International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Airline Customer Satisfaction Prediction

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Abstract
As the aviation industry evolves, understanding customer satisfaction has become critical for airlines pursuing to thrive in a competitive market. This research paper investigates the dynamics of airline customer satisfaction by analyzing reviews posted on Skytrax, a popular online platform known for its extensive collection of airline reviews. The study analyzes the essential features that are required for customer satisfaction in airline business, as well as performs a comparative analysis of various machine learning classifier algorithms by employing different metrics. The purpose of this comparison was to determine the most effective algorithm among them. The dataset utilized in the research consisted of reviews and ratings given by customers obtained through web scraping data from SkyTrax. Before data was transmitted to algorithms, data was cleaned using various techniques, data imputation, and removal of outliers, and removal of dependable and comparable features using various statistical methods. SMOTE imbalance approach was used in analyzing the level of bias in data. The study employs a range of metrics including accuracy score, precision, recall, f1-score, and confusion matrix, in order to compare different machine learning classifier algorithms, such as KNN, Random Forest, Decision Trees, and Logistics Regression, amongst others.

Keywords: customer satisfaction, machine learning, accuracy, F1-score.

1. INTRODUCTION

Civil aviation is a highly competitive industry and makes a substantial contribution to the development process by creating direct and indirect job opportunities and by facilitating improvements in productivity in the movement of goods and services. Business, trade, and tourism may all expand with the help of the civil aviation industry, a crucial component of the infrastructure that has a big impact on the entire economy. Civil aviation industry highly depends on customer satisfaction and highly relies on the customers feedback and reviews. Customer reviews are based on various key components that are very necessary in measuring the satisfaction of customers. Reviews can effectively demonstrate your commitment to exceeding client expectations while directly addressing potential clients' concerns and doubts [1]. Customer satisfaction is an individual's positive, negative and neutral views on quality, value and decision to use the company's services. Consumers evaluate services by contrasting their expectations and perceptions of the services they receive. It is only when a business continuously meets customer service standards that it can build a solid reputation for providing high-quality services [2]. Customer complaints serve as a critical dimension of service quality and customer satisfaction. Today, it is crucial in businesses that the company's preference should be customer's satisfaction so that customers give good reviews and are satisfied to use the services of the airline again in future. A well-known and popular source of user reviews and ratings is Skytrax, one of the many websites devoted to airline reviews. Skytrax is a significant resource for comprehending the elements that influence passenger happiness and perceptions of airline services, as its enormous database of airline reviews covers a wide range of components of the travel experience. Researchers may glean useful insights from these reviews through the use of sophisticated data analytics techniques like machine learning, sentiment analysis, and natural language processing. This enables airlines to make data-driven decisions aimed at enhancing customer gratification. This study aims to illuminate the complexities surrounding airline customer satisfaction by examining Skytrax reviews. Furthermore, the research compared different algorithms to determine which one of them performs the best in analyzing the customer satisfaction after identifying the key values or components in determining the customer satisfaction.

A. Relevant Contemporary Issues

Using several machine learning methods, Cem Baydogan and Bilal Alatas [1] identified consumer happiness on unbalanced and multi-class data. Six distinct airline firms' text data were used in the study. Three distinct class labels—positive, negative, and neutral—are included in this data. These data are processed by NLP processes. Various Machine Learning (ML) algorithms are used to analyze the findings in tables and graphs. Virgin America Airlines, American Airlines, United Airlines, US Airways, and Southwest Airlines are the six airlines whose data were reviewed and used in the study. The paper's training data was generated using the Sequential Minimal Optimization (SMO) classifier, a sophisticated kind of support vector machine, after the probability-based Naive Bayes algorithm. Along with Decision Table and Multi-Class Classification, the K Nearest Neighbors (KNN) method has been used to do classification based on the entered k-value. All six airline datasets are subjected to the study's algorithms, and the effectiveness of the categorization process is noted. After calculating complexity using values for accuracy, precision, Roc area, and F-measure, a tabular representation of each algorithm's performance is displayed. In China's airline industry, Hongwei Jiang and Yahua Zhang [2] conducted research on customer happiness, loyalty, and service quality. In this study, the service quality of four major domestic airlines in China is examined, along with the relationship between service quality and customer satisfaction and the circumstances in which airlines can keep their current client base. The purpose of this essay is to investigate how passenger demographics, airline brand, and service quality affect overall consumer happiness. Yu Li conducted a study on the strategy for evaluating airline service quality from the customers' point of view [3]. The fundamentals of service quality management were used in the study. This study examines the substance of customer-perceived service quality evaluations along with the real service quality provided by airlines, drawing on the theory of the five elements of service quality and the PZB group's theory of the service quality gap model. This paper's model is built on a decision-making problem with target level elements, several values, and a possible solution.

