing dataset is utilized to evaluate their generalization performance. In this study, three classification algorithms are employed, namely Logistic Regression, Decision Tree, and Random Forest. These models are evaluated using standard performance metrics, including accuracy, precision, and recall, to provide a comprehensive assessment of predictive capability.

A key aspect of the proposed workflow is the integration of explainability analysis within the evaluation pipeline. Instead of applying explainability as a separate step, the LIME method is embedded directly into the modeling process to generate local explanations for individual predictions. This allows for a detailed examination of how each feature contributes to churn predictions across different models. By combining model comparison with LIME-based interpretability in a single workflow, this research provides a clearer understanding of both model performance and decision logic. This integrated approach not only improves the transparency of machine learning models but also enhances their practical applicability in supporting data-driven customer retention strategies.

Figure 1. Research Workflow

2.2 Dataset

The data employed in this research originates from the Telco Customer Churn dataset, which is freely accessible on the Kaggle platform at: https://www.kaggle.com/datasets/blastchar/telco-customer-churn. This dataset captures information belonging to subscribers of a telecommunications company and has been broadly utilized across numerous churn-related research efforts. It encompasses a total of 7,043 customer records distributed across 21 distinct attributes, covering aspects such as customer demographics, subscribed service details, and billing account information. Among the attributes featured in the dataset are gender, tenure, contract type, internet service type, monthly charges, and total charges.

The target variable in the dataset is Churn, which indicates whether a customer has discontinued the service. This dataset provides various customer behavioral features that can be used to analyze churn patterns and develop predictive models. Previous studies have also utilized machine learning techniques to analyze customer churn behavior using telecommunication datasets [19], [20]. Before applying machine learning algorithms, several preprocessing steps are performed, including encoding categorical variables into numerical values and preparing the dataset for training and testing processes.

2.3 Model

This study employs three machine learning algorithms, namely Logistic Regression, Decision Tree, and Random Forest, to predict customer churn. In addition, the Local Interpretable Model-Agnostic Explanations (LIME) approach within the Explainable Artificial Intelligence (XAI) framework is integrated to shed light on the reasoning behind the predictions yielded by each of the implemented machine learning models.

2.3.1 Logistic Regression

Logistic Regression is a statistical-based classification technique frequently applied to binary classification tasks. It works by estimating the likelihood that a given data instance belongs to a specific class through the use of a

DOI: https://doi.org/10.31004/riggs.v5i1.7294

logistic or sigmoid function. This sigmoid function transforms the result of a linear equation into a probability score ranging from 0 to 1. Equation 1 illustrates the mathematical expression underlying the logistic regression model.

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \tag{1}$$

where $x_1, x_2, \ldots, x_n$ represent the input features and $\beta_0, \beta_1, \ldots, \beta_n$ represent the model coefficients. The output of the model represents the probability that a customer will churn. If the predicted probability exceeds a predefined threshold, the instance is classified as churn. Logistic Regression is widely used in churn prediction because of its efficiency and interpretability. This model enables researchers to examine the relationship between customer characteristics and the likelihood of churn, making it well-suited for classification tasks involving structured datasets [20]. The sigmoid function employed within logistic regression is visually represented in Figure 2.

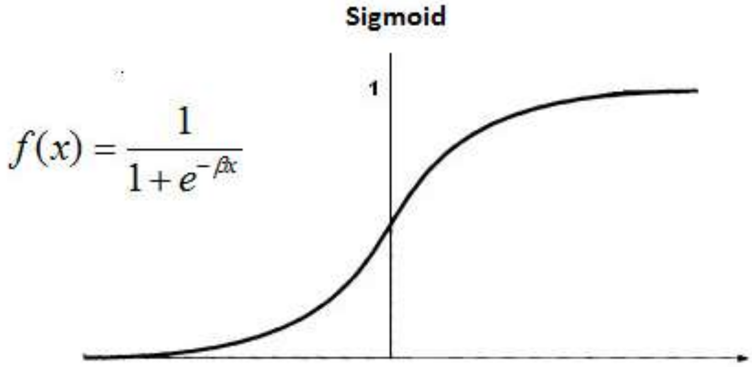

Figure 2. Sigmoid Function

2.3.2 Decision Tree

As a supervised learning approach, Decision Tree conducts classification by systematically breaking down the dataset into increasingly smaller partitions guided by conditions applied to selected features. The resulting structure resembles a tree, in which each internal node embodies a specific decision rule, each branch signifies the possible outcome of that rule, and each leaf node denotes the ultimate class label assigned to a given instance. During the training process, the algorithm selects the most informative features to split the dataset using impurity measures such as the Gini Index or Entropy. The objective is to partition the dataset into subsets that contain observations belonging to the same class. The Gini Index and Entropy used in decision tree algorithm can be seen in Equation 2 and 3.

