Journal of Trends and Challenges in Artificial Intelligence

Vol. 03, No. 02 (2026) 95-104, DOI: 10.61552/JAI.2026.02.004 - http://jai.aspur.rs

PREDICTING CUSTOMER CHURN WITH ADVANCED MACHINE LEARNING APPROACH

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Received 18.04.2025.
Revised 19.06.2025.
Accepted 06.07.2025.

Keywords:

Customer Churn, Rule-Based System (RBS), Attention-Based Model (ABM), Explainable Artificial Intelligence (XAI), random forest, bagging.

Original research

A B S T R A C T

Nowadays telecom business is transforming into a competitive market to take edge over their rivals. The customers are key element for any form of business, so it affects growth, profit, revenue, workload of the particular firm. As a result, large amount of data is collected and updated on regular basis by the customer feedback and behavior analysis of customer. As developing a new lot of customers are more expensive than retaining the existing customers. Telecom business analysts give their verdict about the existing customers likely to churn on the basis of customer behavior and response. Now customer retention policy which is initiated by various telecom businesses for prediction of customer churn allows firms to yield appropriate measures. For performing such measures, firms are applying different techniques and methods to distinguish their customers early through customer retention strategies. Machine learning techniques are utilized for customer churn prediction and classification, the main of aim of the model is to maintain the responses of existing customers' through the help of various machine learning algorithms. In this research, variety of model is developed for customer churn prediction such as Rule Based System (RBS), Attention Based Model (ABM) and Explainable AI (XAI). These set of models are utilized to analyze churn data gathered from customers, which results in effective predictions of churn customers making business management efficient and make proactive decisions during their churn period in order to avoid loss of customer churn as well as profit. The proposed system achieves the AUROC score of 84.8% for RBS, 85.6% for ABM and 88.4% for XAI. Moreover, the research work improves customer churn prediction along with additional features and has potential to be effectively equipped with telecom business.

1. INTRODUCTION

In today's competitive telecom sector, new firms are developing specialized efforts to provide a particular service that the customer not able to find from other providers. On an average, 10 to 30 percent of customers left a company annually in such competitive environment (Kayaalp, 2017). Newly established firms provide this service at a lower rate than the other service providers, which allows them to hold larger market share. As they can analyze the behavior of those customers early who will likely to churn and may retain them with some additional features and offers on the basis of their past records. Nowadays, customer acquisition can be expensive and time consuming, if prior analysis of

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customer behavior is not done then company tend to lose these customers (Jain & Srivastava, 2020). For certain service sectors having great competitive advantage, early prediction of customer churn will enhance additional revenue source (Qureshi et al., 2013). As the competition increases, the rate of the specific service provided by the organization is also increases. The aim of classification models is to identify churn customers accurately from the given dataset. From further studies, it was observed that some classifiers are effective for churn prediction (Pamina et al., 2019). Through the help of machine learning techniques, best predictive models are trained for classifying churning customers. The utilization of developed prediction model should be precisive in telecom industries (Varun et al., 2019).

In developed countries, telecom sector emerged as one of the key industries due to upgrade in technology and increased amount of corresponding supervisors boost the rivalry (Gerpott et al., 2001). Usually, customer churning happens with any service or product when there is variety of solutions for a single problem. Through business intelligence, business outcomes and corporate values are improved along with text analytics method (Pustokhina et al., 2021). Through business intelligence models, business actions like prediction of customer churn are raised (Boone et al., 2019).The main cause of customer churning is due to difficulties or dissatisfaction in the telecom services given by the provider and estimation of churn rate is performed for a specific time. With the help of customer churn dataset the problems faced by the customer are rectified and will be helpful to meet the customer requirements so that they will continue to utilize that service. Hence, customer churn management emerged as a major ask for telecom industry. Through the analysis of a recent research, customer churn prediction is widely performed by applying data mining techniques (Jain & Srivastava 2020). Data mining also able to extract vital input features for customer churn prediction and also increase the sample data through certain data preprocessing methods for further implementation (Kaur, 2017). As the heterogeneous data expands, firms require such technologies and mechanism to analyze such type of data (Raguseo, 2018). To handle lost values, instead of recognizing missing data and feature removal an algorithm called Predictive Mean Matching (PMM) is used (Yildiz & Varlı, 2015). The technique for collecting distributed data is called data wrangling (Berger & Kompan, 2019). In recent times, such a methodology was developed to assess customer churn uplift models through maximum profit uplift measure (Devriendt et al., 2021).