B. Identification of Problem

When the expectations of customers are met, there is customer satisfaction. Different airlines are using different methods to increase physical and social services since Airline services plays a crucial role in attracting new customers and keeping the previous ones. In order to check whether a specific airline is suitable for customer satisfaction, this study identifies the most suitable machine learning algorithm which can analyse the factors that affects customer retention in airline industry and classify customer's satisfaction. The Logistic Regression classifier, Decision Trees, Random Forest, and K-Nearest Neighbours models of machine learning will all be used to assess whether a client would be satisfied with the airline services or not and the algorithm having the best performance metrics will be identified on the different factors.

C. IDENTIFICATION OF TASK

The industry of airlines are continuously growing industry with rapid increase in the competition of airlines and there very much need of customer satisfaction so that there will be more retention in customers. The task is to provide the most reliable and accurate results by assessing customer reviews based on data used and identifying the features on which customer has more retention rate and is satisfied. This study used various machine learning algorithms to provide more precise result.

D. PROBLEM DESCRIPTION AND CONTRIBUTION

As there is increase in competition of airlines and the industry is growing massively there is also need to make sure that the services provided by airlines are enough to satisfy the customer or there is need of improvement based on the different factors. The global economy now includes a significant amount of airline industry. The goal for this research is to identify a machine learning algorithm that can accurately predict whether or not the consumer will be satisfied or not. The analysis made use of a dataset that is created by scraping customer feedbacks and reviews from SkyTrax [1] website. After identifying the factors that have the maximum impact on customer satisfaction, the dataset was pre- processed and prepared. Different airlines can utilize the built system to assess their performance, determine whether or not their services would satisfy a consumer, and improve their services to grow their customer base.

2. RELATED WORK

In order to estimate the likelihood that customers will return to airline services, the authors of [4] "Who will be your next customer: A machine learning approach to customer return visits in airline services" used a machine learning approach based on feedback comments and satisfaction ratings from previous service usage. The professional survey agency that collected the dataset for the study started collecting online surveys in November 2017 and sent them to 309,331 customers who had used airline services in the previous six months. The survey was delivered as a pop-up window to online travelers who had made their flight reservations. The patrons were directed to provide their evaluations and satisfaction scores no later than two or three weeks following their final airline service utilization. The replies on planes that were canceled or delayed, as well as the invalidated responses, were removed. The sentimental expressions of the users were examined by a sentimental analysis of the remarks. The sentimental analysis of the comments was examined using the linguistic inquiry and word count (LIWC). The publication used the sets of four dimensions to select emotive expressions extracted by the LIWC as the features of the analysis of this study. Initially, the qualities known as the "Total Dimension" were chosen from all of the extracted emotive variables. Second, the features known as the "Basic Dimension" included both affective and descriptive variables. The XGBoost classifier outperformed other machine learning classifiers, according to the authors' conclusion. UX and Total dimension in the XGBoost classifier demonstrated the maximum accuracy, 83.42% and 76.02%, in the case of the top 20% word count. Additionally, using Random Forest, the Basic dimension showed the highest accuracy of 76.85%. When compared to other dimensions, the Total dimension offered the maximum accuracy using the XGBoost classifier, while three dimensions—excluding the Total dimension—showed the highest performance in the Random Forest classifier when it came to the top 80%-word count. In order to expand and clarify the definition of airline service, Kandampully & Suhartanto [6] use the term "service storage" to refer to airline employment. This definition is based on Park's [7] model, which identifies four different kinds of service organizations with two job dimensions. Airline services have both fixed and flexible elements. The characteristics are affected by a number of factors, including aircraft type, maintenance, cargo storage, and seat height. A lot of objectives are there to be achieved in this study:

- High accuracy to be achieved by testing on various algorithms.
- Finding the important features for customer satisfaction.
- Finding the most accurate algorithm checking the customer satisfaction.
- Calculating the accuracy matrix such as accuracy score, precision, recall, F1-score.

