A Major Project Report

On

PATRON DEFECTION DATA ANALYSIS

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

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(Approved by AICTE, NEW DELHI and Affiliated to JNTUK, Kakinada)

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CERTIFICATE

This is to certify that the major project entitled "Patron Defection Dta Analysis", is a bonafide work of G.Lakshmi Sravani (20NN1A0575), S.Lavanya (20NN1A05A4), S.Vijaya Lakshmi (20NN1A05B1) and S.Sri Lakshmi Prasanna (21NN5A0508) submitted to the faculty of Computer Science And Engineering, in the partial fulfilment of the requirements for the award of degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING from VIGNAN'S NIRULA INSTITUTE OF TECHNOLOGY AND SCIENCE FOR WOMEN, GUNTUR.

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We hereby declare that the work described in this major project work, entitled "Patron defection data analysis" which is submitted by us in partial fulfilment for the award of Bachelor of Technology in the Department of Computer Science and Engineering to the Vignan's Nirula Institute of Technology and Science for women, affiliated to Jawaharlal Nehru Technological University Kakinada, Andhra Pradesh, is the result of work done by us under the guidance of Dr.A.Naresh, Associate Professor.

The work is original and has not been submitted for any Degree/ Diploma of this or any other university.

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Patron Defection Data Analysis

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ABSTRACT

The modern business environment presents service providers with increasing competition as well as changing customer preferences, which makes it imperative to lower customer churn—the phenomenon when customers stop doing business with a company. This research investigates the effectiveness of different machine learning techniques for churn prediction in a range of businesses, highlighting the necessity of keeping current customers in the face of growing markets and rising acquisition prices. Among the well-known approaches examined are ensemble methods, K-nearest neighbors, neural networks, decision trees, random forests, gradient boosting machines, support vector machines, and gradient boosted trees. Furthermore, it emphasizes how crucial feature engineering is to improving churn prediction models by obtaining relevant consumer information including usage patterns, transaction histories, and demographics. By implementing these techniques, service providers can proactively.

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LIST OF ABBREVIATION

ROI - Return On Investment

KNN - K-Nearest Neighbors

CRM - Customer Relationship Management

CCP - Customer Churn Prediction

SOM - Self-Organized Maps

ANN - Artificial Neural Network

UNL - Unified Modeling Language

NBC - Naïve Bayes Classifier

DT - Decision Tree

LR - Logistic Regression

Chapter – 1 INTRODUCTION

CHAPTER - 1 INTRODUCTION

1. Introduction

In nations with advanced economies, the telecommunications industry has grown to be one of the key sectors. The volume of competition has increased due to advancements in technology and an increase in the number of operators. Businesses are using a variety of tactics and putting in a lot of effort to thrive in this cutthroat environment. To enhance revenue, three primary tactics have been suggested: (1) acquiring new customers; (2) upselling current customers; and (3) lengthening the client retention term. But when these strategies are compared and their respective come back on investment (RoI) is taken into consideration, it becomes clear that the third method is the most effective. It also demonstrates that keeping an existing customer is far less expensive than gathering a new one, and it is also thought to be much simpler compared to the upselling strategy. Using the third technique businesses must lessen the possibility of "the movement of customers from a single provider to another," often known as customer churn.

A major worry in service industries with fierce competition is customer attrition. However, if done early on, identifying the clients who are most likely to abandon the organization might result in a sizable increase in income. Numerous studies have demonstrated how successful machine learning technique is in foreseeing this kind of scenario. This method is used by using lessons learned from historical data.

A common definition of "churning" is the proportion of customers that terminate their contracts because of rivalry. Churners are clients who have left a company because they were dissatisfied with the level of service they received. An analysis of the probability that a client would stop using a good or service is known as a consumer churn analysis.

These days, the market is extremely competitive and dynamic. The availability of a vast array of service providers is the reason behind this. Since they are a company's

main source of income, customers are its most important asset. Companies today understand that maintaining the satisfaction of their current customer base is just as important as acquiring new ones.

A churner is someone who is constantly on the go for a multitude of reasons. When an organization can predict customer mentality with accuracy and create connections between loss of customers and controllable factors, customer churn is reduced.

One binary classification task that distinguishes churners from non-churners is predicting churn ratesAny business that wants to beat out new clients must walk through the sales funnel and use its advertising and sales resources to close the loop. In contrast, customer retention is typically more cost-effective because it has already gained the trust and loyalty of existing clients. Thus, it is critical for a firm to anticipate client attrition early.

