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Telecom Churn Prediction Using ML Algorithm

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ABSTRACT: Telecom customer competition forecasting is an important task for telecom companies to retain customers. Churn is when a customer cancels their subscription or service from a communications company. Predicting customer churn helps telemarketing companies take steps to retain customers by identifying potential churn and providing effective retention strategies for them. This summary explains the context of the communication problem using machine learning. Contacts for problem prediction may include analysis of a customer's historical data, including demographic data, usage patterns, payment details, and service history, to predict whether a customer will leave in the future Telecommunications customer churn prediction using machine learning involves processing customer history data, architectural design, selecting appropriate machine learning algorithms, effectively evaluating performance models using multiple metrics, and using best practices in a production environment. By using these methods, communications companies can reduce customer turnover and increase customer satisfaction.

KEYWORDS*:* Machine Learning, Churn Prediction, Churn, Telecom Churn Random Forest , Decision Tree, XGBoost, Churn, ANN**.**

I. INTRODUCTION

Customer retention in today's highly competitive telecommunications industry is a challenge for service providers. Cu stomer churn, which is when customers cancel their subscriptions or services, is a major concern for telecommunications companies as it leads to loss of revenue and operations. To overcome this challenge, mobile companies are turning to m achine learning technology to predict customer competition and take proactive steps to protect against it. Gaming is impo rtant for phone companies because it helps them retain customers and reduce customer churn rates. Telecommunications companies can prevent customer churn and increase customer satisfaction by identifying potential customer churn and of fering them attractive retention strategies. Additionally, churn forecasting allows telephone companies to improve their marketing and sales by focusing on valuable customers and without affecting users. Telecom churn forecasting is an imp ortant task for telecom companies because it helps them retain existing customers and reduce customer churn. Customer l oss. Churn is the process when a customer stops providing service to a communications company. Using machine learnin g algorithms to predict customers can help phone companies identify factors that drive customer churn and take proactiv e steps to retain customers. Telecom churn forecasting is an important task for telecom companies because it helps them retain existing customers and reduce customer churn. Mobile marketing companies can use machine learning algorithms to create accurate and effective churn prediction models. These models can be integrated into the production environmen t to provide instant predictions and help companies take proactive steps to retain customers.

A. Problem Statement

Telecom churn prediction is a crucial task for telecom companies as it helps them retain their existing customers and reduce customer attrition. Telecom Churn Prediction it helps telecom companies to retain their customers and minimize revenue loss due to customer churn. Churn refers to the percentage of customers who discontinue their subscription or service with at elecom company. Predicting customer churn is essential for telecom companies as it allows them to take proactive measures to retain customers, such as offering personalized promotions, discounts, or better services. Churn refers to the process of customers discontinuing their services with a telecom company. Predicting churn using machine learning algorithms can help telecom companies identify the factors that lead to customer churn and take proactive measures to retain them. Telecom companies can build accurate and effective churn prediction models using machine learning algorithms. The models can be deployed in a production environment to provide real-time predictions andhelp the company take proactive measures to retain customers. The predictive model should take into account various factors such as customer demographics, usage patterns, payment history, customer service interactions, and other relevant data points. It should be able to analyze historical data on customer churn and create a model that can predict future churn behavior.

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B. Objectives of the study

1. The objective of this proposed system is to develop a machine learning model that can accurately predict customer churn in the telecom industry.
2. Churn refers to the phenomenon where a customer discontinues their subscription or service with a telecom company. Predicting churn is crucial for telecom companies as it enables them to take proactive measures to retain customers, reduce churn rates, and improve customer satisfaction.
3. To compare the algorithms that are effective in reducing churn rate in telecom companies
4. The scope of this proposed system includes collecting and preprocessing customer data, feature engineering, selecting and training appropriate machine learning algorithms, and evaluating the performance of the model. The system will also incorporate techniques such as data augmentation, ensemble learning, and hyper parameter tuning to improve the model's accuracy and robustness.
5. The proposed system will be developed using Python and the popular machine learning libraries. The system will be trained and tested on a large and diverse dataset of telecom customer data, which will be obtained from reputable sources such as Kaggle. The system will be designed to be scalable, efficient, and easy to deploy in a production environment