3. PROPOSED METHODOLOGY

A. Dataset Description

The reviews and ratings of various airline features that are available on the website Skytrax [3] are scraped to obtain the data used in the project. Alaska Airlines, Delta Airlines, United Airlines, JetBlue Airways, Aerolineas Argentinas Arline, and American Airlines were the six US carriers whose data was scraped in total. The data was initially scraped for a total of 13 features: the aircraft, the type of traveller, the seat type, the route, the date of travel, the comfort of the seat, the service of the cabin crew, the food and beverages, the in-flight entertainment, the ground service, the wifi & connectivity, the value for money, and the recommended. The data for each airline was scraped independently, and then each airline's dataset underwent missing value imputation. All of the datasets were then combined to create one dataset with a total of 14139 rows and 13 features.

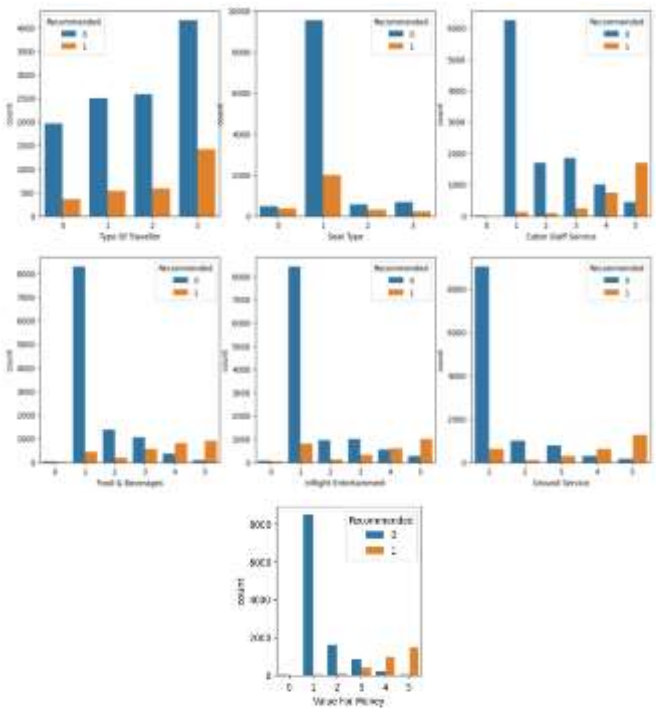


Fig. 1. Visualizations of all the feature variables.

An analysis of the features of the dataset was done using bar plot visualization. The conclusions of it can be drawn from the graphs that have been presented in Fig. 1 thus far are as follows: the majority of people who do not recommend using a particular airline fall into traveller type category 3, have seat types 1 or 1, have rated the cabin services as 1, have rated the food and beverages as 1, have rated the inflight entertainment as 1, have rated the ground service as 1, have rated the value for money as 1, and have rated all of these categories as 1.

B. Data Preprocessing

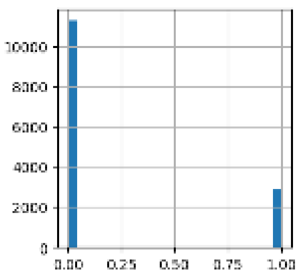
An essential first step in the data analysis process is data preprocessing, especially when working with large datasets like online reviews from Skytrax and other platforms. The raw data must be cleaned, transformed, and arranged in this preprocessing step into a format that can be analyzed. Python is used for pre-processing data. The null values for each feature in the dataset were first determined, and then, using a variety of data visualization techniques, the dataset was examined for anomalous or incorrect values. Subsequently, the mode was used for categorical data and the median for numerical data to impute the missing values. After the data was normalized using the label encoding method, 11240 instances of the recommended class and 2899 instances of the not recommended class were found in the data; as a result, there is bias in the data.

To evaluate this problem, the imbalance in the dataset is handled using the SMOTE technique. The data had a lot of missing values present in the following features "Aircraft", "Route", "Date Flown", "Wifi & Connectivity", "Unamed: 0"therefore they were removed. Correlation analysis was performed on the data and the features with high correlation values among each other were removed to prevent the introduction of bias in the model. The removed feature was Seat Comfort. Then after this the data was normalized using label encoding.