To mitigate the aforementioned discomfort, enterprises need to possess the ability to precisely predict the purchasing patterns of their clientele. Two strategies exist for reducing client attrition: Above all, be (1) Reactive and (2) Proactive. A proactive agency offers the customer enticing options as soon as they request a cancellation in order to keep their business. Since the proactive method foresees that some consumers may go, it offers a plan for them to adhere to. The binary task classifies the churners and non-churners. We applied a couple of machine learning strategies to address this issue: Utilizing boosting methods such as XGBoost, Logistic Regression (LR), the KNN, the decision tree classifier, random-forest classification algorithm. Additional tree classification algorithm, Ridge classifier, and Bagging Ridge classifier,

Chapter – 2 LITERATURE SERVEY

CHAPTER – 2 LITERATURE SERVEY

2. LITERATURE SURVEY

Comparing oversampling techniques to handle the class imbalance problem a customer churn prediction case study" by Amin A, Anwar S, Adnan A, Nawaz M, Howard N, Qadir J, Hawalah A, and Hussain A aimed to tackle the challenge of class imbalance in customer churn prediction models. By employing oversampling techniques, the researchers sought to rebalance the dataset for more accurate predictions.

Evaluation of churn rate using modified random forest technique in telecom industry. The modified random forest model achieved 92.7% accuracy in predicting customer churn, outperforming the standard random forest model. Feature engineering and normalization were key factors in improving the accuracy of the churn prediction model.

A proposed churn prediction model. The clustering step produces 3 clusters for retention strategy evaluation. The churn prediction model aims to detect customers likely to leave a service provider using Data Mining techniques for classification and clustering. The SVM technique yielded the best accuracy rate of 83.7%, with error rates ranging from 16.3% to 22.1% for different techniques.

Comparative Analysis of Different Machine Learning Algorithms to Predict Online Shoppers Behavior. The study compares various machine learning algorithms to predict online shoppers' behavior. Algorithms like Gradient Boosting (GB), Random Forest (RF), Support Vector Machine (SVM), and others were evaluated. The best performing algorithm, GB classifier, achieved an accuracy of around 91% and a precision of 76%.

Developing a Prediction Model for Customer Churn from Electronic Banking Services. The paper presents a predictive model for customer churn in electronic banking services using logistic regression and decision tree algorithms. It achieved high accuracy with an AUC of 0.929 and precision, recall, and F-measure values of 91.81%, 91.00%, and 90.96% respectively.

Customer Churn Prediction Using Four Machine Learning Algorithms. It utilized feature selection, normalization, and feature engineering techniques to enhance model performance. The experiments showed that Gradient Boosting with feature selection outperformed other algorithms, achieving a 99% F1-score and 99% AUC, indicating the effectiveness of machine learning in predicting customer churn in the telecom sector.

Customer churn prediction in telecom using machine learning in big data platform By leveraging a big data platform, the research aims to improve the efficiency and effectiveness of churn prediction models in the telecommunications sector. However, challenges related to data availability and feature engineering remain as potential limitations in this domain.

Customer Churn Prediction in B2B Contexts. The study proposes a two-stage process involving data mapping and prediction modeling to predict customer churn effectively in B2B contexts. It emphasizes the significance of single customers in B2B businesses and the impact of losing them.

A Churn Model for Swiss Mandatory Health Insurance. The model focuses on actuarial pricing, predicts portfolio structure, and considers premium sensitivity. The accuracy of the model is evaluated using metrics like Pricing Loss, Binomial Deviance, and AUC.

A Survey on Customer Churn Prediction using Machine Learning Techniques. The paper reviews popular machine learning algorithms for churn prediction, emphasizing the importance of retaining customers in a competitive market. It discusses the use of SVM with boosting algorithms to address churn issues and suggests constant model development for improved accuracy.

Title	Author	Year	Algorith	Advantag	Accuracy	Limitations
		Publish	ms Used	es		
		ed				
Comparin	Jutla DN,	2016	Gradient	Enhanced	The study	Limited
g	Sivakumar		Boosting	prediction	was 93.3%	availability of
oversampl	SC, Zhan J,		Model,	accuracy	using the	data due to
ing	Guidibande		Weighted	in	XGBOOS	restrictions
technique	V, Parsa		Random	customer	T	from telecom
s to	SPK		Forests,	churn	algorithm	companies
handle the			XGBOOS	models.		