$$Gini = 1 - \sum_{i=1}^{k} p_i^2 \tag{2}$$

$$Entropy\ (S) = -\sum_{i=1}^{n} p_i \log_2(p_i) \tag{3}$$

where p_i represents the probability of a class within a node. Decision Tree models are widely used in classification tasks because the resulting decision rules can be easily visualized and interpreted. This interpretability allows analysts to understand how different customer attributes influence churn predictions. In churn prediction studies, decision trees are often used to identify the key variables that affect customer retention and service usage behavior [2q]. As shown in Figure 3, the Decision Tree model consists of several decision nodes that split the data based on specific feature conditions until reaching the final prediction at the leaf nodes.

DOI: https://doi.org/10.31004/riggs.v5i1.7294

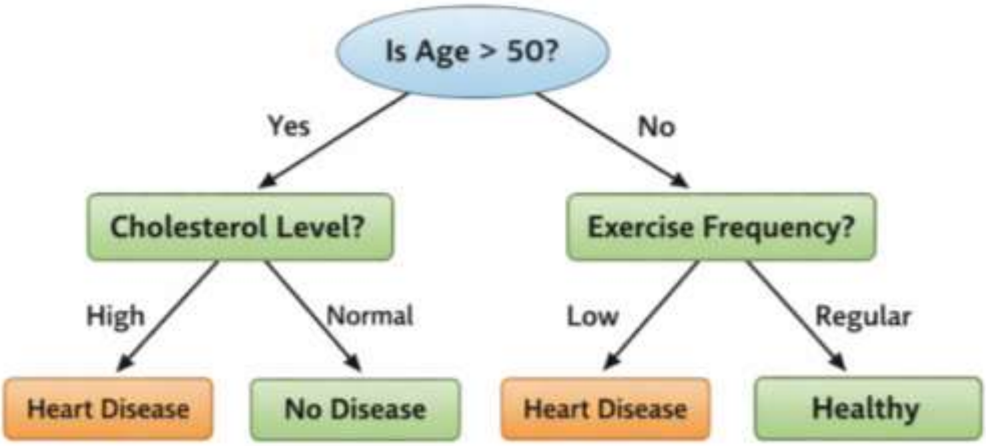

Figure 3. Structure of the Decision Tree Model

2.3.3 Random Forest

Random Forest belongs to the ensemble learning family, whereby a multitude of decision trees are built and aggregated together to yield more accurate predictions while effectively curbing the potential for overfitting to occur during model training. Rather than depending on a solitary decision tree, Random Forest constructs multiple trees during the training process by randomly sampling subsets of both the dataset and its features. The algorithm applies a technique called bootstrap aggregation (bagging), where multiple training samples are generated from the original dataset with replacement. Every sampled subset is employed to construct an individual decision tree, and the ultimate prediction is determined by aggregating the outputs of all trees through a majority voting process. Random Forest is widely used in classification problems because it is capable of handling large datasets and complex feature interactions. Compared to single decision tree models, Random Forest typically produces more stable and accurate predictions. The algorithm has become one of the most commonly used ensemble learning methods in predictive analytics and churn prediction research [22]. The architecture of the Random Forest model, as depicted in Figure 4, comprises several decision trees that collectively collaborate to generate the final prediction outcome.

