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Transparency in Decision-Making: The Role of Explainable AI (XAI) in Customer Churn Analysis

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ABSTRACT In many industries, such as the telecommunications industry, identifying the causes of customer churn is a primary challenge. In the telecommunications industry, it is of great importance to predict which customers will abandon or continue their subscriptions. Machine learning and data science offer numerous solutions to this problem. These proposed solutions have an important place in decision-making processes in various sectors. This study aims to predict lost customers using machine learning algorithms and explain the reasons behind them. Linear Regression, Logistic Regression, Naive Bayes, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Gradient Boosting, XGBoost (eXtreme Gradient Boosting), LightGBM, AdaBoost, and CatBoost were used to find the classification with the best performance on the dataset used. In this process, performance metrics such as Accuracy, Precision, Recall, and F1-Score are used to compare the performance of models. Finally, the LightGBM model, which gave the highest accuracy value (73.085%), was explained using explainable artificial intelligence (XAI) algorithms.

KEYWORDS
Customer churn prediction
eXplainable artificial intelligence (XAI)
LIME
SHAP

INTRODUCTION

The literature on telecommunications customer churn behavior has grown in importance and volume since the early 2000s. This study performed a quantitative bibliometric retrospection of selected journals that qualified for the ABDC journal quality list to examine relevant studies published by them on customer churn research in telecommunication. Using bibliometric data from 175 research articles available in the Scopus database, this review sheds light on the publication trends, articles, stakeholders, prevalent research techniques, and topics of interest over three decades (1985–2019). According to the findings of this review, the current level of contributions are manifested through ten overarching groups of scholarship-namely churn prediction and modeling, feature selection techniques and comparison, customer retention strategy and relationship management, service recovery, pricing and switching cost, legislation, legal, and policy, word-of-mouth and post-switching behavior, new service adoption, brand credibility, and loyalty. The existing literature has predominantly utilized quantitative methods to their full potential. For far too long, scholars, according to the study's central thesis, have ignored the metatheoretical consequences of relying solely on a logical positivism paradigm. In addition, we highlight research directions and the need for customer churn research to go beyond feature selection and modeling (Bhattacharyya and Dash 2022; Ribeiro *et al.* 2024).

Against this backdrop, an ambitious research endeavor unfolds within the telecommunications domain, embracing methodologies encompassing customer churn analysis, Churn Analysis, and Data Mining. This study's primary aim is to decipher the underpinnings of customer attrition within telecom companies and unravel the distinctive profiles of lost customers. Embarking on a meticulous exploration, this study scrutinizes customer churn in the telecommunications sector through a rigorous analysis of 50,137 customers utilizing advanced machine learning techniques. The dataset employed for predicting customer churn is rich in complexity, comprising 55 customer-related parameters. This analytical undertaking emerges as a pivotal stride toward comprehending and forestalling customer attrition within the industry. Subsequent sections of this article will unfold a comprehensive literature review, delving into the realms of customer churn, machine learning, and the telecommunications industry. A detailed exposition of the proposed methodology and algorithms will follow, with section 4 housing information on the application and analysis results. The article will culminate with a results and discussion section.

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In recent years, the utilization of Artificial Intelligence (AI) has proliferated across various domains, offering innovative solutions to complex problems. However, the opaque nature of many AI models poses significant challenges in understanding and trusting their outcomes, leading to concerns about their reliability and accountability. This has spurred a growing interest in eXplainable AI (XAI) methods, which aim to enhance transparency and interpretability in AI systems by providing insights into the decision-making processes of these models. As a result, the adoption of XAI techniques has been on the rise, reflecting a broader recognition of the importance of explainability in AI applications. The significance of explainability in meeting legal demands, addressing user concerns, and aligning with application requirements underscores the importance of XAI in ensuring the reliability and accountability of AI systems. This highlights the relevance of tailoring explanation content to specific user types and application contexts (Ali *et al.* 2023). By presenting an overview of the current state of taxonomies in XAI research and proposing strategies for improvement, this paper aims to provide scholars with valuable insights into the evolving landscape of XAI and facilitate informed decision-making in method selection and application (Speith 2022). This systematic review contributes to the growing body of knowledge on XAI by organizing and clustering scientific studies based on a hierarchical system. By analyzing existing taxonomies and peer-reviewed literature, the review identifies key theories and notions related to explainability, as well as evaluation approaches for assessing the effectiveness of XAI methods (Vilone and Longo 2021).

This escalating challenge underscores the exigency for corporations to pioneer innovative analysis methodologies, thereby discerning the causes of customer churn and augmenting customer allegiance. In this pursuit, the emerging field of Explainable Artificial Intelligence (XAI) plays a crucial role.XAI aims to make the decision processes of machine learning models, such as those used in customer churn analysis, more understandable and transparent. Two prominent techniques in XAI, namely Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), offer valuable insights into the inner workings of complex models.LIME, a model-agnostic method, achieves interpretability by simplifying the understanding of a specific prediction. It perturbs the input data, observes the changes in the model's predictions, and builds a local, interpretable model to explain the decision-making process effectively. On the other hand, SHAP, grounded in Shapley values from game theory, quantifies the contribution of each feature to a model's prediction. By assigning values to each feature, SHAP provides a nuanced understanding of how individual features impact the model's decisions.

In the telecommunications domain, the integration of XAI methodologies, including LIME and SHAP, becomes instrumental. These techniques enable a deeper comprehension of the factors influencing customer churn predictions. The subsequent sections of this article will delve into the comprehensive literature review, incorporating discussions on customer churn, machine learning, and the telecommunications industry. Additionally, a detailed exposition of the proposed methodology, including the application of XAI techniques, will follow, culminating in the analysis results and discussions. In the competitive milieu of today, the burgeoning significance of the customer relationship management (CRM) process is underscored by a paradigm that situates the customer at the epicenter of the customer economy. Essential facets of an effective CRM process, namely customer acquisition, retention, loss, and recovery, accentuate the integral role this study is poised to play. The anticipation is that this research will not only contribute significantly to the comprehension of customer churn in the telecommunications industry but will also offer insights crucial for prevention strategies.