class imbalance problem: a customer churn prediction case study	D.C.	2010	T			
Evaluatio n of churn rate using modified random forest technique in telecom industry	P.Swetha, S.Usha, and S.Vijay anand	2018	Random Forest	Improved evaluation of churn rate in the telecom industry	An accuracy of 92.7% with the random forest technique	It focuses solely on performance of the random forest model without comparing it to other machine learning algorithms.
A proposed churn prediction model	Shaaban E, Helmy Y, Khedr A, Nasr M	2012	Churn prediction model- DT, SVM, and NN for classificat ion and K Means for clustering	Predicts customer churn effectivel y	SVM technique yields an accuracy rate of 83.7% and an error rate of 16.3%	Lacks in-depth interpretation of churn reasons and detailed discussion on classification technique
Comparat ive Analysis of Different Machine Learning Algorithm s to Predict Online Shoppers Behaviour	Veena Parihar, Surendra Yadav	2022	Gradient Boosting (GB) classifier, Random Forest (RF), Support Vector Machine (SVM), and others	GB classifier showed the best performan ce with 91% accuracy and 76% precision	The accuracy of the best performin g algorithm, Gradient Boosting (GB) classifier, in predicting online shoppers' behavior was around 91%	he study focused on online shopping behavior prediction, may not cover all aspects of consumer behavior
-	Keramati A, Ghaneei H, Mirmoham madi SM	2016	Logistic regression , decision tree	Prediction model developm ent for	Achieved an AUC of 0.929 with precision,	A time-consuming process of data extraction.

Customer Churn				electronic banking	recall, and F-measure	
from				services	values of	
Electronic					91.81%,	
Banking					91.00%,	
Services					and 90.96%	
Customer	Alanoud	2023	Random	Integratin	Achieved	The lack of
Churn	Moraya	2023	Forest,	g feature		detailed
Prediction	Aldalan,		Decision	selection	accuracy	comparison
Using	Abdulaziz		Tree	and	rates, with	with a broader
Four	Almaleh			normaliza	the	range of
Machine				tion in the		algorithms
Learning				telecom	Boosting model	beyond the four selected.
Algorithm s				sector	outperfor	Tour selected.
3					ming the	
					other	
					experimen	
					ts by	
					achieving a 99% F1-	
					score and	
					99% AUC.	
Customer	Abdelrahim	2019	Random	Enhanced	The	Limited
churn	Kasem		Forest,	prediction	accuracy	availability of
prediction in telecom	Ahmad, Assef Jafar,		Neural Networks,	accuracy using	achieved in the	data for research
using	Kadan		Support	machine	telecom	purposes
machine	Aljoumaa		Vector	learning	sector	Purposes
learning	3		Machine,	technique	using	
in big data			Gradient	S	machine	
platform			Boosting		learning	
					was 93.3% with the	
					XGBOOS	
					T	
					algorithm.	
Customer	Iris Figalist,	2020	Enables	Data	Accuracy	Lack of
Churn	Christoph		prediction	mining	rates	research on
Prediction in B2B	Elsner, Jan		based on	technique	above 80%	achieving
in B2B Contexts	Bosch, and Helena		customer and end-	s, Random Forest	are considered	customer churn
Contexts	Holmström		user data,	Torest	good for	prediction in
	Olsson		considers		customer	B2B contexts,
			influencin		churn	challenges in
			g factors,		prediction	applying B2C
			and helps		in B2B	approaches to
			in		contexts	B2B
			retaining			environments,