C. Synthetic Minority Over Sampling Technique

When observed frequencies of a categorical variable are significantly varied over its range of potential values, the data is said to be imbalanced. To achieve data augmentation, the SMOTE algorithm appends artificial data points to the real data points. We select the minority cases that are close to the feature space. Subsequently, a fresh sample is drawn at a point on the feature space line that connects the examples.

The project employs a hybrid methodology called SMOTE+ENN. Additional observations are eliminated from the sample space by employing a hybrid SMOTE + ENN approach. Here, the undersampling technique known as ENN is used to determine each member of the majority class's closest neighbors. If the closest neighbors categorize that particular instance erroneously, the majority class instance is removed. Comprehensive data cleaning can be achieved by combining this technique with the oversampled data from SMOTE. Here, samples from the two classes that NNs misclassified are removed. This leads to a class division that is more precise and succinct. The class distribution of the target variable before applying SMOTE is displayed in Fig. 2 and after applying SMOTE is displayed in Fig. 3.



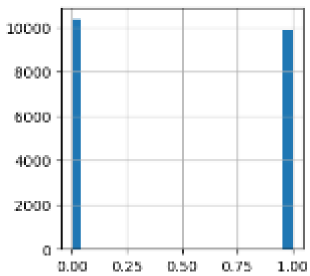


Fig. 2. Class Distribution before SMOTE. Fig. 3. Class Distribution after SMOTE

D. Model Building

After pre-processing the data is then split into train and test data with 80 percent being the train data and

20 percent being the test data. This is performed using Python inbuilt library of sklearn which is "sklearn.model_selection.train_test_split". The models were implemented in Python using various libraries like sklearn, numpy, pandas etc. The model was tested on logistic regression, k-nearest neighbor, decision trees and random forest, AdaBoost, Extra Trees, SVC.

- **Decision Tree Classifier**

The decision tree classifier is a machine learning technique that is widely used for classification tasks. Based on a set of training data, the algorithm builds a model that looks like a decision tree with possible outcomes. Each node in the tree represents a decision point, and the branches that sprout from it represent the possible results of that choice. The method iteratively partitions the data into subsets based on the values of the input features until it generates leaf nodes containing the expected class labels.

- **Random Forest**

Using a combination of many Decision Trees, the Random Forest Classifier is an ensemble learning model that produces precise predictions for classification problems. Using randomized selections of the input features and data, many Decision Trees are built to generate the model. Independently trained, the trees base their projections on a majority vote among themselves. A Random Forest Classifier needs a lot of parameters to be built. Among these parameters are the number of trees (n estimators), the criterion for measuring impurities (gini or entropy), the maximum depth of the trees (max depth), the minimum number of samples required for splitting an internal node (min samples split), the minimum number of samples required for being in a leaf node (min samples leaf), and the maximum number of features considered for each split (max features). These parameters can be changed to modify the model's performance for a particular dataset and task.

- **KNN**

The K-Nearest Neighbors (KNN) approach is a type of non-parametric classification algorithm that can be used for binary and multi-class classification problems. Instead of trying to learn a generalized function that maps the input features to the output classes, the model employs instance-based learning in this way by keeping all training cases in memory and using them to categorize new instances. The KNN algorithm finds the k training examples that are closest to the new instance based on some distance metric (e.g., Manhattan distance or Euclidean distance). The hyperparameter k, which determines the number of neighbors that will be considered throughout the classification process, is controllable by the user. The algorithm then allocates the new instance to the class that includes most of its k nearest neighbors. One advantage of the KNN algorithm is its ability to handle complex decision boundaries and its resilience to noisy input. However, the KNN approach can be computationally expensive, particularly for large datasets, and requires a distance measure that is appropriate for the data. The algorithm is fed the training data, which comprises the attributes and labels for every data point. When a new data point needs to be classified,The algorithm determines the distance between each new data point and every other point in the training set using a distance metric, such as the Manhattan distance or the Euclidean distance. Based on the estimated distances, the algorithm then chooses the k-nearest neighbours to the new data point.