RELATED WORKS

In the field of customer churn prediction in the telecommunications industry, various studies have contributed to understanding and addressing this critical issue. Pettersson (2004) emphasized the effectiveness of Statistical Process Control (SPC) methods in tracking customer movements and churn. These methods, as discussed by Pettersson, involve monitoring usage patterns to detect decreasing volumes indicative of churn.

Feature selection is a crucial aspect of customer churn prediction models. Huang *et al.* (2010) proposed a new filter feature selection approach specifically tailored for telecommunications churn prediction. This underscores the need for advanced techniques in a competitive market where efficient churn prediction models are essential for retaining customers. Imbalance in data distribution is a common challenge in churn prediction. Idris *et al.* (2012) explored the significance of Particle Swarm Optimization (PSO)-based undersampling in collaboration with various feature reduction techniques. Their study addressed the imbalanced data distribution problem, contributing to the development of more robust churn prediction models.

Non-technical innovation, such as customer engagement strategies, has been examined by Cambra-Fierro *et al.* (2013) in the context of marketing capabilities and commercial processes. This perspective highlights the importance of innovative approaches beyond technical aspects in retaining customers. Shen *et al.* (2014) focused on improving churn prediction by employing a complementary fusion of multilayer features based on factorization and construction. Their work delves into the optimization of feature subsets and prediction techniques for enhanced accuracy in the telecommunications industry.

Alawin and Al-ma'aitah (2014) contributed to decision-making in the telecom sector by proposing research models and utilizing On-Line Analytic Processing (OLAP) and On-Line Data Mining (OLDM) techniques. Their models aimed at optimizing sales points, reducing costs, and identifying profitable customers. Chouiekh and Haj (2017) addressed the importance of machine learning techniques, specifically in the prepaid subscriber segment of the telecom industry in Morocco. Their study aimed at determining the best prediction model to enhance the competitiveness of the Moroccan telecommunications sector. Yuan (2023) investigated telecom customer churn prediction using a composite model composed of logistic regression and neural networks. The adoption of a combinatorial model highlights the need for sophisticated approaches in predicting customer churn.

In addition to telecom-related studies, Gaurav and Tiwari (2023)) explored the application of Explainable AI (XAI) in the banking sector, specifically addressing inefficiencies in the onboarding process. This reflects a broader perspective on the use of advanced technologies across different industries. The acceptance of telemedicine technology among health professionals was studied by Mohammed *et al.* (2023) in the context of the Moroccan public sector. Their research contributes to understanding the factors influencing the successful implementation of telemedicine technology. Franchini and Balzan (2023) introduced an influential theory of increasing returns to explain lock-in phenomena between competing commercial products. This theoretical perspective offers insights into economic dynamics and product adoption.

Harahap *et al.* (2023) explored the role of religious education in improving the work ethic of Micro, Small, and Medium Enterprises (MSME) owners. Their study provides valuable insights into factors influencing work ethic and the potential role of religious education. Suryawan *et al.* (2023) empirically proved the influence of relationships and service quality on guest loyalty in the hotel industry. Their findings contribute to understanding the factors affecting customer loyalty in the hospitality sector. Ogungbire and Pulugurtha (2023) investigated the perception of non-motorists toward autonomous vehicles after a fatal crash. Their study provides insights into how external events may influence attitudes towards emerging technologies. Hmoud *et al.* (2023) addressed the underdeveloped use of chatbots in the Arabic banking sector and examined the technological aspects affecting customer adoption. This study focuses on the specific challenges in the Arab world regarding chatbot applications.

Almrshed *et al.* (2023) analyzed the relative importance of dynamic capabilities in manufacturing SMEs, emphasizing the role of technology adoption in moderating innovative financial strength and customer satisfaction. Sun and Moon (2023)) applied DINESERV to a food brand, Shake Shack, shedding light on the accountability of DINESERV in understanding casual dining customer behavior. These studies collectively contribute to the understanding of customer churn prediction, technological adoption, and innovation across various industries, offering valuable insights for future research and practical implementations.

MATERIAL AND METHODS

The work done in this article was carried out on a computer with a 12th Gen Intel(R) Core(TM) i7-12700H 2.70 GHz processor, 16.0 GB RAM, and Windows 10 operating system, using version 3.11.4 of the Python programming language.

Dataset

In this study, the Kaggle "cell2cell" dataset was used (Amin 2024). The relevant data set includes 58 parameters from 71,047 customers. With the data pre-processing techniques applied to the dataset, these values were transformed into 50,137 customer numbers and 55 parameters. In the first examinations made on the data set 7.,2% of customers continued their subscriptions, while 28.8% terminated their subscriptions.

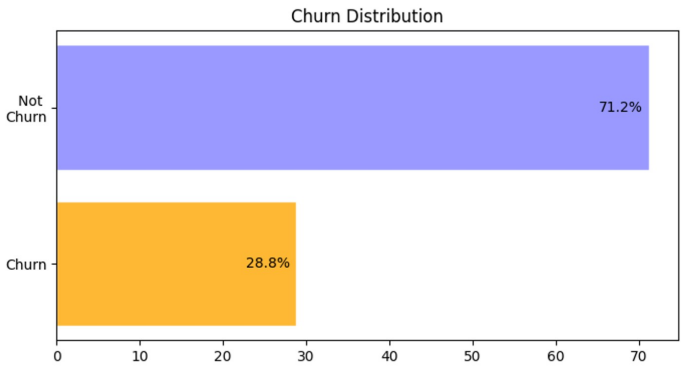

Figure 1 Churn or not churn distribution

In another analysis, the Correlation method was used to see the relationship between the parameters and the results were visualized.