Insurance	A Churn	Lena	2022	customers in B2B environm ents	Logistic	Model	and differences in perceived value between B2B and B2C customers Evaluation of
y Health Insurance Predicts portfolio structure. Develops pricing loss function A Survey Saran Customer Churn Chandrakal Prediction using Machine Prediction using Machine Learning Techniqu es Ocontext, Predicts machine Pricing Loss, Binomial Deviance, and AUC Providing insights hoosting may lack interpretability accuracy strategies and machine Prediction with Boosting and Constant work development needed for structure. Develops pricing loss function A Survey Saran Customer and Dr. Networks, for algorithms interpretability interpretability accuracy and affect prediction and Dr. SVM strategies accuracy and affect prediction accuracy. Constant development needed for survey work development needed for structure. Develops machine extensively researched Pricing Loss, Binomial Deviance, and AUC SVM with boosting may lack interpretability interpretability accuracy and affect prediction accuracy affect work development needed for survey.	Swiss	Schütte		actuarial	,	ce	performance
Structure. Develops pricing loss function A Survey Saran on Kumar.A Customer Churn Chandrakal Prediction using Machine Learning Techniqu es Structure. Develops pricing loss function Hybrid Providing SVM with boosting may lack insights hoosting algorithms interpretability accuracy interpretability accuracy and affect performan ce as accuracy. Forests, shooting may lack interpretability accuracy and affect performan ce as accuracy. Constant work development needed for	y Health			context,	boosting	using	pricing risk not
A Survey Saran customer Churn Chandrakal Prediction a D. A Survey Saran Survey Saran Survey on Kumar.A Customer Churn Chandrakal Prediction a D. A Survey Saran Survey Saran Survey on Kumar.A Survey on Kumar.A Survey on Kumar.A Survey on Kumar.A Survey Saran Survey Saran Survey Survey on Survey on Survey on Survey Survey on				structure.		Binomial	researched
A Survey Saran 2016 Hybrid Providing SVM with Some models Neural insights boosting may lack Networks, for algorithms interpretability Interpretability SVM strategies and Interpretability Interpretability SVM strategies and Interpretability Inte				pricing			
on Customer and Dr. Churn Chandrakal Prediction using Machine Learning Techniqu es Neural Neural insights for algorithms for higher accuracy and affect work accuracy. Algorithm s future work development needed for higher accuracy.							
Customer Churn Chandrakal Prediction using Machine Learning Techniqu es	A Survey		2016	•	_		
Churn Prediction a D. Random targeted for higher accuracy and affect performan ce as future Solution work development solution. Data imbalance can accuracy and affect performan ce as future work development needed for	_				_	_	-
Prediction using Machine Learning Techniqu es				· · · · · · · · · · · · · · · · · · ·		_	
Machine Learning Techniqu es Model with Boosting Algorithm s performan prediction accuracy. Constant development needed for	Prediction			Forests,	marketing	accuracy	imbalance can
Techniqu es Boosting Algorithm s future work Constant development needed for	_			Model	C	performan	prediction
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s needed for	Techniqu						
	es			Algorithm		work	*
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models							_

Chapter - 3 SYSTEM ANALYSIS

3.1 EXISTING SYSTEM:

The existing system for a Patron Defection Data Analysis project involves a combination of tools and technologies designed to collect, store, analyze, and report on customer data. Data collection tools, such as CRM systems and online surveys, gather information from various sources like transactions and interactions. This data is then stored securely using databases or data warehouses. Before analysis, the data undergoes preprocessing to clean and transform it. Statistical analysis and predictive modeling techniques are then applied to identify patterns and forecast patron defection. Visualization tools help communicate the findings through charts and dashboards, while integration and automation streamline processes. Security measures ensure data privacy and compliance with regulations, and ongoing monitoring and maintenance ensure the system's reliability and performance.

Drawback:

One drawback of the existing system is the potential for data fragmentation and security concerns due to disparate sources and complex integration processes.

3.2 PROPOSED SYSTEM:

This paper is a relative study on the implementation of models using Logistic Regression and XGBoost algorithms, applied on a dataset that is taken from Kaggle repository. With respect to the results of accuracy, precision, recall, specificity and False Positive Rate the efficiencyof each algorithm is calculated and compared. All algorithms are written in python and executed in Google Colab, the Scientific Python Development Environment. Our experiments have shown that both Logistic Regression and XGBoost are the best algorithms for prediction with an accuracy of 80.38% and 80.103% each individually. As a result of our study that XGBoost is the extremely fast, stable, faster to tune and robust to randomness, which is well suited for tabular data where as A logistic regression model will try to guess the probability of belonging to one group or another. The logistic regression is essentially an extension of a linear regression, only the predicted outcome value is between [0, 1]. The model will identify relationships between our target feature, Churn, and our remaining features to apply probabilistic calculations for determining which class the customer should belong to.

- 1. Accuracy is high.
- 2. Efficient inference
- 3. Rate of hyper-parameter tuning (shorter the optimization time, the better)

Advantage:

XGB boosting is an algorithm consisting of a group of weaker trees that add up their calculations to predict their target variable with better accuracy.

3.3 PURPOSE OF THE SYSTEM:

The globalization and advancements of telecommunication industry, exponentially raises the number of operators in the market that escalates the competition. In this competitive era, it has become mandatory to maximize the profits periodically, for that various strategies have been proposed, namely, acquiring new customers, up-selling the existing customers & increasing the retention period of existing customers. Among all the strategies, retention of existing customers is least expensive as compared to others. In order to adopt the third strategy, companies have to reduce the potential customer churn i.e., customer movement form the one service provider to other. The main reason of churn is the dissatisfaction of consumer service and support system. The key to unlock solutions to this problem is by forecasting the customers which are at risk of churning.