In real world, organizations have developed business intelligence methods to convince attentive customers. This results in planning and fulfilling client maintenance specifications for that organization. There are certain limitations of using existing methods that didn't meet with the current problem of churning. It seems to be a massive help for development of effective retention policies for a variety of churn customers depending upon their respective churn factors. In this research, a number of models are incorporated on the same dataset. Among those models the best fit for churning is described according to their respective accuracy scores. The potential models with effective important variables affecting the target variable are: Rule Based System (RBS), Attention Based Model (ABM) and Explainable AI (XAI). The key idea behind churn prediction is to minimize churns along with retaining the existing customers and also recommend the best solutions for telecoms.

The paper can be organized as follows: section 2 consists of the literature review of works and methods developed in recent times and milestones achieved, section 3 gives an overall description of our model or proposed system, section 4 shows the results obtained along with comparative study of deployed methodologies, and section 5 concludes the paper with its future aspects and limitations.

2. LITERATURE REVIEW

In this section, literature review of the research associated to customer churn prediction in industries such as telecom, banking and subscription based firms is mentioned. Various observations are done on customer churn prediction in different ways such as datasets, algorithms, feature extraction etc., for telecom industries. Distinct churn prediction systems or models have been developed in recent times. A churn model for the unofficial requirements, so that Recency Frequency Monetary (RFM) model is applied to predict those customers likely to churn using available datasets (Buckinx & Van den Poel, 2005). The detailed criteria related to knowledge in business analytics. Here input variables are preprocessed with implementation of advanced regularization methods to avoid overtraining (Feindt & Kerzel, 2006). The issue of unbalanced datasets imported in models and compared performance of various churn prediction models through the help of AUC and Lift metrics (Burez Van den Poel, 2009). There is a basic layout for upgrading data mining applications through enhanced technique which supports data mining technologies. This methodology is implemented in telecom industry in order to predict prepaid customers' attrition (Kraljevic & Gotovac, 2010). Genetic programming with AdaBoost boosting algorithm so as to identify churn problem in telecoms along with use of two datasets- Orange Telecom and cell2cell (Idris et al., 2012). Certain boosting algorithms in order to enhance performance of prediction models by separating them in dedicated clusters based on corresponding weights (Lu et al., 2014). Overcoming problems related to customer churn using big data platforms. It tests the affects of big data on analysis and performance of churn prediction model which largely depends on volume, variety and velocity of the data (Huang et al., 2015). Inter Arrival Times (IAT) factor in the gamma Cumulative SUM (CUSUM) table which utilizes a mixture model based on efficient decision interval and reference value as well as