- **Logistic Regression**

A popular statistical technique for binary classification issues in machine learning is logistic regression. This parametric algorithm models, as a function of the input features, the probability of the binary outcome. The algorithm consumes the training data, which consists of the binary outcome variable and the input features.It fits a logistic regression model to the training data by determining the model parameters that maximize the likelihood of the data given the model. The model can be trained and then used to predict, given fresh data points, the likelihood of a binary result. The anticipated probabilities can then be converted into binary forecasts by applying a decision threshold. The linear relationship between the input features and the binary result variable is assumed by logistic regression, which may not be realistic for complex issues. In datasets where the relationships between the input characteristics and the binary result variable are very nonlinear, it might not perform well. The independent and uniform distribution of the errors is an assumption made by logistic regression that may not apply to all datasets. It may be susceptible to the existence of anomalies or significant observations. Before using the logistic regression algorithm, it is crucial to thoroughly preprocess the data and create informative features.

- **AdaBoost**

AdaBoost's central concept is the creation of a "strong" classifier by fusing a number of "weak" classifiers. A weak classifier outperforms random guessing only somewhat, whereas a strong classifier outperforms random guessing significantly. Iteratively adding weak classifiers to the overall model and increasing the weight of the incorrectly categorized instances in each consecutive iteration are how the algorithm operates. The approach chooses a new weak classifier after each iteration in order to reduce the weighted error rate over the training instances. Depending on whether a training example was correctly or wrongly classified by the previous weak classifier, its weight is changed. The model's final output is a weighted sum of the weak classifiers, where more weights are assigned to the classifiers that outperformed the training samples. AdaBoost is a potent algorithm that excels in a variety of classification and regression issues with high accuracy. It is very helpful when working with complex datasets that have a lot of features because it may choose the most crucial features and disregard the less significant ones.

- **Extra Tree Classifier**

The Extra Tree Classifier is a powerful machine learning model used for classification tasks. A final prediction is made using an ensemble learning technique that integrates different decision trees. Although there are some significant variations, the Extra Tree Classifier and Random Forest algorithms are comparable. Contrary to the Random Forest algorithm, the Extra Tree Classifier chooses random splits from the random thresholds for each feature, which may result in a bigger variance in the model. This extra randomness aids in lowering overfitting and enhancing the algorithm's generalization capabilities. The Extra Tree Classifier uses the consensus of all the predictions from the ensemble's decision trees to produce a prediction. It operates by allocating an instance of an input to the class that receives the majority of votes from the various trees. Because more randomness is added during the model construction process, it is less prone to overfitting than other decision tree-based algorithms like Random Forest.

- **SVC:**

The SVC algorithm finds the hyperplane that divides the training data into the various classes most effectively. The decision boundary that maximizes the margin between the two classes is known as the hyperplane. To optimize the SVC algorithm's performance for a particular classification task, a number of important parameters can be changed. The kernel function, which is used to shift the data into a higher dimensional space where it may be more easily separated, is one of the most crucial elements. Kernel functions including linear, polynomial, and radial basis function (RBF) kernels are frequently employed in SVC. The regularization parameter C, which regulates the trade-off between maximizing the margin and minimizing classification errors, and the gamma parameter, which regulates the contour of the

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E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

decision boundary, are additional significant parameters for the SVC algorithm in addition to the kernel function.

4. RESULTS EVALUATION

The models were evaluated using accuracy, precision, recall, F1 score and confusion matrix.

- **Accuracy:**

Accuracy is one metric for evaluating classification models. Formula for accuracy score is Number of correct predictions divided by Total number of predictions.

- **Precision:**

Precision is part of data taken according to the required information. In binary classification precision can be considered equivalent to positive predictive value.

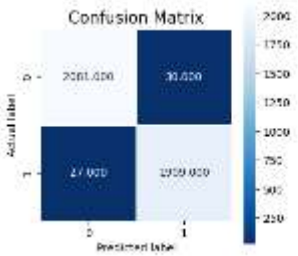
$$\text{Precision} = \frac{\text{True Positives}}{(\text{True Positive} + \text{False Positive})}$$

- **Recall:**

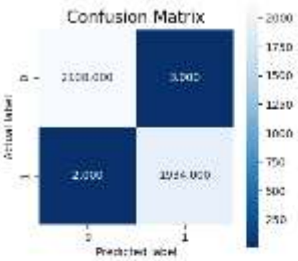
Recall is determined by dividing the total number of positive samples by the number of positive samples that were correctly categorized as positive. The recall gauges how well the model can identify positive samples. Positive samples are found in greater numbers the higher the recall.