One of the main aim of Customer Churn prediction is to help in establishing strategies for customer retention. Along with growing competition in markets for providing services, the risk of customer churn also increases exponentially. Therefore, establishing strategies to keep track of loyal customers (non-churners) has become a necessity. The customer churn models aim to identify early churn signals and try to predict the customers that leave voluntarily. Thus many companies have realized that their existing database is one of their most valuable asset and according to Abbasdimehr, churn prediction is a useful tool to predict customers at risk

By knowing which clients are at the highest risk of leaving, we can better target our rescue efforts. For example, we can reach out to these clients with a marketing campaign, reminding them that they haven't purchased from us in a while, or even offering them a benefit. In addition to knowing which clients to target, we can use the churn model to

calculate the maximum benefit price that is still worthwhile.

In our existing model, every involved weak classier is generally given a weight in conformity with the accuracy further training it using the re-weighted training data. XGBoost algorithm consisting of a group of weaker trees that add up their calculations to predict a target variable with better accuracy.

3.4 FEASIBILITY STUDY:

Feasibility Study in Software Engineering is a study to evaluate feasibility of propose project or system. Feasibility study in one of stage among important four stages of Software Project Management Process. Feasibility study is carried out based on many proposes to analyze whether software product will be right in terms of development, implantation, contribution of project to the organization etc. During system analysis the feasibility study of the proposed system is to be carried out. Feasibility study is so important stage of Software Project Management Process as after completion of feasibility study it gives a conclusion of whether to go ahead with proposed project as it is practically feasible or to 13 stop proposed project here as it is not right/feasible to develop or to think/analyze about proposed project again.

Three key considerations involved in the feasibility analysis are,

- TECHNICAL FEASIBILITY
- ECONOMICAL FEASIBILITY
- SOCIAL FEASIBILITY

Technical Feasblity

In Technical Feasibility current resources both hardware software along with required technology are analyzed/assessed to develop project. This technical feasibility study gives report whether there exists correct required resources and technologies which will be usedfor project development. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to highdemands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

Economical Feasbility

In Economic Feasibility study cost and benefit of the project is analyzed. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Social Feasbility

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level ofacceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar within it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system

Chapter - 4 SOFTWARE REQUIREMENTS SPECIFICATIONS

CHAPTER – 4 SOFTWARE REQUIREMENTS SPECIFICATIONS

4.1GENERAL

These are the requirements for doing the project. Without using these toolsand software's we can't do the project. So, we have two requirements to do the project. They are:

- 1. Hardware Requirements.
- 2. Software Requirements

4.2HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the wholesystem. They are used by software engineers as the starting point for the system design. It should what the system does and not how it should be implemented.

Processor: Core i5

RAM: 4 GB

• OS: Windows 7/8/10 (32 or 64 bit)

4.3 SOFTWARE REQUIREMENTS

The software requirements document is the specification of the system. It should includeboth a definition and a specification of requirements. It is a set of what the system shoulddo rather than how it should do it. The software requirements provide a basis for creatingthe software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity.

- Python libraries such as pandas, NumPy.
- Sklearn library using with many subordinate models such as model selection classifiers, and metrics etc.
- SUBLIME TEXT for implementation purpose.
- Sublime Text is a shareware cross-platform source code editor.

4.4FUNCTIONAL REQUIREMENTS

A functional requirement defines a function of a software-system or its component. A function is described as a set of inputs, the behavior, in proposed system, XGBoost is an ensemble learning algorithm, and is used for classification, regression and for ranking problems. XGBoost has the advantage over other algorithms that it is highly flexible, uses the power of parallel processing, and supports Regularization, faster than Gradient Boosting. It has been found to provide a good estimate of generalization error and resistant to overfitting. In Patron Defection Data Analysis, Customer churn dataset is collected and divided it as 80% of data set for training and 20% of data for testing. Using XGBoost, user can run cross validation after each iteration. Finally, the optimization is done and the accuracy obtained by XGBoost is 80.103% and Logistic Regression is 80.38%.

Chapter – 5 SYSTEM DESIGN

CHAPTER – 5 SYSTEM DESIGN

5.1 WORK FLOW:

The data was provided by a Finnish insurance company that wanted to predict whether acustomer is going to stay or leave after the current period or not. Leaving or churning is defined as "Yes" and not leaving is defined as "No" in this dataset. The selection of a data set from a choice of separate or distinct implicitly applicable ones seem to be nothing but a numerical comparison between the essentials of the business with the practicable data quality enumerated in the metadata description.