gathering of different customers through help of ranked Bayesian model (Chen, 2016). A hybrid algorithm to predict churners is performing better than normal firefly algorithm. Ultimately, hybrid firefly algorithm is executing the model with reduced time latency (Ahmed & Maheswari, 2017). A churn prediction model using rough set theory and the rough set classification algorithm is generating better outcomes than Linear Regression, Voted Perception Neutral Network and Decision Tree (Makhtar et al., 2017).
Comparison of Boltzmann machine and Convolutional Neural Network (CNN) algorithms in order to predict customer churn in retailing industry (Dingli et al., 2017). A churn prediction model using Naïve Bayes machine learning algorithm for classification purposes and further applied Elephant Optimization algorithm on the dataset (Saraswat & Tiwari, 2018). A model for classifier's certainty estimation using distance factors for churn prediction, where dataset is grouped into several zones depending on the distance, which were separated into two classes having high and low certainty zones. Naïve Bayes had acquired an accuracy score in the zone belonging to high certainty as compared with those placed in the zone belonging to low certainty (Amin, 2019). A dataset consisting of huge customer records belonging to a telecom with their respective attributes having 2900 churners from the total customers. There is implementation of cross approval methods and learning models to monitor the exactness of the prediction (Andrews, 2019). A methodology whose outcomes display that their expectation model results in better performance to handle certain calculations using K-means grouping (Ullah et al., 2019). The process of feature extraction during customer churns prediction using state-of-art methods. It can be utilized to explore the features of existing models through distance zone methods, as their time complexity is very high (Geetha et al., 2020). Several prediction models as well as compared the efficiency and quality of prediction models. According to results obtained the accuracy of decision tree was found to be greater than other techniques and proved that it is an effective technique (Khalid et al., 2021). Another comparative analysis of developed churn prediction models, the model has utilized three machine learning algorithms with an optimization algorithm. Due to low ratio undersampling, some base versions perform lesser than other algorithms (Nabahirwa et al., 2022). A comparative analysis of various machine learning algorithms for customer churns prediction in telecom sector. While applying ensemble learning, it was found that Adaboost and XGBoost resulting in best accuracy, with AUC of 84% for churn prediction ensemble model (Lalwani et al., 2022). A hybrid resampling methods for churn prediction like SMOTE-ENN and SMOTE Tomek-Links, other productive resampling techniques for customer churn prediction (Kimura, 2022).
But sometimes the performance of the existing system is less, which can be decisive in the case of retaining the customers and gaining profit. To avoid such problems, various customer churn prediction models are deployed and compared to give best approach. The model proposed uses RBS, ABM and XAI techniques to effectively identify the clients who want to churn as well as to collect individual's response for the telecom sector.

3. METHODOLOGY

In this section, description of the model, system architecture, methodologies deployed and proposed algorithm is explained briefly.

3.1 Architecture of the Proposed Model

Customer churn prediction can be executed by using various machine learning techniques. Here the proposed methodology comprises of a few phases, as shown in Figure 1. The dataset is extracted from Kaggle as an input. During initial phases, knowledge analysis and preprocessing, feature extraction and selection are performed. Further, the input data is separated into train and test data in 70:30 ratio. The random forest models are implemented within the predictive system. Ultimately, generate a decisive system to predict customer churn. The resultant outcome of the developed model is analyzed and compared with other models. The aim of this analysis is to recommend best solutions for customer satisfaction and assist telecom industries to gain profit.

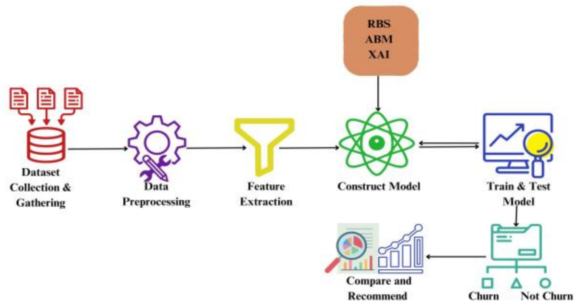

Figure 1. Flowchart of the proposed model.

3.2 Methodologies Deployed

The customer churn prediction can be done using three different methodologies of Machine Learning (ML) and Artificial Intelligence (AI) mentioned below.