C. Features of Project

1) Real-time monitoring
2) Fraud detection
3) Historical Customer Data
4) Customer demographics
5) Customer service interactions
6) Network performance metrics
7) Competitor information
8) Social media sentiment analysis
9) Customer satisfaction surveys/NPS scores

II. RELATED WORK

1. Dr. O. Rama Devi, Sai Krishna Pothini has launched a model targeting individuals who use premium OTT platf orms to stream video content on any device. This study used a survey to collect information from participants of each population. Data collection needs to go through many processes before it can be made suitable for machine learning models. Use this platform. This information is important for OTT companies to understand and optimiz e their marketing and retention processes. This process involves cleaning data, selecting important features, and training machine learning models. The model is then tested and validated through performance testing. The resul ts can inform OTT companies to improve their customer acquisition and retention processes. [one]
2. The system proposed by QiuYing Chen and SangJoon Lee uses Orange3 software to create a churn prediction m odel for product delivery. Choosing the best gradient boosting algorithm for churn prediction on a food delivery platform. Model estimation using gradient boosting algorithm gives good and accurate results, easy to use. It als o offers important features that make the use of gradient boosting methods more effective, unlike the results of g eneral learning methods. Especially in ecommerce, it is more useful to use additional development methods to pr edict the customer without a contract. [2]
3. The system proposed by Weijie Yu and Weinan Weng aims to identify the factors affecting customer churn and create a good model to predict and analyze the data obtained from the results found. Customer churn prediction consists of several stages such as preliminary data, data analysis, measurement and evaluation, and machine lear ning algorithms. It also includes data preprocessing, data cleaning, transformation and classification. The selecte d machine learning methods are Logistic Regression, SVM, Random Forest, AdaBoost, GBDT, XGBoost, Light GBM and CatBoost. Classifiers are evaluated using performance metrics such as accuracy, precision, recall, AU C, and F1 score. According to the paper, the results show that Light GBM is better at identifying potential candi dates than other classifications. [3] Chapte
4. Gavriel et al. To predict prepaid customer churn, an advanced data mining method is proposed using call data of 3333 customers with 21 characteristics and the associated churn parameter with two outcomes (yes/no). Some of the features include recordings of incoming and outgoing calls and voicemails for each customer. The authors u sed a keypoint analysis algorithm (PCA) to reduce the remaining data. Use three machine learning algorithms to estimate loss factors: neural networks, support vector machines, and Bayesian networks. The author uses AUC t o measure the performance o the algorithm. The AUC values of the Bayesian network, neural network, and supp

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ort vector machine are 99.10%, 99.55%, and 99.70%, respectively. The data used in this study were small and ha d no missing values. [4]