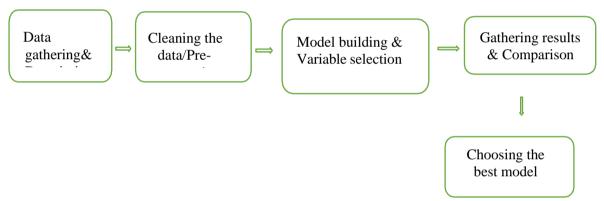


Fig 5.1: Process of Choosing the Best Model

Implementation of various models to predict churn on the data before and after oversampling the data, after splitting the data into test and train set. The train set includes the values in the churn column which is used to train the model and same model will be applied on test set, to test the quality of the model.

5.2 MODEL DEVELOPMENT:

The Data

As mentioned above, the data is sourced from Kaggle. In our dataset, we have 7043 rows(each representing a unique customer) with 21 columns: 19 features, 1 target feature (Churn). The data is composed of both numerical and categorical features, so we will need to address each of the datatypes respectively.

Target:

• **Churn** — Whether the customer churned or not (Yes, No)

Numeric Features:

- **Tenure** Number of months the customer has been with the company
- MonthlyCharges The monthly amount charged to the customer
- TotalCharges The total amount charged to the customer

Categorical Features:

- CustomerID
- **Gender** M/F
- SeniorCitizen Whether the customer is a senior citizen or not (1, 0)
- **Partner** Whether customer has a partner or not (Yes, No)
- **Dependents** Whether customer has dependents or not (Yes, No)
- **PhoneService** Whether the customer has a phone service or not (Yes, No)
- **MulitpleLines** Whether the customer has multiple lines or not (Yes, No, NoPhone Service)
- **InternetService** Customer's internet service type (DSL, Fiber Optic, None)
- OnlineSecurity Whether the customer has Online Security add-on (Yes, No,No Internet Service)
- OnlineBackup Whether the customer has Online Backup add-on (Yes, No, NoInternet Service)
- **DeviceProtection** Whether the customer has Device Protection add-on (Yes,No, No Internet Service)
- TechSupport Whether the customer has Tech Support add-on (Yes, No, NoInternet Service)
- **StreamingTV** Whether the customer has streaming TV or not (Yes, No, NoInternet Service)
- **StreamingMovies** Whether the customer has streaming movies or not (Yes,No, No Internet Service)
- **Contract** Term of the customer's contract (Monthly, 1-Year, 2-Year)
- **PaperlessBilling** Whether the customer has paperless billing or not (Yes, No)
- PaymentMethod The customer's payment method (E-Check, Mailed Check, Bank Transfer (Auto), Credit Card (Auto))

Algorithms

Implementation of various models to predict churn on the data before and after oversampling the data, after splitting the data into test and train set. The train set includes the values in the churn column which is used to train the model and same model will be applied on test set, to test the quality of the model. Following are the different models used to predict churn with its implementation considering ensemble modelling and boosting methods for best results:

Random Forest: Random Forest, like the name indicates, conforms a substantial number of unique decision trees that emits a class prediction and administer as an ensemble. Finally, the model's prediction is decided to be the class with the maximum votes.

A great number of relevantly uncorrelated models is the reason that the random forest model strives so well i.e., the individual trees administering as a committee performs better than any of the individual component models.

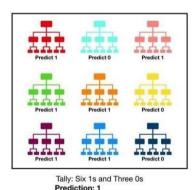


Fig – 5.2: Random Forest Architecture

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples andtakes their majority vote for classification and average in case of regression.

One of the most important features of the Random Forest Algorithm is that it can handlethe data set containing continuous variables as in the case of regression and categorical variables as in the case of classification. It performs better results for classification problems.

KNN Classifier: "The k-nearest neighbors (KNN) algorithm" is an absolute and easy to implement machine learning algorithm. It makes an assumption that alike entities exist incloseness to each other.

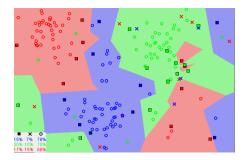


Fig – 5.3: KNN Classifier

In the Fig-5.3, majority of the time, the data points that are similar to each other are near each other. For this algorithm to be useful, it assumes this to be true. The KNN algorithmdetermines the proximity by calculating the distance between the points on the graph.

K Nearest Neighbor algorithm falls under the Supervised Learning category and is used for classification (most commonly) and regression. It is a versatile algorithm also used for imputing missing values and resampling datasets. As the name (K Nearest Neighbor) suggests it considers K Nearest Neighbors (Data points) to predict the class or continuous value for the new Datapoint.

Logistic Regression: Logistic regression predicts the probability of a classification by calculating the relationship between one or more independent features with a dependent variable. Definitively, logistic regression predicts the chances of a data point that belongsto the default bracket. It is a classification model, which is very easy to realize and achieves very good performance with linearly separable classes. It is an extensively employed algorithm for classification in industry. The logistic regression model, like the Adaline and perceptron, is a statistical method for binary classification that can be generalized to multiclass classification.