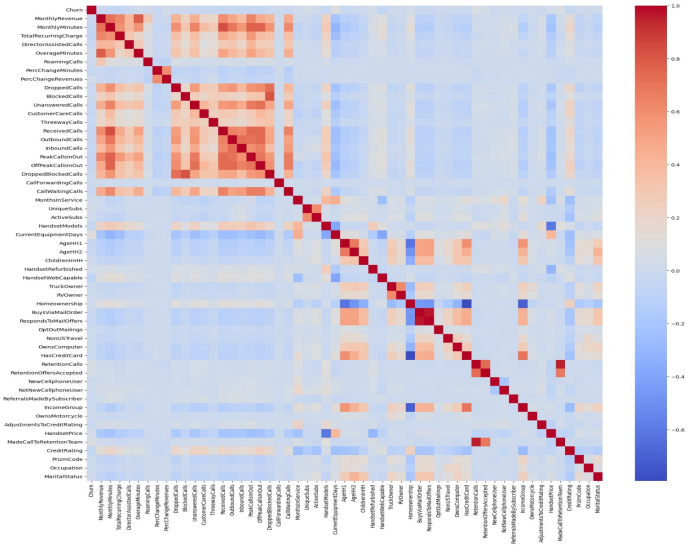

Figure 2 Relationship of parameters with correlation method

Data Pre-processing

In order to improve the quality of the data set, optimize model performance, and obtain clearer results, several processes were applied to the data set before moving on to the machine learning step. The parameters that did not impact the results, namely 'CustomerID,' 'ServiceArea,' and 'Handsets,' were removed from the dataset. As a result of this process, the initial 58 parameters were reduced to 55.

Empty cells in our dataset were filled out by calculating the average values in their respective columns. However, the procedure was deemed inappropriate for the cells in the 'Churn' column. Consequently, rows with empty cells in the 'Churn' column were excluded from the dataset. As a result of this process, the number of samples was reduced from 71,048 to 50,138. In another step of data pre-processing, numerical values were assigned to categorical data in the dataset to accommodate the requirements of machine learning algorithms, which inherently operate with numerical inputs. Specifically, the values 'No' and 'Yes' were transformed into '0' and '1'.

The data set underwent normalization, and it was noted that the parameters within the data set did not share the same maximum and minimum values. In order to address this disparity, the widely employed Min-Max Normalization method was utilized.

Min-Max Normalization It converts the values in the data set to values in the [0-1] range. The mathematical function of Min-Max Normalization is given below.

$$X_s = \frac{(x_i) - (x_{\min})}{(x_{\max}) - (x_{\min})} \tag{1}$$

Here, X_s is the normalized X value and takes values between $[0, 1]$. x_i is the original value, $x_{\min}$ is the minimum value in the data set, and $x_{\max}$ is the maximum value in the data set.

Machine Learning Algorithms

Machine Learning algorithms are computational models that allow users to make predictions or decisions based on data (Nahzat and Yağanoğlu 2021).

In this study, 11 different machine learning algorithms were examined. First of all, the data resulting from data pre-processing

was divided into 80% training and 20% testing. The training data were trained on Linear Regression, Logistic Regression, Naive Bayes, Decision Tree, Random Forest, K-Nearest Neighbors, Gradient Boosting, Extreme Gradient Boosting, LightGBM, Adaptive Boosting, and CatBoost algorithms, respectively. Then, our models were tested on test data, and success criteria were examined. In the next section, the philosophy and mathematical approaches of the algorithms used are explained.

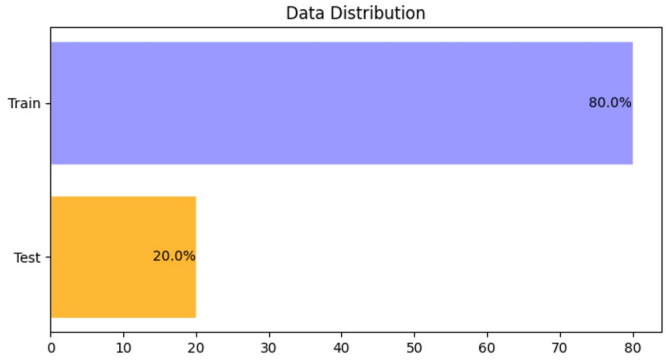

Figure 3 Train and test data distribution

Linear Regression Linear regression is used to find or predict the relationship between at least two parameters that have a cause-effect relationship between them. The general equation of linear regression is given below.

$$Y = Y_0 + m \cdot x \tag{2}$$

Here x is the selected independent variable; Y, predicted value; Y_0 is the point where the line intersects the y axis, and m is the slope of the line.

Logistic Regression Logistic Regression is a statistical method used to model the relationship of a dependent variable (usually categorical) with independent variables. The logistic regression function is given below.

$$P(Y|1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k)}} \tag{3}$$

In this function, $P(Y|1)$ represents the probability that the dependent variable is 1. e is the Euler number, which is the base of the natural logarithm (≈ 2.71828). β_0 is a constant term. $x_1, x_2, \ldots, x_k$ are the coefficients of the independent variable.

Naive Bayes Naive Bayes classifier is a supervised learning class algorithm that is widely used in fields such as data mining, machine learning, and emotion analysis (Şahinaslan *et al.* 2022).

The Naive Bayes algorithm makes the naive assumption that the independent variables are given together, which is why it is called "naive" (Orulluoğlu 2023). The Naive Bayes function is as follows:

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)} \tag{4}$$

In this equation, $P(C|X)$ represents the probability that the class is at a particular data point. $P(X|C)$ represents the probability that a data point belongs to a particular class, given its observed properties. $P(C)$ represents the probability that the class is general. $P(X)$ represents the probability that the observed features are general.

The expression $P(X|C)$ is equal to the product of the probabilities determined by the class of each feature in the data point.

$$P(X|C) = P(X_1|C) \cdot P(X_2|C) \cdot \cdots \cdot P(X_n|C) \tag{5}$$

Here $X_1, X_2, \ldots, X_n$represent features in the data point.

Decision Tree A decision tree is a machine-learning algorithm that is used to solve classification and regression problems (Gülkesen *et al.* 2010). This algorithm tries to reach a conclusion through a series of decisions by analyzing the features in the data set.

The general formula of decision trees is as follows:

$$f(x) = \sum_{m}^{M} c_m \cdot \mathbb{I}(x \in R_m) \tag{6}$$

In this equation, $f(x)$ refers to the predicted output for the input feature vector x. M represents the total number of nodes in the tree. R_m refers to the region at node m. $\mathbb{I}(x \in R_m)$ is the indicator function, which takes the value 1 if x belongs to the region R_m, and 0 otherwise. c_m refers to the estimated value at node m.

Random Forest Random Forest is an ensemble learning algorithm that combines multiple decision trees (Özdemir 2018). The main idea behind the mathematical formula of the Random Forest model is to combine the predictions of each decision tree and average them or make a vote. The mathematical formula is given below (Equation 7).