- **F1 Score:**

By taking the harmonic mean of a classifier's precision and recall, the F1-score aggregates these two metrics into a single figure. It is employed to contrast two classifiers' performances.



a. Confusion Matrix of AdaBoost Classifier



b. Confusion Matrix of Extra Trees Classifier

Fig. 4. Confusion Matrix of all the classifiers.

The performance metrics considered for model evaluation were accuracy, precision, recall, F1-score and confusion matrix. It can be noted from Fig. 4a. that Adaboost is performing well in classifying the recommended and non recommended classes. Fig. 4b. shows that Extra Trees perform better in that respect. Further Table 1 represents the values of the performance metrics when no imbalancing technique was employed and Table 2 represents the values of the performance metrics after employing SMOTE technique for addressing the imbalance problem. From the table 2 it can be inferred that Extra Trees Classifier is performing the best for classification as it has an accuracy of 100% on train and 99.87% on test along with high precision and recall values of 0.998, 0.999 and F1 score of 0.999.

S. No	Models	Accuracy on Train (%)	Accuracy on Test (%)	Precision	Recall	F1 Score
1	Decision Tree Classifier	97.96	94.51	0.88	0.849	0.864
2	Random Forest Classifier (max depth - 10)	98.65	95.68	0.906	0.881	0.894
3	KNN Classifier	96.3	96.14	0.926	0.883	0.904
4	Logistic Regression	95.52	95.65	0.915	0.869	0.891
5	AdaBoost Classifier	95.6	95.68	0.914	0.873	0.893
6	Extra Trees Classifier (max depth - 13)	98.65	95.33	0.907	0.861	0.883
7	Support Vector Classifier	95.84	95.96	0.93	0.86	0.89

Table 1: Algorithms along with performance metrics without SMOTE

S. No	Models	Accuracy on Train (%)	Accuracy on Test (%)	Precision	Recall	F1 Score
1	Decision Tree Classifier	99.98	99.67	0.996	0.997	0.997
2	Random Forest Classifier (max depth - 10)	100	99.87	0.999	0.998	0.999
3	KNN Classifier	99.59	99.55	0.996	0.994	0.995
4	Logistic Regression	98.35	98.46	0.985	0.982	0.984
5	AdaBoost Classifier	98.37	98.59	0.985	0.986	0.985
6	Extra Trees Classifier (max depth - 13)	100	99.87	0.998	0.999	0.999
7	Support Vector Classifier	98.71	98.86	0.99	0.987	0.98

Table 2: Algorithms along with performance metrics with SMOTE

III. CONCLUSION AND FUTURE WORK

A. Conclusion

In this study, we suggested a machine learning method for classifying airline customer contentment. We collected a dataset by scraping the reviews and feedbacks from Skytrax [1]. The acquired data was then combined, erroneous data was removed, and key features were chosen using a variety of preprocessing techniques. We used two approaches, firstly we tested all models' accuracies without employing an method to assess the issue of imbalance of the target variable class present in the dataset, in the second approach we used SMOTE technique to address the issues and observed that the models performed better after using SMOTE. Finally, we evaluated how well different machine learning models performed in predicting customer satisfaction from airline passenger data. Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors, AdaBoost, Extra Trees classifier, SVC were the machine learning methods employed for classifications. According to accuracy metrics like accuracy score, precision, recall, F1-score all the outcomes of the machine learning algorithms are recorded in the results section. The best algorithm was Extra Trees Classifier after using SMOTE, which had an accuracy of 100% on train and 99.87% on test along with high precision and recall values of 0.998, 0.999 and F1 score of 0.999.

B. Future Work

The airline sector is expanding quickly, and there is more rivalry from different airlines. Customers' satisfaction with airline features is crucial in this highly competitive sector, and it's critical for the industry to identify the key elements that influence customer retention. To determine which machine learning algorithm produces the most accurate results, we employed a variety of methods in this investigation. If additional features are extracted and their accuracy is verified, the findings may be more accurate.

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