5. Huang et al. The problem of customer churn on the big data platform was investigated. The researcher's goal is t o show that big data improves the process of predicting customers based on the volume, variety and speed of dat a. At China's largest telecommunications company, processing information from the support office and business support requires a large amount of information to resolve the problem. Use the random forest algorithm and mea sure using AUC. [5]
6. This article describes our work on churn analysis and forecasting for these types of services. We work on data m ining techniques to accurately and effectively predict whether users will switch (lose) to other providers offering the same or similar services. The information we use is evidence and facts compiled by Orange Telecom for the KDD 2009 competition. Many groups score high on this information, which requires the use of important infor mation. Our goal is to find other ways to match or improve the high scores recorded by using more efficient and effective resources. In this study, we focused on a set of metaclassifiers that were individually trained and select ed based on their performance.
7. Idris proposed a method based on AdaBoost genetic programming to simulate the problem of loss in communic ation. The model was tested on two data sets. One is provided by Orange Telecom and the other is provided by c ell2cell. The accuracy of the Cell2cell dataset is 89%, while the accuracy of the other dataset is 63%. [7]
8. He et al. A prediction model based on neural network algorithm is proposed to solve the customer churn proble m of a large telecommunications company in China with approximately 5.23 million customers. The model is ve ry accurate, reaching 91.1% accuracy.
9. AZhang Y proposed a combination method to build a binary classifier. This method is a combination of the knea rest neighbor algorithm and the logistic regression method. The knearest neighbor algorithm works by dividing m onedimensional data into mdimensional data sets. This hybrid KNNLR classifier improves the classification a ccuracy of logistic regression in some cases where the predictor and target variables result in a nonlinear relation ship. Experimental results on four test data show that the quality of the method compares with wellknown classif ication algorithms such as C4.5 and RBF. It also shows the results of its application in customer churn predictio n based on real customer data.
10. ShinYuan Hung proposed a different methodology to develop predictive models for interactive customer engage ment. Following recommendations from previous research by Wei and Chiu (2002) , we included customer servi ce and customer dissatisfaction inputs in the model. We examined the effects of insufficient information on desi gn. Our empirical analysis shows that data mining techniques can help mobile service providers meet customer n eeds effectively.
11. Combine dynamic gradient boosting with physical data to estimate losses. Selected data were used in this study f rom the WSDM Cup 2018 competition of KKBOX, a music streaming service. This study used supervised mach ine learning with decision trees to develop a reliable testing model to predict customer churn in the existing XG Boost library. Improved accuracy by combining the LightGBM library with the main XGBoost model. The stan dard model outperforms other models submitted to the competition due to its high accuracy. Future research will include further optimization of the XGBoost and LightGBM models using Stack Net search and unprecedented performance models.
12. Dolatabadi and Keynia presented various neural studies and data mining techniques. The data was collected over a year and a half and provides information on all employees and customers. By comparing methods such as deci sion trees, naive Bayes, support vector machines, and neural networks, this article concludes that support vector machines can be used to produce reliable and accurate consumer products. Future work will include analyzing c ustomer and employee performance to improve predictive models and increase the reliability of participating co mpanies
13. Hoppner et al. proposed the development phase model of decision tree, introduced a new loss classification calle d ProfTree, and developed an evolutionary algorithm to optimize EMPC [10]. The data used is a real churn datas et from different communication providers, containing 889 customers and 10 different descriptions. ProfTree, E vTree, CART, ctree etc. It is generally the most awardedmodel that measures the complexity and effectiveness o f other tree methods such as. By creating and collecting various valuable trees, the value of the property will incr ease.
14. Fei et al proposed a new method, a Naive Bayes classifier, to predict users using the K method. K shows the bett er accuracy and precision of the combination Naive Bayes classification method compared to the Naive Bayes cl assification method combined with EWD. However, they have weaknesses in predicting true negative and positi ve outcomes. This information is collected from clean data received from telecommunication companies. The se lected data included five thousand callers and twentyone features. The project aims to build models by learning t

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emporal bounds that affect the future learning rate of a classifier. The technology can be enhanced with different algorithms such as support vector machine, decision tree and Bayesian networks.

15. Kumar, A.S. and Chandrakala, D. proposed an improvement method such as AdaBoost classification using vect or machines to overcome many classification problems, using detection tools as predictions, combining AdaBoo st SVM, NBTree and support removal vector machine classification. The data set used is the bank. To effectivel y predict customer churn rate, the plan is to get a more comprehensive distribution.
16. Xia and Jin, Customer churn prediction demand based on support vector machine (SVM). Data analysis from th e University of California Machine Learning and Home Telecommunications repository. Compared with BPAN N, C4.5 decision tree, logistic regression, and naive Bayesian classification systems, SVM has better predictive ability, greater reproducibility, and better similarity.