1. Rule-Based System (RBS)
2. Attention-Based Model (ABM)
3. Explainable Artificial Intelligence (XAI)

3.3 Rule-Based System

Rule-Based System (RBS) is an important approach in Artificial Intelligence (AI) that applies some predefined rules in order to perform tasks or make decisions according to input data. These rules are primarily operated in a formal language like if-then statements, where distinct situations lead to equivalent actions. Through the combination of Rule-Based System (RBS) and Machine Learning (ML) both provides a way to enhance performance of the system. The purpose of applying ML is to develop and update the rules, while the main aim of applying RBS is to produce a structured architecture for applying these rules. Inference engine is responsible for assigning these rules with a given input. The mathematical representation for a rule-based system to provide precise decision making consists of two axioms:

Axiom 1: If condition (I) is true, then conclusion (O) is true.

Axiom 2: Therefore,

$$\mathbf{R} = (\mathbf{I}, \mathbf{O}) \tag{1}$$

where:

- I = Set of rules/Boolean condition
- O = Set of facts that satisfies the condition/Boolean conclusion
- R = Action to be performed based on certain rules

Algorithm of Rule-Based System

1. Gather significant data for training the RBS-ML model.
2. Perform feature extraction on the input data.
3. Train the RBS-ML model.
4. Perform rule extraction from the resultant model.
5. Use domain knowledge to update the extracted rules.
6. Apply the updated rules in the RBS-ML model
7. Implement RBS-ML for new data input using the inference engine.
8. Evaluate the performance of the system.

Firstly, the model retrieves input customer churn data required to be processed. Then, evaluation of input data is done using inference engine in contrast to predefined rules assigned by knowledge base. If the rules are met according to conditions declared, then the further actions will take place; otherwise whole process terminates. The developed system performs actions only when the rules are triggered and the outcomes of the actions are displayed to the user. The complete design of RBS is depicted in Figure 2.

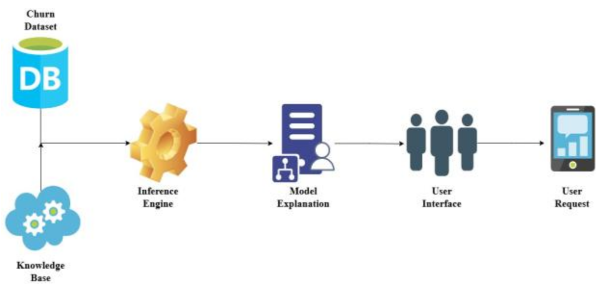

Figure 2. Flowchart of Rule-Based System.

3.4 Attention-Based Model

Attention-Based Model (ABM) is an elementary component in various machine learning models, especially in computer vision and Natural Language Processing (NLP). These models generally highlight on specific modules of input data and assign varying weights or labels to different units according to their importance of task at hand. Ultimately, improving their ability to gather key information and knowledge. These mechanisms facilitate models to dynamically arrange different input components through their weigh importance. The mathematical representation for an attention-based model to provide precise decision making is as follows:

- Let us consider an input sequence of size S and a hidden layer p, the attention weights α for each time v, W(c), W(p) and W(x) are learned parameters.
- x represents the input parameter with respect to time t.
- c represents the context vector which denotes a weighted sum of all input elements and the weights assigned are the attention weights.

$$\mathbf{c} = \Sigma\, \mathbf{t}.\boldsymbol{\alpha}.\mathbf{x} \tag{2}$$

- t can be calculated as follows:

$$\boldsymbol{\alpha} = \mathbf{softmax(q)} \tag{3}$$

$$\mathbf{q} = \mathbf{v^S\,tanh\,(W(p)\,.\,p + W(x).\,x)} \tag{4}$$

- The resultant output of the attention-based models is obtained by a combination of context vector (c) and the hidden layer (p):

$$\mathbf{p' = tanh\;(W(c)\,.\;c + W(p)\,.\;p)} \tag{5}$$

Algorithm of Attention-Based Model

1. The model gathers an input sequence of components from the customer churn dataset.
2. Encoding of input components into hidden layers.
3. For each hidden layer, corresponding attention weights are calculated.
4. Apply softmax function on attention weights.
5. Computation of context vector using resultant attention weights.
6. The resultant outcome is generated on the basis of context vector and hidden layers.