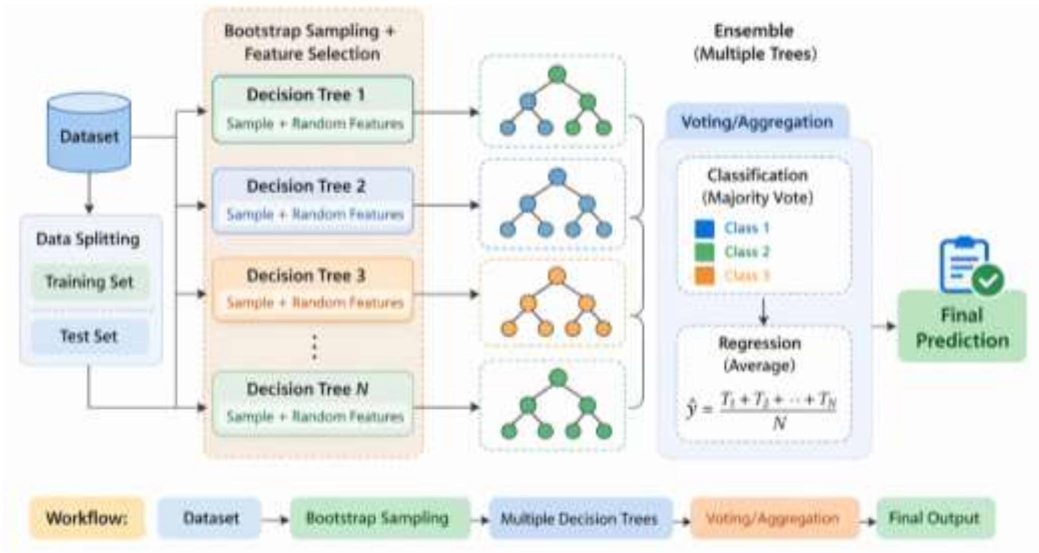

Figure 4. Random Forest Ensemble Architecture

2.3.4 Explainable Artificial Intelligence using LIME

Despite their ability to deliver high predictive accuracy, many machine learning algorithms operate as black-box systems whose internal decision-making mechanisms remain difficult to understand. Such lack of transparency may impede the practical application of machine learning models in real-world environments where decision-makers demand a clear and justifiable rationale underlying every prediction generated by the system. To overcome this challenge, the present study incorporates Explainable Artificial Intelligence (XAI) through the Local

DOI: https://doi.org/10.31004/riggs.v5i1.7294

Interpretable Model-Agnostic Explanations (LIME) method. LIME works by explaining the predictions of complex machine learning models through the construction of simpler and more interpretable models within the local neighborhood surrounding a particular data instance [23].

The LIME algorithm generates synthetic samples around the instance being analyzed and observes how the machine learning model behaves for those samples. Based on this local approximation, LIME identifies the most influential features contributing to the prediction result. These explanations allow researchers to understand how different customer attributes influence the churn prediction produced by the model [24]. By applying LIME in this research, the predictions generated by Logistic Regression, Decision Tree, and Random Forest models can be interpreted to identify the most important features influencing customer churn. This interpretability is important for improving transparency in machine learning models and supporting data-driven decision-making in customer retention strategies. Figure 5 illustrates the mechanism of the LIME method used to interpret the predictions of the machine learning model.