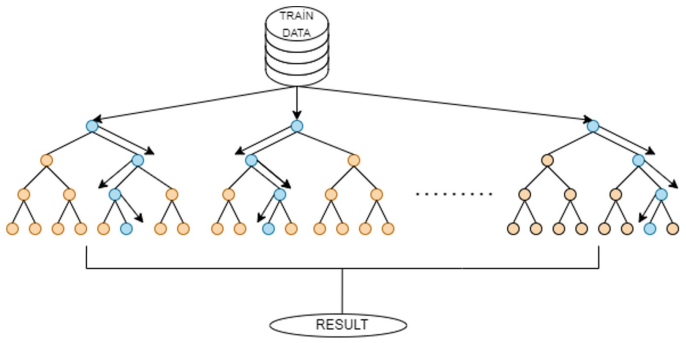

Figure 4 Random forest structure

$$f(x) = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \tag{7}$$

In this formula, $f(x)$ represents the predicted target variable, N represents the total number of trees, and $f_i(x)$ represents the prediction of tree i for the input dataset x.

This formula takes the prediction of each tree, and then these predictions are averaged or voted to get the final prediction. This can help the model be more stable and perform better overall, as the error proneness of one tree can compensate for the errors of other trees. This algorithm also introduces randomness into the creation of trees, ensuring that each tree is different from each other.

K-Nearest Neighbors K-nearest neighbors is a classification and regression algorithm. The basic working principle consists of the training and prediction phase. In the training phase, the model learns the labeled dataset (Kılınç *et al.* 2016). In the prediction

phase, when an unknown sample is given, it first finds its neighboring points and examines the labels of these points. In the case of classification, it uses the most repeated label as the prediction, while in the case of regression, it uses the average of the labels of the neighboring points as the prediction.

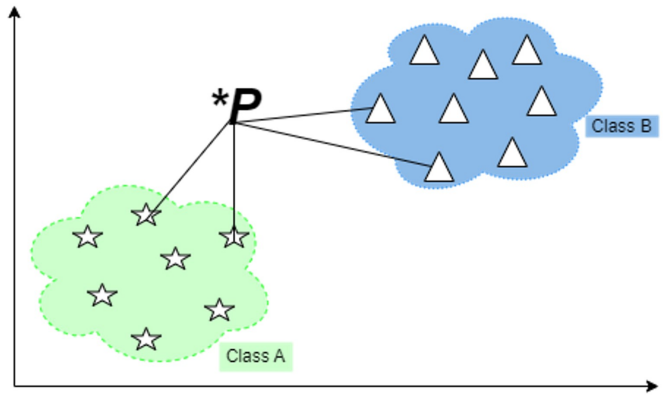

Figure 5 K-Nearest Neighbors algorithm

The mathematical formulas used by the K-Nearest Neighbors algorithm for classification are as follows:

$$\text{distance}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{8}$$

$$\hat{y} = \arg\max_{j} \sum_{i=1}^{k} \mathbb{I}(y_i = j) \tag{9}$$

The Euclidean distance is found in Equation 8. In this equation, x and y are the vectors between the two samples, and n is the dimension of the vectors.

Equation (9) contains the mathematical expression that the algorithm uses to make a prediction by finding the neighboring points of the unknown sample and then classifying them through the labels of these points. In this formula, $\hat{y}$ is the predicted class, K is the number of neighbors, and y_i is the label of the i^{th} neighbor. $\mathbb{I}(\cdot)$ is the point representation function that takes the value 1 if the expression is true and 0 otherwise.

The article could contain subtitles where required, be written in scientific language, put thoughts together from diverse disciplines, combine evidence-based knowledge and logical arguments, and convey views about the aim and purpose of the article. It must address all readers in general. The technical terms, symbols, and abbreviations must be defined the first time they are used in the article.

Gradient Boosting Gradient boosting is a machine learning method and generally uses tree-based learning algorithms (Nusrat *et al.* 2020). It basically aims to create a strong prediction model by combining weak students.

Let it be a data set consisting of (x_i, y_i), $i = 1, 2, 3, \ldots, N$ points. Here, x_i represents the input features and y_i represents the target variable. The model's prediction is initially set to zero.

$$F_0(x) = 0 \tag{10}$$

A new prediction model is added at each iteration to minimize the error function:

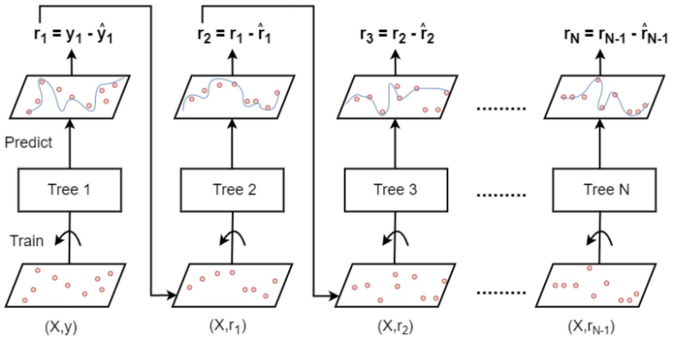

Figure 6 Gradient Boosting Algorithm.

$$F_m(x) = F_{m-1}(x) + \rho \cdot h_m(x) \tag{11}$$

In this Equation (11), m represents the number of iterations, ρ represents the learning rate, and h_m represents the newly added weak model.

With the aim of minimizing the error function, we choose Q using a specific loss function. When determining Q, optimization methods such as gradient descent are used. This is stated as follows:

$$h(x) = \arg\min_{h} \sum_{i=1}^{N} L\left(y_i, F_{m-1}(x_i) + \rho \cdot h(x)\right) \tag{12}$$

In this Equation (12), L refers to the $\arg\min_h$ function that will minimize the error function if the loss function is h.

The general formula for the prediction model would be:

$$f(x) = \sum_{i=1}^{N} h_i(x) \tag{13}$$

In this formula, $f(x)$ represents the prediction model and $h_i(x)$ represents the prediction value of each tree. In the training phase, a certain step size of each $h_i(x)$ gradient boosting algorithm is multiplied by ρ and added to the total.