The below curve is known as the Sigmoid Curve. The sigmoid function is represented by the symbol sigma. Its graphical behavior has been described in the below figure.

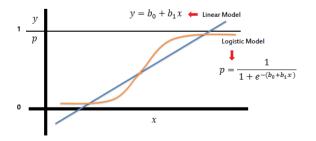


Fig – 5.4: Logistic Regression Graph

Logistic Regression, a method for classifying the data in Machine Learning. Logistic regression is generally used where we have to classify the data into two or more classes. One is binary and the other is multi-class logistic regression. As the name suggests, the binary class has 2 classes that are Yes/No, True/False, 0/1, etc. In multi-class classification, there are more than 2 classes for classifying data.

Decision Tree Classifier: The decision tree classifier creates the classification model by building a decision tree. Each node in the tree specifies a test on an attribute, each branch descending from that node corresponds to one of the possible values for that attribute. Each leaf represents class labels associated with the instance. Instances in the training set are classified by navigating them from the root of the tree down to a leaf, according to the outcome of the tests along the path. Starting from the rootnode of the tree, each node splits the instance space into two or more sub-spaces according to an attribute test condition. Then moving down the tree branch corresponding to the value of the attribute, a new node is created. This process is then repeated for the subtreerooted at new node, until all records in the training set have been classified.

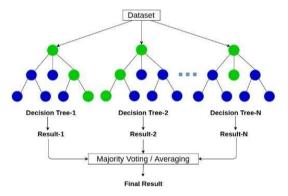


Fig – 5.5: Decision Tree Classifier

Extra Tree Classifier: Extremely Randomized Trees Classifier (Extra Trees Classifier) is a type of ensemble learning technique which aggregates the results of multiple de-correlated decision trees collected in a "forest" to output its classification result. In concept, it is very similar to a Random Forest Classifier and only differs fromit in the manner of construction of the decision trees in the forest.

Extra Trees Forest is constructed from the original training sample. Then, at each test node, each tree is provided with a random sample of k featuresfrom the feature-set from which each decision tree must select the best feature to split thedata based on some mathematical criteria (typically the Gini Index).

Gradient Boost Classifier: Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees. When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest. A gradient-boosted trees model is built in a stage- wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

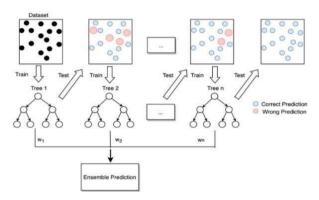


Fig -5.6: Gradient Boosting Classifier

Ridge Classifier: Ridge regression is a model tuning method that is used to analyze any data that suffers from multicollinearity. This method performs L2 regularization. When issue of multicollinearity occurs, least-squares are unbiased, and variances are large, this results in predicted values being far away from the actual values.

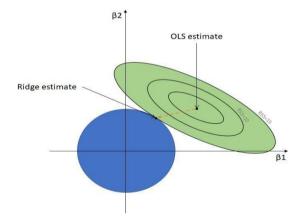


Fig -5.7: Ridge Classifier Graph

The Ridge Classifier, based on Ridge regression method, converts the label data into [-1,1] and solves the problem with regression method. The highest value in prediction is accepted as a target class and for multiclass data multi-output regression is applied.

Bagging Ridge Classifier: A Bagging regressor is an ensemble meta-estimator that fits base regressors each on random subsets of the original dataset and then aggregate their individual predictions (either by voting or by averaging) to form a final prediction. Such a meta-estimator can typically be used as a way to reduce the variance of a black-box estimator (e.g., a decision tree), by introducing randomization into its construction procedure and then making an ensemble out of it.

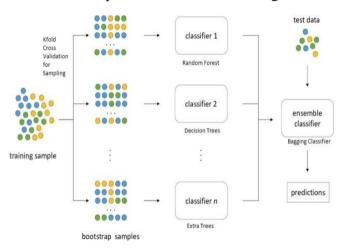


Fig – 5.8: Bagging Ridge Classifier

When random subsets of the dataset are drawn as random subsets of the samples, then this algorithm is known as Pasting. If samples are drawn with replacement, then the method is known as Bagging. When random subsets of the dataset are drawn as random subsets of the features, then the method is known as Random Subspaces. Finally, when base estimators are built on subsets of both samples and features, then the method is known as Random Patches.

XGBoost Classifier: XGBoost is the implementation of the gradient boosted tree algorithms that is commonly used for classification and regression problems. Gradient boosting is an algorithm consisting of a group of weaker trees that add up their calculations to predict a target variable with better accuracy.