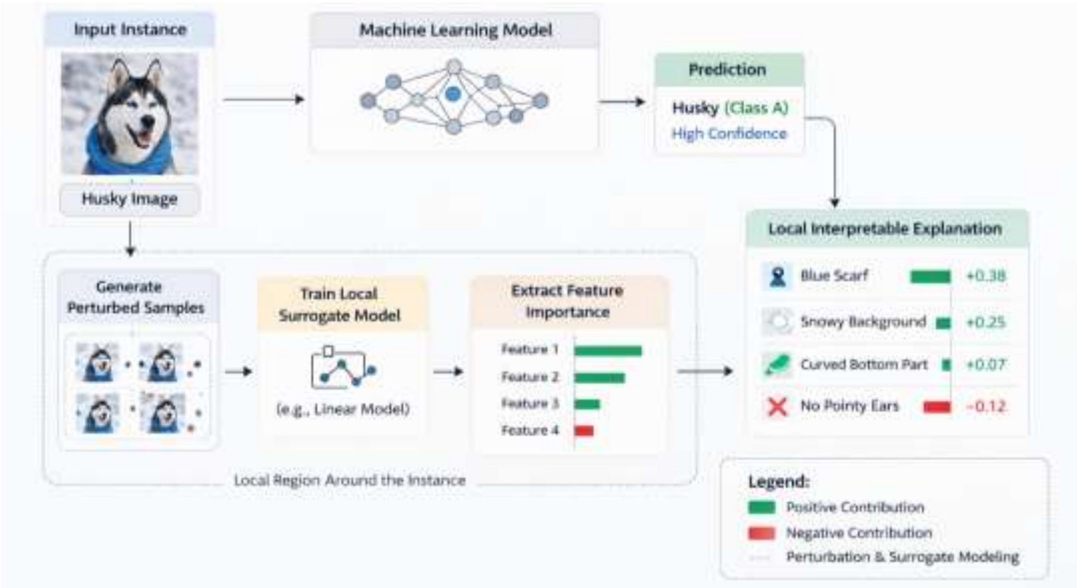

Figure 5. LIME Explanation Mechanism

2.4 Metric Evaluation

To assess how well the models of machine learning developed in this study perform, three measurement benchmarks are applied, consisting of accuracy, precision, and recall. These metrics are broadly recognized as standard tools for assessing the performance of classification models and have been widely adopted across numerous machine learning studies [25]. The evaluation framework is grounded in the confusion matrix, which systematically compares predicted classification outputs against actual class labels. Four essential elements make up a confusion matrix, namely True Negative (TN), True Positive (TP), False Negative (FN), and False Positive (FP). True Positive captures the number of genuine churn cases that the model correctly flagged as churn, whereas True Negative reflects the number of non-churn instances that were appropriately categorized as non-churn. False Positive represents cases where non-churn customers were incorrectly labeled as churn, while False Negative refers to instances where actual churn customers were mistakenly predicted as non-churn.

2.4.1 Accuracy

Accuracy represents the proportion of instances that were correctly categorized relative to the entire set of predictions generated by the model. This metric functions as a broad measure of how well the model performs across all classification outcomes. A notably higher accuracy score signifies that the model possesses a stronger capacity to differentiate between customers who churn and those who do not. The mathematical formula used to derive accuracy is outlined in Equation 4.

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TN} \quad (4)$$

2.4.2 Precision

Precision computes the fraction of true positive instances among all cases that were labeled as positive by the model. In customer churn prediction, this metric conveys how reliably the model's churn predictions correspond to customers who have actually discontinued their services. A high precision value means that the model produces fewer false positive predictions. The equation of precision metric can be seen in Equation 5.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

2.4.3 Recall

Recall, commonly referred to as sensitivity, measures the fraction of actual positive instances that the model successfully identifies. In the context of churn prediction, recall reflects how well the model is able to correctly recognize customers who genuinely discontinue their services. A higher recall value suggests that the model is more capable of capturing true churn cases. The formula for calculating recall is provided in Equation 6.

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

3. Results and Discussions

This section presents the results obtained from implementing three machine learning approaches for the purpose of customer churn prediction, encompassing Logistic Regression, Decision Tree, and Random Forest. The capability of each model is gauged through accuracy, precision, and recall as broadly recognized benchmarks for evaluating classification performance. Selecting appropriate evaluation metrics is essential to determining which model is best suited for addressing a given problem [26]. Beyond measuring predictive capability, the LIME technique is further employed to shed light on how each model arrives at its predictions and to pinpoint the most significant features that drive churn prediction outcomes.

3.1 Model Performance Evaluation

The predictive effectiveness of each machine learning model is assessed through accuracy, precision, and recall as evaluation benchmarks. Together, these metrics offer a thorough measurement of classification performance, particularly in terms of the model's capacity to correctly identify customers who are at risk of churning. The comparison of the model performance is presented in Table 1.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall
Logistic Regression	0.8211	0.6885	0.5925
Decision Tree	0.7289	0.4912	0.5228
Random Forest	0.7928	0.6417	0.4826

Based on the evaluation results, Logistic Regression achieved the highest accuracy value of 0.8211, indicating that it provides the most reliable overall performance among the evaluated models. Random Forest achieved the second highest accuracy value of 0.7928, while Decision Tree produced the lowest accuracy value of 0.7289. The precision metric measures how many customers predicted as churn actually belong to the churn class. Logistic Regression obtained the highest precision value of 0.6885, indicating that this model performs better in minimizing false positive predictions compared with the other models. Random Forest also produced relatively good precision with a value of 0.6417, while Decision Tree achieved the lowest precision value of 0.4912.

Regarding recall, which reflects how effectively each model captures genuine churn cases, Logistic Regression once again recorded the highest score of 0.5925, with Decision Tree following at 0.5228 and Random Forest posting the lowest figure of 0.4826. A relatively higher recall score signifies that the model demonstrates a greater capacity to successfully detect customers who genuinely discontinue their services. Overall, the results indicate that Logistic Regression provides the most balanced performance across the evaluated metrics. This suggests that the Logistic Regression model is the most effective model for tthis study. The relatively strong performance of Logistic Regression may be attributed to the nature of the dataset, which contains structured tabular data that can be effectively modeled using linear decision boundaries.