III. METHODOLOGY

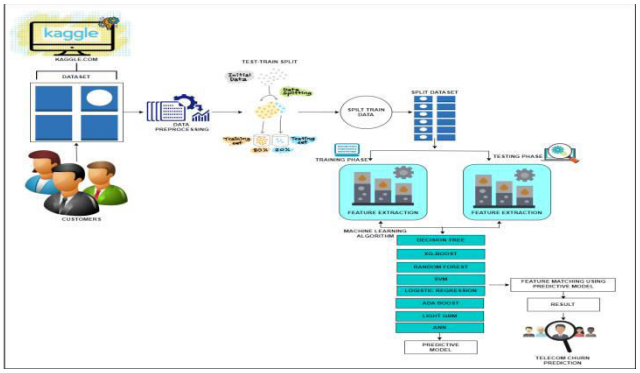

Fig.1.Representation Of The Methodology.

The simple formula for predicting future loss is historical data. We look at profiles of customers who have already st opped using the app (responders) and their characteristics/behaviors before churn occurs (predictors). The data set inclu des customers' details, their total costs and the services they received from the company. There is churn data for many c ustomers from Kaggle from more than 21 features. This method falls into the category of educational supervision.

IV. EXPERIMENTAL RESULTS

This section discusses about the experimental setup for the model and also highlights on the result analysis for the accuracy, confusion matrix, and cluster formation.

A. Experimental Setup

The machine utilized for our models was equipped with a Windows 11 operating system. It featured an Intel i3 CPU runningat2.10GHz,offering 8cores.The system boasted 4GB of RAM and a 512GB SSD for storage.Toac- celebrate computations, it incorporated an Nvidia GPU.

B. Analysis of Results

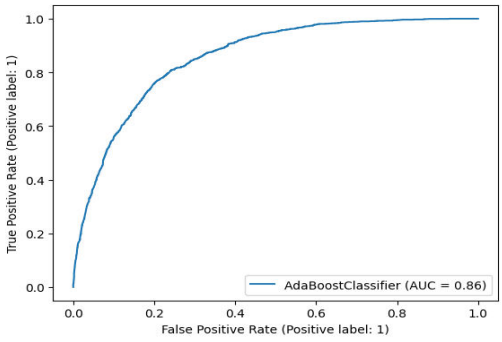

Fig 2: AUCROC ADB for training

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AUCROC The AUCROC (Area Under the Receiver Operating Characteristic Curve) ADB (AdaBoost) algorithm is a popular ensemble learning method that combines multiple weak learners to create a strong classifier. During training, the ADB algorithm iteratively improves the classification performance by assigning higher weights to the misclassified samples in each iteration. The AUCROC metric is used to evaluate the performance of the ADB model during training. It measures the trade-off between the true positive rate and the false positive rate, providing a comprehensive assessment of the model's ability to distinguish between different classes. As the ADB algorithm progresses through the iterations, the AUCROC value is calculated at each step to monitor the model's performance and guide the learning process. The goal is to maximize the AUCROC value by adjusting the weights of the weak learners and optimizing the decision boundaries to improve the overall classification accuracy. the AUCROC ADB algorithm is an effective and robust method for training classification models, especially when dealing with imbalanced datasets or complex decision boundaries. It provides a reliable measure of the model's performance and guides the training process towards better predictive accuracy.