Extreme Gradient Boosting (XGBoost) XGBoost is a machine-learning algorithm and a tree-based model. XGBoost is a federated model that combines a set of weakly learned decision trees. These trees are put together in a way that complements each other and corrects errors. XGBoost is often used to solve regression and classification problems (Korkmaz and Kaplan 2023). The mathematical equation of XGBoost can be written as follows:

$$\text{Objective Function} = L(\theta) + \Omega(\theta) \tag{14}$$

In this Equation (14), $L(\theta)$ represents the loss function and measures how much the model's predictions deviate from the true values. This can often include mean square error for regression or various loss functions for classification.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) \tag{15}$$

In this Equation (15), n represents the total number of data points, y_i represents the true value of the i^{th} data point, $\hat{y}_i$ represents the model's prediction for the i^{th} data point, and $l(y_i, \hat{y}_i)$ represents the loss function for each data point. Mean square error

(Equation 16) for regression or cross-entropy functions (Equation 17) for classification can be used as loss functions.

$$L(\theta) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{16}$$

$$l(y_i, \hat{y}_i) = -\left(y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)\right) \tag{17}$$

The other term of Equation (18), $\Omega(\theta)$, represents the regularization term and is used to control the complexity of trees. This term imposes punishment to limit the size and number of trees. This protects against overfitting.

$$\Omega(\theta) = \gamma T + \frac{\lambda}{2} \sum_{j=1}^{T} w_j^2 \tag{18}$$

In this equation, T represents the number of trees and w_j represents the node weights of the j^{th} tree. γ adds a regularization term to each tree and controls the addition of trees. λ controls the complexity of the tree by the square of the node weights.

The third term of the Equation (14), θ, represents the parameters of the model. These parameters include decision rules, weights, and other properties at the nodes of each tree.

LightGBM LightGBM is an implementation of the Gradient Boosting framework, a machine learning framework. Therefore, the mathematical formula of LightGBM is generally similar to the formula of Gradient Boosting algorithms. LightGBM stands out with features such as histogram-based learning and scaled gradient descent (Korkmaz and Kaplan 2023). Basically, the mathematical equation is:

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \tag{19}$$

In this equation, $F_m(x)$ is the sum of the prediction when m trees are added. $F_{m-1}(x)$, $m-1$ is the estimate with trees added. η represents the learning rate and $h_m(x)$ is the contribution of the m^{th} tree. LightGBM specifically uses histogram-based learning. In this way, the learning process accelerates and allows lower memory usage.

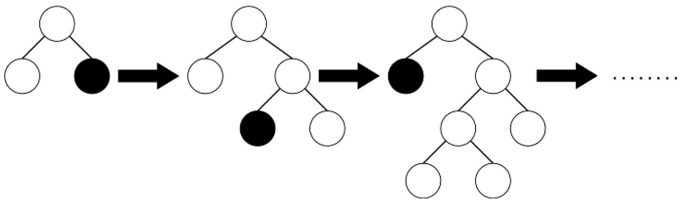

Figure 7 LightGBM structure.

Adaptive Boosting (AdaBoost) AdaBoost is an ensemble learning algorithm that creates a strong learner by combining a number of weak learners (Kul and Sayar 2021).

After training each student, thanks to its weighted error function, AdaBoost weights each example according to its misclassification rate. This error represents the difference between the actual label y_i and the predicted label $h_t(x_i)$.

$$\epsilon = \sum_{i=1}^{N} w_{(t,i)} \cdot \Pi\left(h_t(x_i) \neq y_i\right) \tag{20}$$

In this Equation (20), N is the data point, the t^{th} student, and $w_{(t,i)}$ is the weighting factor. $\Pi(\cdot)$ representation is the Indicator Function.

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1 - \epsilon_t}{\epsilon_t}\right) \tag{21}$$

In this formula (Equation 21), ϵ_t represents the weighted error rate (Equation 20). With this formula, each student is assigned a weight. These assigned weights depend on the student's achievement.

The following formula is used to update the weights:

$$w_{t+1,i} = \frac{w_{t,i} \cdot e^{-\alpha_t \cdot y_i \cdot h_t(x_i)}}{Z_t} \tag{22}$$

Here, Z_t is the normalization factor, which ensures that the weights sum to 1.

With the contributions of all students, a strong student is created with the following formula:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right) \tag{23}$$

In this way, AdaBoost combines a number of weak students to create a strong student.

CatBoost CatBoost is a Gradient Boosting algorithm designed to deal with categorical variables. CatBoost is basically an ensemble learning model created by combining many decision trees (İpek 2021).

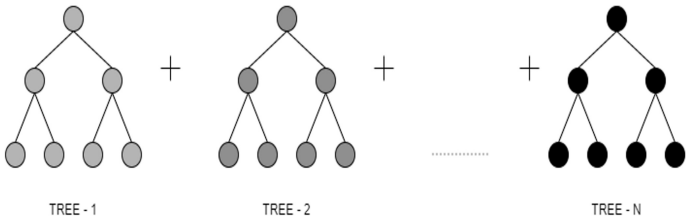

Figure 8 CatBoost structure.

The main components of CatBoost are the Objective Function, Decision Trees, and Gradient Boosting Algorithm. In addition, it has a special structure that processes categorical variables. Thanks to this structure, more effective processing is achieved by using the internal order of categorical variables.

Success Metrics

Various metrics are used to evaluate the success of machine learning algorithms. These metrics help us understand how well a model is performing and measure the model's predictive capabilities. In this study, the philosophy and mathematical approaches of five different success criteria are given. The success of 11 different algorithms used was examined according to these success criteria.

Confusion Matrix A complexity matrix is used to interpret the results of an established classification model and to cross-examine the errors in the relationship between real and predicted values.

- **True Positive**: Correctly predicting the positive situation.
- **True Negative**: Correctly predicting the negative situation.
- **False Positive**: Incorrectly predicting the positive situation.
- **False Negative**: Predicting the negative situation incorrectly.

Table 1 Confusion Matrix

Confusion Matrix		Actual Values	
		Positive (1)	Negative(0)
Predicted Results	Positive (1)	TP [1,1]	FP [1,0]
	Negative(0)	FN [0,1]	TN [0,0]

Accuracy, Precision, Recall, F1-score These scores are derived from the confusion matrix and allow us to see the success of the model more clearly.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{25}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{26}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{27}$$

eXplainable Artificial Intelligence (XAI)

Explainable artificial intelligence (XAI) refers to a set of processes and methods that aim to provide a clear and understandable explanation for the decisions offered by machine learning (ML) models.