Initially, preprocessing of the received input sequence is occurred along with generation of queries, keys and values. Further calculating the attention weights by mapping each query with available keys, also calculating attention weights for each hidden layer. All the weights are normalized with the help of softmax function so that resultant attention weights are obtained. Next, a context vector is assigned by weighted sum of values according to respective attention weights. Ultimately, outcome is generated through the combination of context vector and hidden layers. The complete design of ABM is depicted in Figure 3.

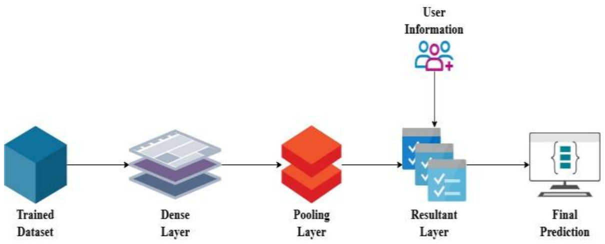

Figure 3. Flowchart of Attention-Based Model.

3.5 Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) is an essential domain in machine learning whose main concept is to build decision-making models for AI systems which is understandable to humans. It is usually necessary in fields where decisions have some noticeable effect on the product or service such as telecom. XAI develops such technique that enables the users to understand and trust the outcomes generated by machine learning algorithms. Explainability was raised in order to resolve the vulnerabilities associated with traditional methods, usually leads to doubt among users. A popular method called LIME (Local Interpretable Model-Agnostic Explanations), which estimates a models's predictions by locally fitting an interpretable model. The mathematical representation for an Explainable AI model to provide precise decision making is as follows:

$$\mathbf{E(a) = L(m, n, \Pi_a) + \Omega(n)} \quad \mathbf{(6)}$$

where:

- a is a binary vector
- E(a) is the explanation function
- m describes the feature set
- n is a machine learning model
- $L(m, n, \Pi_a)$ measures the fidelity of local approximation
- $\Omega(n)$ quantifies the complexity of the model n

Algorithm of Explainable AI

1. Train the developed machine learning model on the customer churn data.
2. Select a relevant XAI technique based on working of model with proper explanation.
3. Apply the selected XAI technique on trained model.
4. Understand the decision making of model to analyze the explanations assigned by XAI technique.
5. Compute Feature Importance based on the resultant model.
6. Generate vital explanations for Predictive models and evaluate.
7. Update the model according to the observations taken from the explanations if necessary.

Initially, collect the input data and prepare it for the desired machine learning model. Further train the model using preprocessed data, which can recognize and learn key patterns. Next, the prediction of machine learning model is done. LIME is implemented on the model in order to estimate a model's prediction through local fitting of an interpretable model based on requirements. This method provides the feature contribution and makes prediction on the most important feature. These explanations are evaluated according to feature importance of each component of the model. Ultimately, it can be forwarded to the customer to understand the specifications related to the telecom service. The complete design of XAI is depicted in Figure 4.

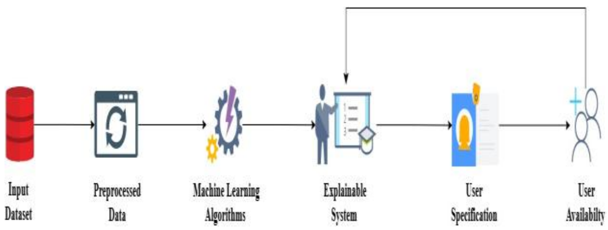

Figure 4. Flowchart of Explainable Artificial Intelligence.

3.6 Dataset Analysis

The dataset for customer churn prediction is gathered from Kaggle. This dataset consists of data of an organization that provides telecom service to some customers.

Table 1. Dataset Attributes.