3.2 Model Interpretability Using LIME

While performance metrics offer valuable insight into model accuracy, understanding the reasoning behind each prediction is equally essential. Many machine learning models function as black-box systems, making their internal

DOI: https://doi.org/10.31004/riggs.v5i1.7294

decision-making processes difficult to interpret. To tackle this concern, the present study employs the LIME method to generate explanations for the predictions produced by each model. LIME constructs localized explanations by fitting a simpler and more transparent model in the vicinity of a specific data instance. This approach enables researchers to determine which features carry the greatest influence over a given prediction outcome.

3.2.1 Logistic Regression Explanation

The LIME explanation for the Logistic Regression model indicates that the analyzed customer is predicted to churn with a probability of 0.70, while the probability of not churning is 0.30. This prediction suggests that the model identifies several risk factors associated with customer churn. The most influential feature contributing to churn prediction is the month-to-month contract type. Customers with month-to-month contracts generally have greater flexibility to discontinue the service compared with customers who have long-term contracts. This characteristic often makes them more likely to churn.

Another significant feature is the fiber optic internet service, which may indicate that customers using high-speed internet services have higher expectations for service quality. If these expectations are not met, customers may decide to switch to other service providers. Additionally, the absence of online security and technical support services also increases the probability of churn, suggesting that customers who do not receive additional support services may feel less satisfied with the service. Other contributing features include paperless billing, lack of dependents, and streaming movie services, which also contribute to increasing the likelihood of churn. On the other hand, attributes such as total charges and phone service availability slightly reduce the probability of churn, indicating that these features have a smaller influence on the prediction. The LIME explanation for the Logistic Regression model is illustrated in Figure 6.

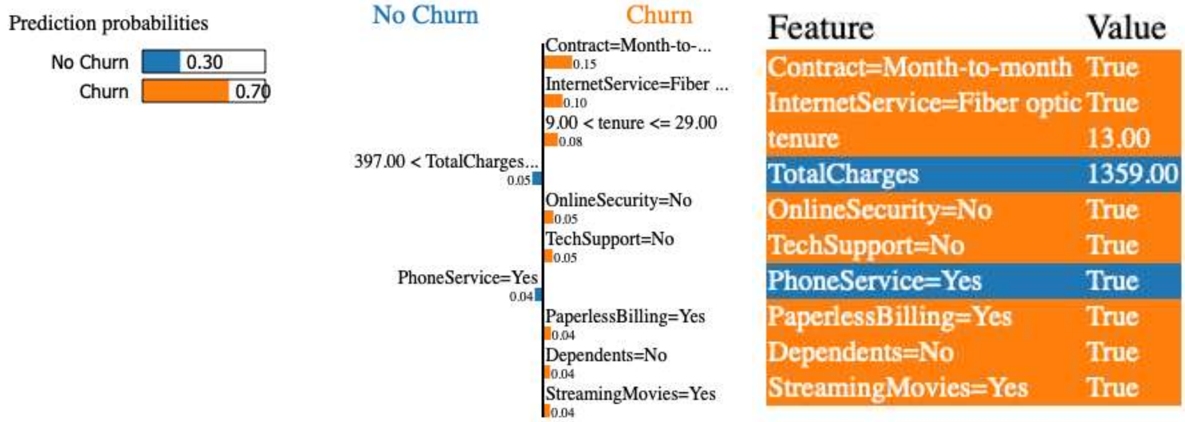

Figure 6. LIME Explanation for Logistic Regression

3.2.2 Random Forest Explanation

The LIME explanation for the Random Forest model shows that the customer is predicted to churn with a probability of 0.67, while the probability of not churning is 0.33. The results indicate that several features strongly influence the prediction outcome. Similar to the Logistic Regression model, the month-to-month contract type is the most influential feature contributing to churn prediction. This finding highlights the importance of contract type as a key factor affecting customer retention.

In addition, the fiber optic internet service and high monthly charges exceeding 89.90 significantly increase the likelihood of churn. Customers who pay higher monthly charges may have higher expectations for service quality and value. If the perceived value of the service does not match the cost, customers may consider switching to other providers. Other factors such as lack of online security, absence of technical support, streaming services, and paperless billing also contribute to increasing the probability of churn. Such outcomes indicate that the presence of supplementary service features and accessible customer support contributes significantly to overall customer satisfaction and their likelihood of staying. The LIME-based interpretation for the Random Forest model is visually depicted in Figure 7.