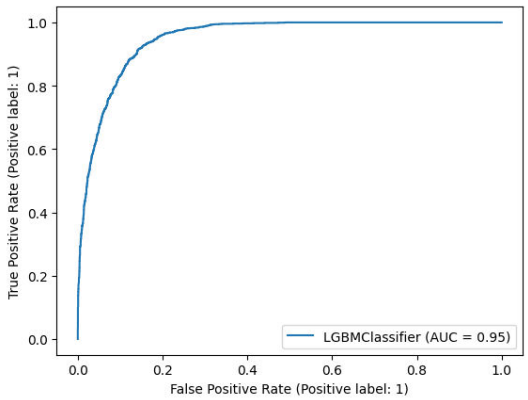

Fig 3: AUCROC LGBM Training

AUCROC (Area Under the Receiver Operating Characteristic curve) is a performance metric commonly used to evaluate the predictive power of a classification model, such as LightGBM (LGBM). Training LGBM with AUCROC involves optimizing the hyperparameters of the model in order to maximize the AUCROC score, which indicates how well the model can distinguish between different classes. During training, the LGBM algorithm is applied to a training data set to learn the patterns that differentiate between the classes. The algorithm iteratively adjusts the model parameters in order to minimize the loss function and improve its predictive accuracy. The AUCROC score is calculated by measuring the area under the Receiver Operating Characteristic curve, which is a plot of the true positive rate against the false positive rate at various threshold values. By training LGBM with AUCROC, we aim to create a high-performing classification model that can accurately predict the class labels of new data samples. This process helps to ensure that the model makes informed decisions and generalizes well to unseen data, ultimately leading to more reliable and robust predictions.

	precision	recall	f1-score	support
0	0.84	0.90	0.87	1291
1	0.66	0.54	0.59	467
accuracy			0.80	1758
macro avg	0.75	0.72	0.73	1758
weighted avg	0.79	0.80	0.80	1758

Fig 4: Classification Report on LR testing

Classification Report is a performance evaluation metric used in machine learning for classification models. It provides a breakdown of key metrics such as precision, recall, F1 score, and support for each class in the classification model.For a logistic regression (LR) model, the Classification Report would show the precision, recall, F1 score, and support for each class predicted by the model. Precision measures the proportion of true positive predictions among all

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positive predictions, recall measures the proportion of true positive predictions among all actual positives, and the F1 score is the harmonic mean of precision and recall. The support is the number of occurrences of each class in the dataset.A Classification Report on LR testing would provide insights into the performance of the LR model in classifying different classes. By analyzing the precision, recall, and F1 score for each class, you can determine how well the LR model is able to correctly classify instances of each class. This report can help you identify any potential issues or areas for improvement in the LR model's performance.

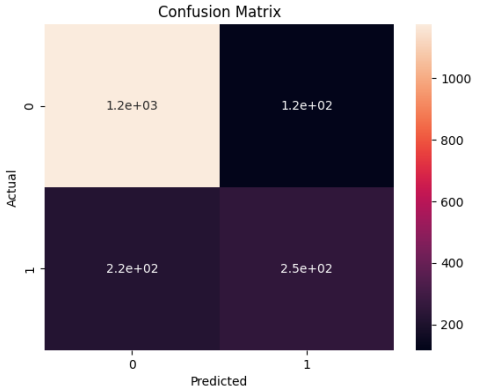

Fig 5: CM Testing

Configuration management (CM) testing is a process that ensures that the changes made to a software or system configuration are properly documented, tested, and verified before being implemented. This testing process evaluates the impact of configuration changes on the system's functionality, performance, and security. It helps to prevent issues such as configuration conflicts, system instability, and security vulnerabilities. CM testing also helps to ensure that the changes are properly tracked, managed, and deployed in a controlled and systematic manner. Overall, CM testing plays a crucial role in maintaining the integrity and reliability of systems and software configurations.

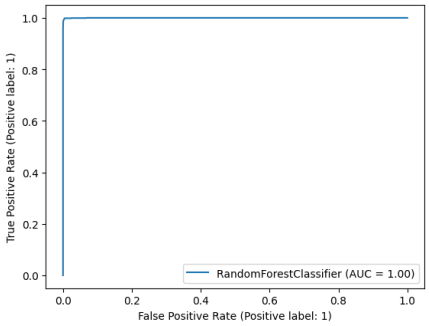

Fig 6: AUCROC RF Training

AUCROC RF Training is a machine learning training process that utilizes the Random Forest algorithm to evaluate the performance of a model through the area under the receiver operating characteristic curve (AUCROC). This training process involves building an ensemble of decision trees to classify data and calculate the AUCROC score, which is a measure of the model's ability to distinguish between classes. By training the model with the Random Forest algorithm, it can effectively handle large datasets with high-dimensional features and provide accurate predictions for classification tasks. This training process helps improve the model's performance and enhance its ability to make informed decisions based on the input data.