S. No	Column	Count	Non-Null	Dtype
0	customer_id	243553	non-null	int64
1	telecom_partner	243553	non-null	object
2	gender	243553	non-null	object
3	age	243553	non-null	int64
4	state	243553	non-null	object
5	city	243553	non-null	object
6	pincode	243553	non-null	int64
7	date_of_registration	243553	non-null	object
8	num_dependents	243553	non-null	int64
9	estimated_salary	243553	non-null	int64
10	calls_made	243553	non-null	int64
11	sms_sent	243553	non-null	int64
12	data_used	243553	non-null	int64
13	churn	243553	non-null	int64

It describes the complete history of the customers who have exited, retained or continued to pursue their service. Also gathered information from the customers through digital feedback that are churned and analyzed their

behavior before happening of actual churn. Each column of data provides information about.
Key insights of the dataset:-
1. Clients who left or got churned
2. Type of administrations used by customers
3. Customer account information
4. Segment data concerning customers

The elements of the dataset along with some indexes are shown in Table 1.

3.7 Feature Selection

The collected dataset for customer churn prediction can be split into train and test data in a scale of 70:30 respectively. Feature selection is necessary to achieve model's quality. Due to unwanted data present in input dataset while training the desired model, resulting in decrement of model's performance. Therefore, feature selection is utilized to resolve these issues. Its main aim is to improve accuracy, reduce overfitting and generate less complex algorithms.
Random forest is the machine learning algorithm comprises of multiple decision trees. Due to greater number of decision trees, performance is enhanced during prediction. More trees led to more robustness during prediction with greater performance. Bagging is the technique to build a non-correlated collection of decision trees working more precisely than an individual decision tree. Decision trees generate their own output after inserting churn dataset, such that final output will be examined from the bulk of trees. Selection of any random attribute from the churn dataset is done through the support of decision trees. The mathematical representation of random forest for effective feature selection is as follows:

- Consider a random forest n_T with T_i decision trees (where i=1, 2,…, n_T) such that each tree is constructed using random training data and features at every split.
- The predicted output $\hat{y}$ for an input vector x can be obtained by averaging the individual tree prediction:

$$\hat{\mathbf{y}} = \frac{1}{n_T}\sum_{i=1}^{n_T} \mathbf{T_i(x)} \quad (7)$$

where $T_i(x)$ is the prediction made by an individual tree i.

- For node splitting, Gini impurity is used during construction of each tree. The Gini impurity I at any node j for tree T_i can be calculated by the following expression:

$$\mathbf{I(j) = p(j)(1 - p(j))} \quad (8)$$

where p(j) is portion of sample data arriving at node j.

- Ultimately, the feature importance f_j across all trees can be calculated as-

$$\mathbf{f_j = \frac{1}{T}\sum_{t=1}^{T} norm\ f_{ij}} \quad (9)$$

where T is total number of trees in forest and norm f_{ij} is normalized importance of a feature j in tree t.

Algorithm of Random Forest
1. Select alter random samples from the trained sample data. 2. Select random features from total available features. 3. Construct a decision tree consisting of selected random samples and features. 4. Split the node further into child nodes according to calculated split criterion. 5. Repeat steps 1 to 3 to build multiple decision trees, forming a forest of such decision trees. 6. Pass new data point across decision trees to draw predictions. 7. For customer churn prediction, bagging is applied to make final prediction. 8. Evaluate the model's performance using AUROC metrics.

Initially, random data points and features are selected. Then, decision trees are constructed on the basis of trained data. Select N trees which results in forest of such trees further making prediction on those trees. Average predictions are obtained before final prediction in order to analyze the behavior of customers effectively. The working of random forest is depicted in Figure 5.