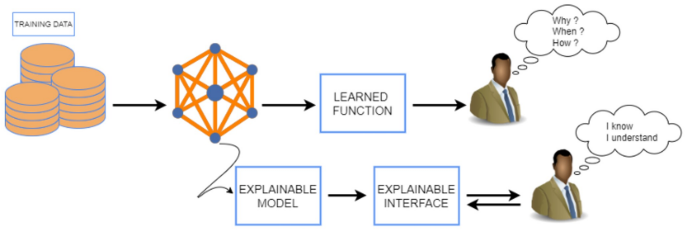

Figure 9 XAI Structure.

XAI architecture depends on specific approaches and methods used to provide transparency and interpretability in the machine learning model. However, in general, the XAI architecture can be thought of as a combination of three basic components. These are the machine learning model, Description Algorithm, and Interface respectively (Gunning *et al.* 2019).

The machine learning model is the core component of XAI and represents the basic algorithms and techniques used to make predictions and inferences from data. The explanation algorithm is the XAI component of the model used to provide information about the most relevant and effective factors in the predictions. The interface component is used to present the information generated by the annotation algorithm to actors. In this study, XAI's two most popular algorithms were reviewed. The philosophical and mathematical approaches of these algorithms were explained.

LIME (Local Interpretable Model-agnostic Explanations) Lime is a popular XAI approach that uses the model's native approach to provide interpretable and explainable information about the factors most relevant and influential in the model's predictions.

The general mathematical expression of the LIME model is as follows:

$$\text{explanation}(x) = \arg\min_{g \in \mathcal{G}} (f, g, \pi_x) + \Omega(g) \tag{28}$$

In this equation 28, x is an instance being explained. The explanation of x is the result of the maximization of the fidelity term (f, g, π_x) with complexity of $\Omega(g)$. f represents a black-box model, which is explained by an explainer, represented by g (Knapič *et al.* 2021).

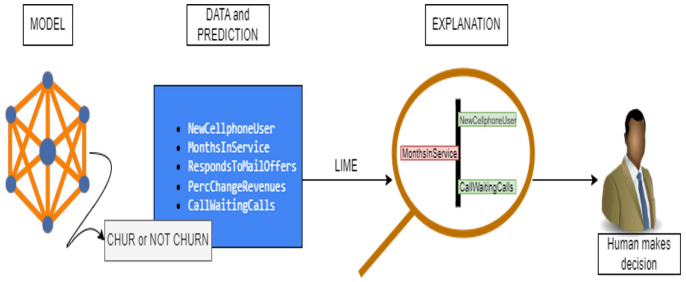

Figure 10 LIME structure.

The LIME algorithm generally follows the stages of categorizing numerical variables, obtaining new observations similar to the distribution of the data set, and determining the effects of the variables on the observation by developing an explainable model based on this data set (Garreau and von Luxburg 2020).

SHAP (SHapley Additive exPlanations) SHAP is an XAI approach and uses Shapley values derived from game theory to provide explainable information about the most important and influential factors in the model's predictions (Zhang *et al.* 2023; Feng *et al.* 2021). Shapley values come from cooperative game theory and are a concept that fairly measures a player's contribution. SHAP provides a framework for understanding how a model creates its predictions using these values.

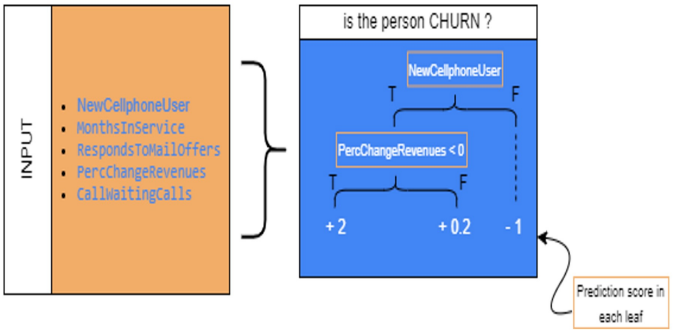

Figure 11 SHAP structure.

The mathematical equations of Shapley value (29) and SHAP (30) value are as follows:

$$\phi_i(v) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} [v(S \cup \{i\}) - v(S)] \tag{29}$$

In this equation (29), N represents the set of players and v represents a value function. $v(S)$ represents the value produced

by coalition S. Each player's (i) Shapley value is the average of the player's values with the other players in the coalition.

$$\phi_i(f) = \frac{1}{N!} \sum_{\pi} \left[f(x_{\pi(i)}) - f(x_{\pi}) \right] \tag{30}$$

In this equation (30), $f(x)$ represents the *output of the model* (where x is the input features). Here π represents all $N!$ permutations, and $x_{\pi(i)}$ is the π permutation of the i^{th} property of x. The SHAP value adapts Shapley values to understand the contribution of each parameter in creating a model's estimate.

RESULTS

The "cell2cell" dataset available on Kaggle was passed through the Data Pre-Processing methods mentioned above and divided into two (80% training, 20% testing) to be used in machine learning algorithms. The test data was passed through the algorithms, and the created models were tested on the test data. The success of the models was compared based on the accuracy score.

Table 2 Accuracy Score Table of Machine Learning Algorithms

ML Algorithms	Accuracy Score (%)
*LightGBM	73.085
CatBoost	73.045
Gradient Boosting	72.626
Random Forest	72.567
KNN	72.138
Linear Regression	72.138
AdaBoost	72.118
Logistic Regression	72.108
XGBoost	72.108
Decision Tree	61.836
Naïve Bayes	54.128

As a result of the examinations, the LightGBM algorithm became the best-performing model with an accuracy score of 73.085%. The outputs of this model were later announced together with the XAI algorithms. At this stage, XAI's two most popular algorithms were used. The results were visualized.

According to Figure 12, we saw that red (Churn) and blue (Not Churn) colors occupy half of the horizontal rectangles for each class. This means that each attribute has an equal impact on the label. But 'CurrentEquipmentDays' is the feature that has the most power. On the other hand, 'CustomerCareCalls', 'OffPeakCallsInOut' and 'RespondsToMailOffers' have the least power.