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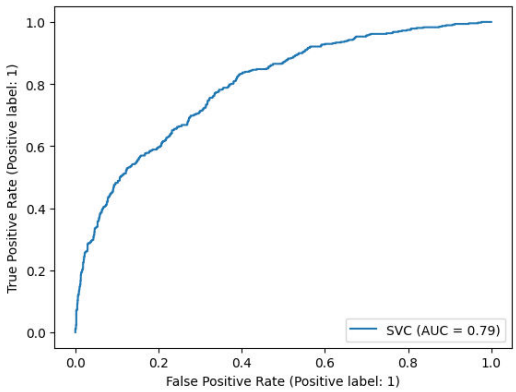
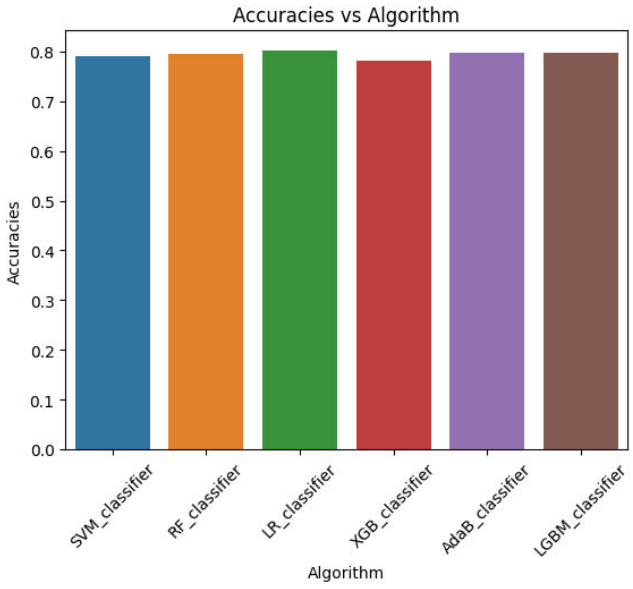


Fig 7: AUC ROC SVM Testing

Testing the performance of a Support Vector Machine (SVM) using the Area Under the Receiver Operating Characteristic Curve (AUC ROC) involves evaluating how well the model is able to distinguish between different classes or categories. The AUC ROC curve is a graphical representation that shows the trade-off between the true positive rate and the false positive rate of the model across different threshold values. The AUC ROC score is a single metric that summarizes the performance of the model, with a higher score indicating better discrimination between classes. During testing, the SVM model is trained on a labeled dataset and then tested on a separate set of data to evaluate its ability to classify new instances accurately. The AUC ROC score is calculated based on the predictions made by the model on the test set, comparing the predicted probabilities with the actual labels. By analyzing the AUC ROC score, we can assess the overall performance of the SVM model in terms of its ability to correctly classify instances and differentiate between classes. This information can help us understand how well the SVM model is performing and identify any areas for improvement.



Fi 8: Accuracy Comparision Testing

Accuracy comparison testing is a process in which multiple products, systems, or methods are tested to determine their accuracy and reliability in achieving a specific outcome. This type of testing involves evaluating the performance of each product in a controlled environment and comparing the results to determine which one is the most accurate. During accuracy comparison testing, various metrics are used to measure the performance of each product, such as precision, sensitivity, specificity, and error rate. These metrics help to determine the reliability and consistency of each product in producing accurate results. Accuracy comparison testing is commonly used in industries such as healthcare,