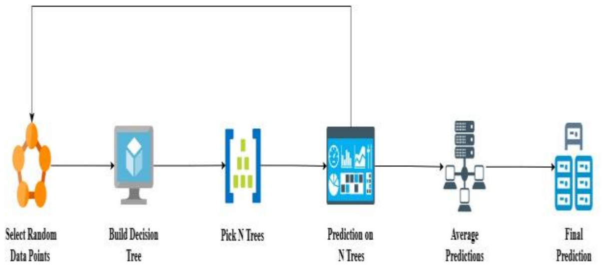

Figure 5. Working of Random Forest.

Essential components responsible for churning after applying random forest model are arranged according to feature importance, which is shown in Figure 6.

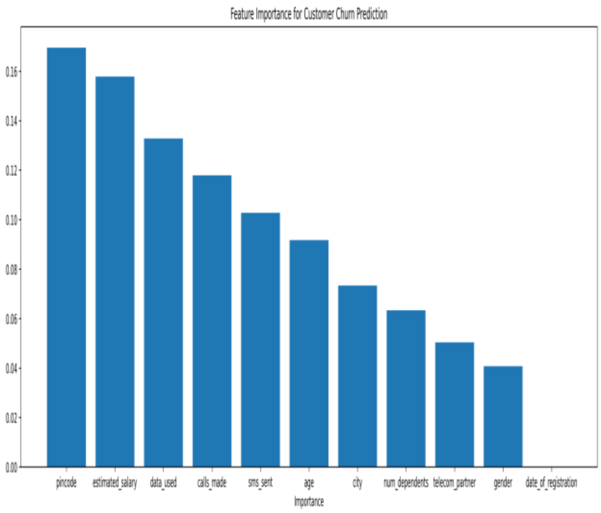

Figure 6. Feature Importance.

4. RESULTS AND DISCUSSIONS

In this section, results are obtained after the application of proposed algorithm with RBS, ABM and XAI. Jupyter libraries were employed with Python programming language to provide results, which comprises of several vital libraries. The results are gathered after evaluating the performance of an individual model and ultimately compared with each other on the basis of some evaluation metrics.

4.1 Prediction of the RBS

In RBS, random forest is deployed as a classification algorithm to identify churn patterns. The results acquired from customer churn prediction are shown in Figure 7. The training accuracy score is 0.846, the testing accuracy is 0.837 and the AUROC is 0.842.

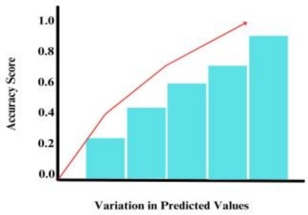

Figure 7. Predicted Graph (RBS).

4. 2 Prediction of the ABM

In ABM, random forest is deployed as a classification algorithm to identify churn patterns. The results acquired from customer churn prediction are shown in Figure 8. The training accuracy score is 0.864, the testing accuracy is 0.857 and the AUROC is 0.861.

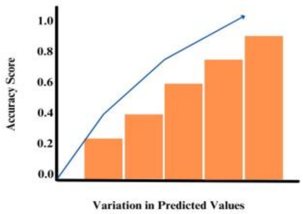

Figure 8. Predicted Graph (ABM).

4.3 Prediction of the XAI

In XAI, random forest is deployed as a classification algorithm to identify churn patterns. The results acquired from customer churn prediction are shown in Figure 9. The training accuracy score is 0.886, the testing accuracy is 0.878 and the AUROC is 0.882.

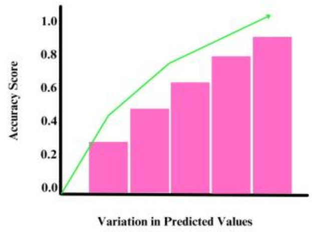

Figure 9. Predicted Graph (XAI).

4.4 Overall Comparison of the Models

The three developed models are taken for comparative analysis depicted in Table 2. All models were compared on the basis of their ROC values are given in Figure 10. It was observed that XAI performs better than RBS and ABM. Further, comparison and analysis of all models according to evaluation metrics is given in Figure 11.

Table 2. Comparison of RBS, ABM and XAI.