DOI: https://doi.org/10.31004/riggs.v5i1.7294

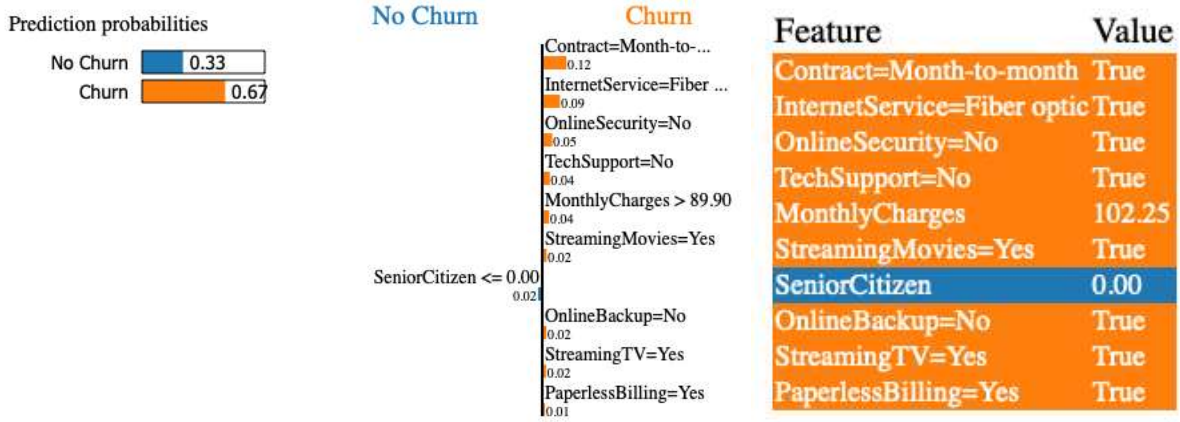

Figure 7. LIME Explanation for Random Forest

3.2.3 Decision Tree Explanation

Unlike the previous models, the Decision Tree model predicts that the analyzed customer will not churn, with a probability of 1.00. This difference in prediction illustrates how different machine learning algorithms may interpret the same input features in different ways.The LIME explanation indicates that several features contribute to the prediction of no churn. One of the important features is monthly charges greater than 89.90, which in this case appears to support the prediction that the customer will remain with the service provider. Additionally, the model also considers the fact that the customer is not a senior citizen, which may indicate lower churn risk for this specific instance. Other features influencing the prediction include tenure between 9 and 29 months, having a partner, and the availability of phone services and streaming services. These factors may indicate that the customer has an established usage pattern with the service provider, which reduces the likelihood of churn. Figure 8 illustrates the LIME-based interpretation generated for the Decision Tree model.

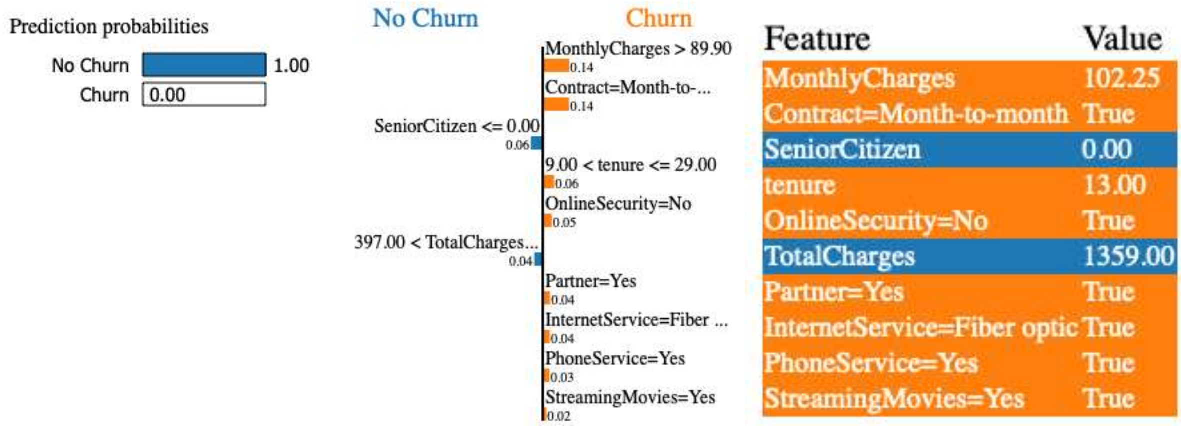

Figure 8. LIME Explanation for Decision Tree

3.3 Discussion

The results of the LIME explanations reveal that several customer attributes consistently influence churn predictions across different machine learning models. Features such as contract type, internet service type, monthly charges, tenure, and additional services such as online security and technical support play a significant role in determining whether a customer is likely to churn. Interestingly, both Logistic Regression and Random Forest predict that the analyzed customer will churn, while the Decision Tree model predicts that the customer will not churn. This difference highlights how different machine learning algorithms capture patterns and relationships within the dataset differently. In general, the integration of machine learning models with explainable AI techniques such as LIME offers a more comprehensive understanding of customer behavior and the underlying factors that drive churn predictions. Such insights can empower organizations to gain a clearer picture of customer needs and formulate more targeted strategies aimed at strengthening customer retention and enhancing overall service quality.