In Figure 13 and Figure 14 there is a summary chart of the Churn or Not Churn labels. In these graphs, the -y axis represents the features ranked according to their average SHAP values. While the -x axis represents SHAP values, positive values for a particular feature indicate that the model's prediction approaches the examined label. For example, in Figure 13, since the MonthlyMinutes feature is concentrated in positive values and this graph belongs to label number 1 (Churn), this feature approaches label number 1. We may not be able to make these inferences for some features. The SHAP algorithm also provides us with dependency graphs.

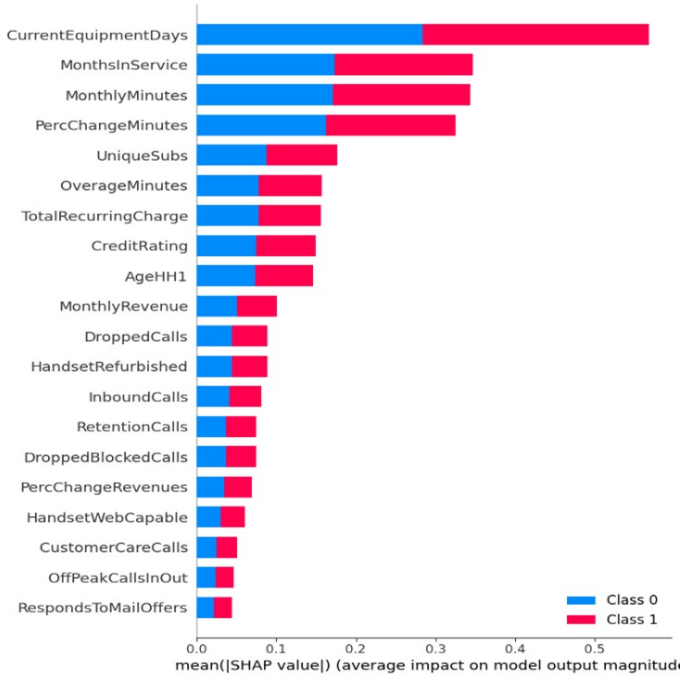

Figure 12 Variable importance graph.

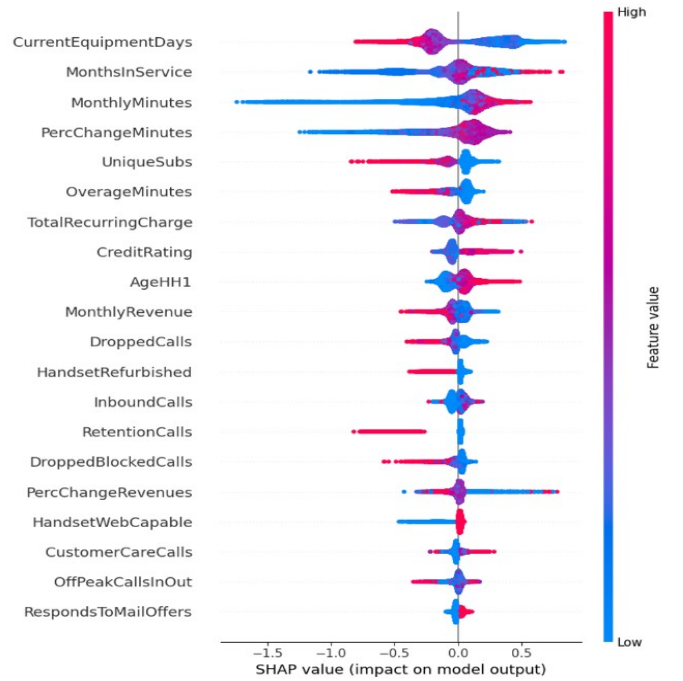

Figure 13 Summary chart of churn label (1).

We extract the information from the dependency graphs that we do not extract from the summary table.

Figure 15 shows the dependency graph of the 'CurrentEquipmentDays' feature. According to this graph, in cases where the 'CurrentEquipmentDays' value is higher than 0.2, the Churn is high. On the other hand, if this value is lower than 0.2, the Not Churn status is high.

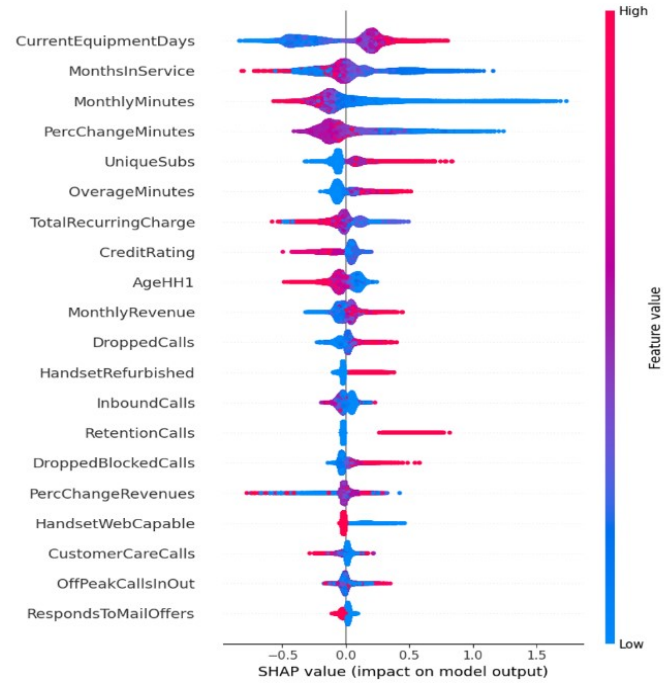

Figure 14 Summary chart of churn label (0).