Scope	RBS	ABM	XAI
Description	Based on the results of the inference process, the system makes a decision or takes an action.	The weighted inputs are combined to produce the final output, where the more important elements contribute more significantly.	Explainability can help identify and mitigate biases within machine learning models, ensuring that they are fair and equitable.
AUROC	0.842	0.861	0.882
Benefit	Rule-based systems can be easier to develop and maintain compared to complex machine learning models.	Attention weights can provide insights into the model's reasoning, making it easier to understand how it arrived at a particular decision.	Explainability can facilitate collaboration between AI experts and domain experts, leading to more effective AI solutions.
Comparison	Gives decent performance	Better than RBS	Provides Best Performance

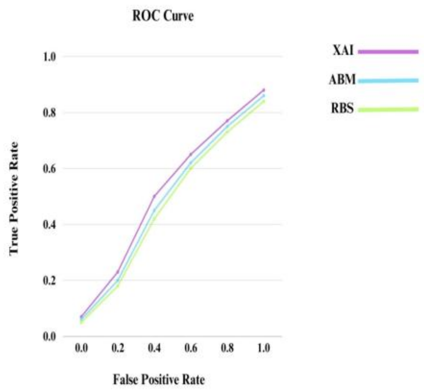

Figure 10. ROC Plot for Proposed Models.

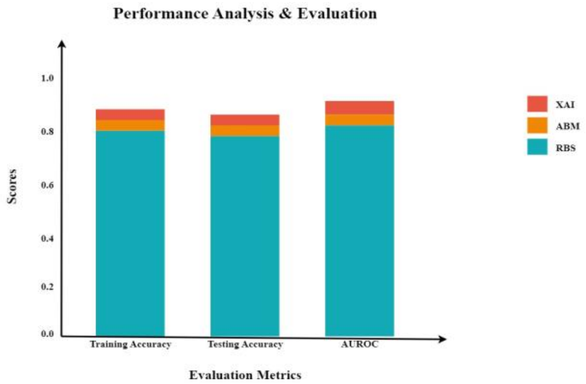

Figure 11. Comparative Analysis of RBS, ABM and XAI.

Therefore, XAI can be useful in telecom industries in order to predict better churn rates, enhanced retention rates and increased revenue. The proposed model can be amended into customer management portal in order to observe customer behavior and further predict corresponding retention rate. It will be useful to classify the customers likely to churn and can further upgrade according to their needs.

5. CONCLUSIONS

The proposed model has analyzed the customer churn dataset and makes predictions according to the three developed models- RBS, ABM and XAI. Further the performance of all models was examined for analyzing better algorithm. Receiver Operating Characteristics (ROC) and Area Under Curve (AUC) were used to evaluate the performance of all models. Further, it is drawn that XAI model performs better with an AUROC of 0.88. It can be concluded that the incorporated model works effectively in order to fulfill the vital components for analyzing the desired machine learning algorithm necessary for building customer churn prediction models. Further, identifies churn causes so that better retention strategies and methods would be provided. Also, employees present in the customer management cell of the telecom industries should analyze that customer loss will occur later according to which they adapt to these circumstances. Therefore, proposed model is efficient to solve such problems which would be crucial for existence of any telecom company. Hence, this research aims to identify optimal machine learning model for customer churn prediction and picking the genuine reasons that make customers churn in telecom industry. Ultimately, it is observed that moderating customer effort is one such approach to improve customer retention. In future, this churn prediction system will become more complex and advanced to provide precise support. Further Recurrent Neural Networks (RNN's) is utilized to identify complex patterns between data variables to assess survival likelihood. Also the research can be focused to perform tasks like dataset cleaning and extensive tuning. In order to carry out precise machine depth better techniques and methods will be developed.

Acknowledgement: I would like to express my sincere gratitude to Dr. Sachin Gaur for their guidance and support throughout this research.

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