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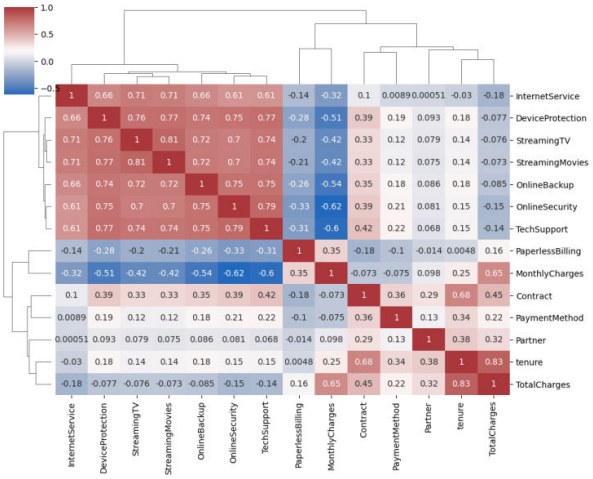
manufacturing, and technology to evaluate the performance of different tools, equipment, or software. By conducting this type of testing, organizations can make informed decisions about which product to use based on their accuracy and reliability in achieving the desired outcome.



9: correlation of features

A correlation value can range from -1 to 1, with 0 indicating no correlation, 1 indicating a perfect positive correlation, and -1 indicating a perfect negative correlation. Correlation analysis helps to understand how features are related to each other and can be used to identify patterns and relationships within the data. High correlation between features may indicate redundancy or multicollinearity, which can affect the performance of machine learning models. On the other hand, low or moderate correlation may suggest independent or complementary features that provide valuable information for prediction or classification tasks. Correlation of features plays a crucial role in data analysis and model building, helping to identify important relationships and optimize the selection of features for predictive modeling.

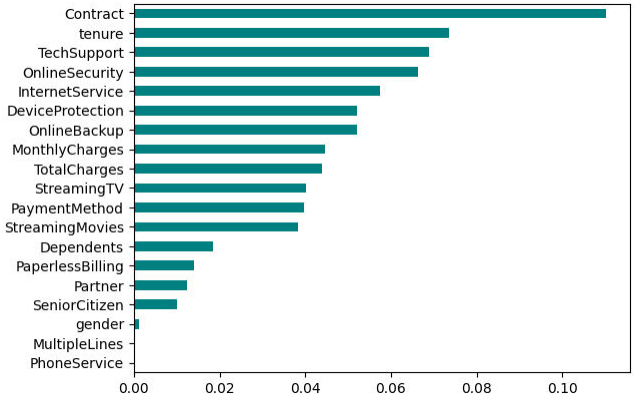


Fig 10: feature Selection using SelectKbest

SelectKBest is a feature selection method in machine learning that selects the k best features from a dataset based on their individual scores. The SelectKBest method evaluates the importance of each feature through a statistical test and assigns a score to each feature. The SelectKBest method can be applied to both classification and regression problems. It helps improve the performance of machine learning models by selecting only the most relevant features and reducing the dimensionality of the dataset. This can lead to better model accuracy, faster training times, and improved interpretability of the results. SelectKBest works by ranking the features based on their scores and then selecting the top k features with the highest scores. It allows you to specify the number of features to select (k) and the scoring function to use. Common scoring functions include chi-squared for classification tasks and f_regression for regression tasks.

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SelectKBest is a powerful feature selection technique that helps in identifying the most important features in a dataset and improving the overall performance of machine learning models.

V. CONCLUSION

In conclusion, churn prediction is a critical challenge for telecom companies as it affects revenue, market share, and customer satisfaction.The challenges involved in churn prediction include dealing with large volumes of historical customer data, handling noisy, incomplete, and highly dimensional data, and addressing imbalanced datasets. Various machine learning algorithms such as Random Forest, DecisionTree,XGBoost . can be used to solve this problem depending on the nature of the data and the specific requirements of the telecom company. By implementing machine learning algorithms for churn prediction, telecom companies can reduce churn rates, improve customer satisfaction, and gain a competitive advantage in the market

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