DOI: https://doi.org/10.31004/riggs.v5i1.7294

4. Conclusion

This study proposes an integrated framework for customer churn prediction that combines machine learning model comparison with explainable artificial intelligence to address the gap between predictive performance and model interpretability. The proposed approach incorporates multiple machine learning algorithms, namely Logistic Regression, Decision Tree, and Random Forest, within a unified evaluation pipeline, while embedding the LIME method as a core component for interpreting prediction outcomes. The experimental results demonstrate that Logistic Regression achieved the best performance with an accuracy of 0.8211, followed by Random Forest with 0.7928 and Decision Tree with 0.7289. In addition, Logistic Regression also obtained the highest precision and recall values, indicating its ability to provide more balanced and reliable predictions in identifying customers at risk of churn. These findings highlight that simpler and more interpretable models can outperform more complex models when evaluated under a consistent framework. Furthermore, the integration of LIME within the modeling pipeline enables detailed local interpretability of prediction results. The analysis reveals that contract type, internet service category, monthly charges, tenure, and additional services such as online security and technical support are the most influential factors affecting customer churn. This integrated approach not only enhances transparency but also bridges the gap between technical model outputs and actionable business insights. Overall, this study demonstrates that combining predictive modeling with explainable AI within a unified framework provides a more comprehensive and decision-oriented approach to customer churn prediction. The proposed framework supports both accurate prediction and meaningful interpretation, enabling organizations to design more effective, data-driven customer retention strategies. Future research may extend this work by incorporating more advanced models, larger and more diverse datasets, or alternative explainability techniques to further improve both predictive performance and interpretability.

Reference

[1] Imani, M., et al. "Customer Churn Prediction: A Systematic Review of Recent Advances, Trends, and Challenges in Machine Learning and Deep Learning," in Machine Learning and Knowledge Extraction, vol. 7, no. 3, 2025, doi: 10.3390/make7030105.

[2] M. Mamun. "Advancements in machine learning for customer retention: A systematic literature review of predictive models and churn analysis," in Journal of Sustainable Development and Policy, vol. 1, no. 01, pp. 250–284, 2025, doi: 10.63125/9b316w70.

[3] Chang, V., et al. "Prediction of Customer Churn Behavior in the Telecommunication Industry Using Machine Learning Models," in Algorithms, vol. 17, no. 6, 2024, doi: 10.3390/make7030105.

[4] Adeniran, I., et al. "Implementing machine learning techniques for customer retention and churn prediction in telecommunications," in Computer Science & IT Research Journal, vol. 5, no. 8, pp. 2011–2025, 2024, doi: 10.51594/csitrj.v5i8.1489.

[5] Pathak, P., et al, "Customer churn prediction and personalised recommendations in banking," in International Conference on Artificial Intelligence and Smart Energy, 2024, pp. 409–421, doi: 10.1007/978-3-031-61475-0_32.

[6] Shukla, K., et al, "Hybrid Ensemble Modeling for Customer Churn Prediction: Integrating CatBoost with XGBoost and Random Forest," in 2025 IEEE 3rd International Symposium on Sustainable Energy, Signal Processing and Cybersecurity, 2025, pp. 1-6, doi: 10.1109/iSSSC66652.2025.11388858.

[7] Haider, R., et al. "Illuminating the black box: Explainable AI for enhanced customer behavior prediction and trust," in International Journal of Science and Research Archive, vol. 15, no. 3, pp. 247–268, 2025, doi: 10.30574/ijsra.2025.15.3.1674.

[8] S. Oprea, A. Bara. "Customer-centric decision-making with XAI and counterfactual explanations for churn mitigation," in Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 2, pp. 129, 2025, doi: 10.3390/jtaer20020129.