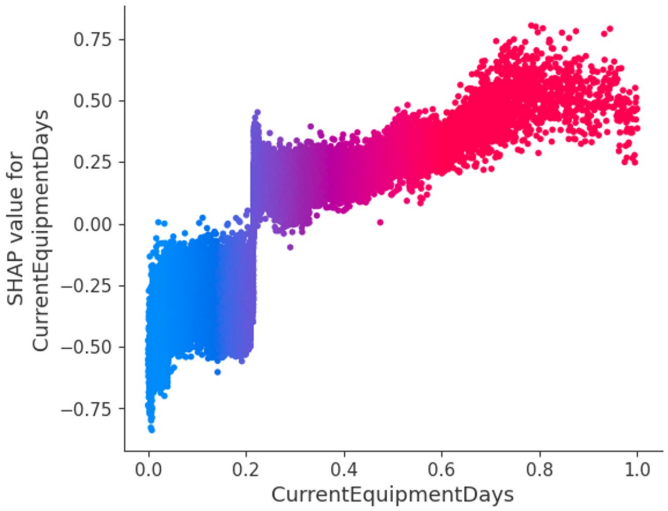

Figure 15 SHAP dependency chart of CurrentEquipmentDays parameter.

The results given by machine learning models are evaluated with the SHAP algorithm; first, the general effect of the parameters on the result was examined, then the class labels and the parameters that they affected the most were examined, and finally the effect of any parameter value on the result was examined. Another algorithm of XAI, LIME algorithm, explains the results by interpreting them locally, that is, it tries to explain the model's prediction for the samples in the dataset. The results of the LIME algorithm are given below. The results of LIME charts contain three main information from left to right. The leftmost information gives the predictions of the model, the middle information gives the contributions of the parameters, and the rightmost information gives the actual value of each feature.

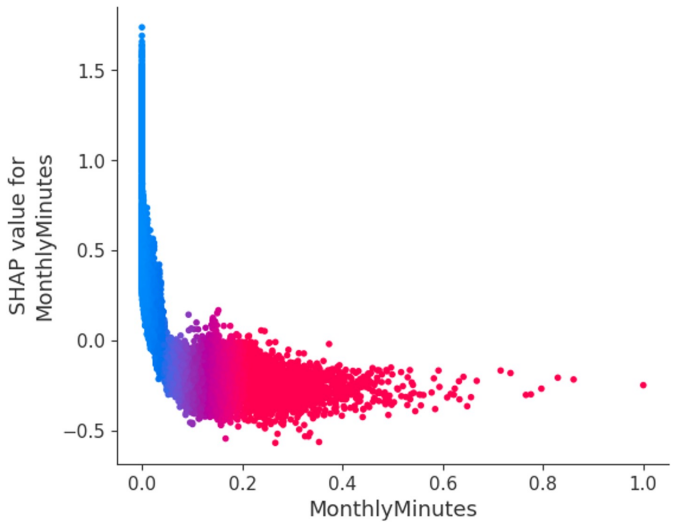

Figure 16 SHAP dependency chart of MonthlyMinutes parameter.

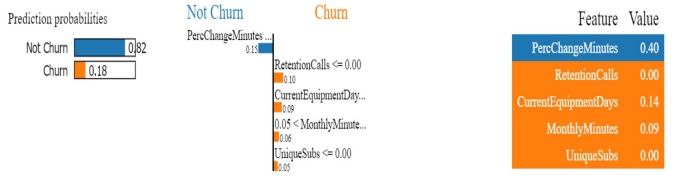

Figure 17 Results of the LIME Algorithm 1.

The information in this graph (Figure 17) shows the status of the 1000th person in the data set. According to this review, this person will not unsubscribe with 82.0% confidence.

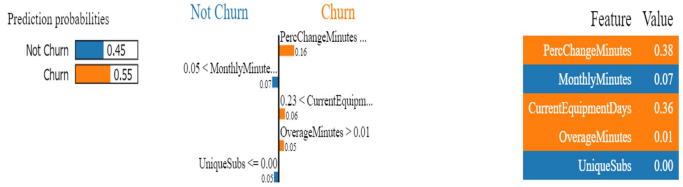

Figure 18 Results of the LIME Algorithm 2.

The information in this graph (Figure 18) shows the status of the 500th person in the data set. According to this review, this person will unsubscribe with 55.0% confidence.

CONCLUSION

Initially, a meticulous examination of the dataset was conducted. Identifying and eliminating parameters such as 'CustomerID,' 'ServiceArea,' and 'Handsets' that did not contribute significantly to the analysis resulted in a refined dataset comprising 55 parameters. Categorical variables were adeptly converted into numerical counterparts, and missing values, excluding the target variable, were filled with the mean of the respective parameter. Rows with missing values in the 'Churn' parameter were subsequently removed. Following these pre-processing steps, the dataset evolved into a robust set containing 55 parameters and 50,137 samples. Correlation analysis revealed no discernible linear relationships among the parameters.

The 'Churn' variable was designated as the target, and the dataset was partitioned into 80% training and 20% testing sets. This stratification facilitated the evaluation of the new datasets using 11 diverse Machine Learning algorithms. Remarkably, LightGBM emerged as the top-performing model, boasting an impressive accuracy score of 73.085%. Other models, such as CatBoost and Gradient Boosting, closely followed with accuracy scores of 72.626% and Random Forest at 72.567%, respectively. Notably, ensemble algorithms exhibited superior predictive capabilities, surpassing similar studies and achieving commendable accuracy using the entire set of 55 features.

Subsequently, the interpretability of Machine Learning outcomes was elucidated using Explainable Artificial Intelligence (XAI) algorithms. Two XAI algorithms were employed, and the SHAP algorithm's graphical representation unveiled the impact of each parameter on the target variable. Notably, 'CurrentEquipmentDays' emerged as the most influential parameter, while 'CustomerCareCalls,' 'OffPeakCallsInOut,' and 'RespondsToMailOffers' exerted minimal influence. A further exploration using SHAP highlighted that 'MonthlyMinutes' predominantly influenced the '1' label, whereas 'MonthsinServices' and 'PercChangeRevenues' were impactful on the '0' label. This nuanced analysis underscored that monthly minute usage was a primary driver for customer churn.

Furthermore, dependency graphs provided by SHAP illustrated the relationship between parameters and results. For instance, if the value of the 'CurrentEquipmentsDays' variable remained below 0.2, the risk of unsubscription was significantly lower. The interpretability exploration extended to LIME, another XAI algorithm. Examining the results with LIME for a specific customer (e.g., the 1000th customer) indicated an 82.0% confidence level that the customer was unlikely to unsubscribe.

Author Contributions

The author conceptualized and designed the study, conducted experiments, collected and analyzed data, and drafted the manuscript.

Availability of Data and Material

Not applicable.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Financial Disclosure

Not applicable.

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