[9] Topuz, K., et al. "Interpretable machine learning and explainable artificial intelligence," in Annals of Operations Research, vol. 347, no. 2, pp. 775–782, 2025, doi: 10.1007/s10479-025-06577-w.

[10] Q. Lyu, S. Wu. "Explainable artificial intelligence for business and economics: methods, applications and challenges," in Expert Systems, vol. 42, no. 4, pp. e70017, 2025, doi: 10.1111/exsy.70017.

[11] I. Boukrouh, A. Azmani. "Explainable machine learning models applied to predicting customer churn for e-commerce," in Int J Artif Intell ISSN, vol. 2252, no. 8938, pp. 8938, 2025, doi: 10.11591/ijai.v14.i1.pp286-297.

[12] M. Ribeiro, S. Singh, C. Guestrin, "" Why should i trust you?" Explaining the predictions of any classifier," in Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 2016, pp. 1135–1144, doi: 10.1145/2939672.2939778.

[13] C. Ozkurt. "Comparative analysis of xai techniques on telecom churn prediction using shap and interpreted ml partial dependence," in Türk Doğa ve Fen Dergisi, vol. 14, no. 2, pp. 11–25, 2024, doi: 10.46810/tdfd.1529139.

[14] G. Marín Díaz. "A Fuzzy-XAI Framework for Customer Segmentation and Risk Detection: Integrating RFM, 2-Tuple Modeling, and Strategic Scoring," in Mathematics, vol. 13, no. 13, 2025, doi: 10.3390/math13132141.

[15] D. Bujor, A. Constantin, "AI-driven predictive customer analytics for forecasting behavior, churn and future buying patterns," in Proceedings of the International Conference on Business Excellence, 2025, pp. 981–994, doi: 10.2478/picbe-2025-0077.

DOI: https://doi.org/10.31004/riggs.v5i1.7294

[16] T. Trinh, V. Vu, T. Nguyen. "A multi-task test case optimization framework with integrated explainable AI for customer churn prediction: TB Trinh et al.," in The Journal of Supercomputing, vol. 81, no. 14, pp. 1326, 2025, doi: 10.1007/s11227-025-07816-4.

[17] I. Ekanayake, S. De Alwis. "Explainability, risk modeling, and segmentation based customer churn analytics for personalized retention in e-commerce," in arXiv preprint arXiv:2510.11604, 2025, doi: 10.48550/arXiv.2510.11604.

[18] G. Marín Díaz, R. Gómez Medina, J. Aijón Jiménez. "A Methodological Framework for Business Decisions with Explainable AI and the Analytic Hierarchical Process," in Processes, vol. 13, no. 1, 2025, doi: 10.3390/pr13010102.

[19] Chang, V., et al. "Prediction of customer churn behavior in the telecommunication industry using machine learning models," in Algorithms, vol. 17, no. 6, pp. 231, 2024, doi: 10.3390/a17060231.

[20] Bhuse, P., et al, "Machine learning based telecom-customer churn prediction," in 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, pp. 1297–1301.

[21] Wagh, S., et al. "Customer churn prediction in telecom sector using machine learning techniques," in Results in Control and Optimization, vol. 14, pp. 100342, 2024, doi: 10.1016/j.rico.2023.100342.

[22] I. Boukrouh, A. Azmani. "Explainable machine learning models applied to predicting customer churn for e-commerce," in Int J Artif Intell ISSN, vol. 2252, no. 8938, pp. 8938, 2025, doi: 10.11591/ijai.v14.i1.pp286-297.

[23] Haider, R., et al. "Illuminating the black box: Explainable AI for enhanced customer behavior prediction and trust," in International Journal of Science and Research Archive, vol. 15, no. 3, pp. 247–268, 2025, doi: 10.30574/ijsra.2025.15.3.1674.

[24] E. Tjoa, C. Guan. "A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 11, pp. 4793-4813, 2021, doi: 10.1109/TNNLS.2020.3027314.

[25] Putra, V., et al, "A Comparative Analysis of Custom CNN, Inception-V3, MobileNet, RestNet-50, and VGG-19 in Detecting AI-Generated Images," in 2025 12th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 2025, pp. 619–624, doi: 10.1109/EECSI67060.2025.11290536.

[26] Firdaus, R., et al, "Optimizing YOLOv11 for Vehicle Detection in Low-Visibility CCTV Footage," in 2025 5th International Conference of Science and Information Technology in Smart Administration (ICSINTESA), 2025, pp. 416-421, doi: 10.1109/ICSINTESA68165.2025.11413760.