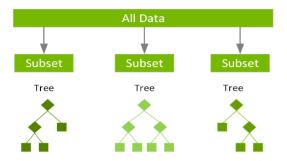


Fig -5.9: XGBoost Classifier

In this algorithm, decision trees are created in sequential form. Weights play an importantrole in XGBoost. Weights are assigned to all the independent variables which are then fed into the decision tree which predicts results. The weight of variables predicted wrongby the tree is increased and these variables are then fed to the second decision tree. These individual classifiers/predictors then ensemble to give a strong and more precise model. It can work on regression, classification, rank and user-defined prediction problems.

5.2 UML DIAGRAMS:

General

Configuration Engineering manages the different UML [Unified Modeling language] graphs for the execution of task. Configuration is a significant designing portrayal of a thing that willbe constructed. Programming configuration is an interaction through whichthe prerequisites are converted into portrayal of the product. Configuration is where quality is delivered in programming. Configuration is the way to precisely make an interpretation of client necessities into completed item.

Diagrams in UML can be broadly classified as:

Structural Diagrams – Capture static aspects or structure of a system. Structural Diagrams include: Component Diagrams, Object Diagrams, Class Diagrams and Deployment Diagrams.

Behavior Diagrams – Capture dynamic aspects or behavior of the system. Behavior diagrams include: Use Case Diagrams, State Diagrams, Activity Diagrams and Interaction Diagrams.

5.3.1 Class Diagram:

In software engineering, a class diagram in the Unified Modeling Language is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations, and the relationships among objects. The class shape itself consists of a rectangle with three rows. The top row contains the name of the class, the middle row contains the attributes of the class, and the bottom section expresses the methods or operations that the class may use. Classes and

subclasses are grouped together to show the static relationship between each object

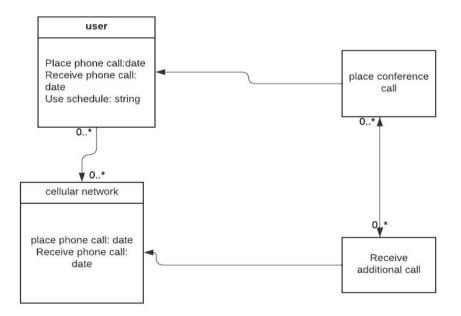


Fig – 5.10: Class Diagram

5.3.2 Use case Diagram:

The purpose of a use case diagram in UML is to demonstrate the different ways that a user might interact with a system. In the Unified Modeling Language (UML), a use casediagram can summarize the details of your system's users (also known as actors) and their interactions with the system. To build one, you'll use a set of specialized symbols and connectors.

UML is the modelling toolkit that you can use to build your diagrams. Use cases are represented with a labelled oval shape. Stick figures represent actors in the process, and the actor's participation in the system is modelled with a line between the actor and use case. To depict the system boundary, draw a box around the use case itself.

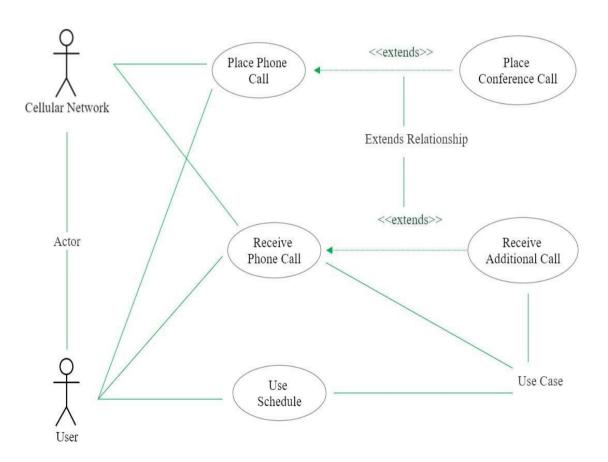


Fig – 5.11: Use Case Diagram

5.3.3 Activity Diagram:

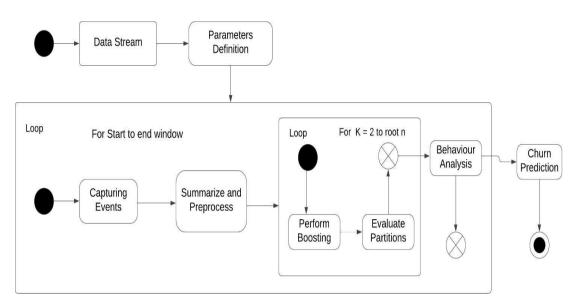


Fig –5.12: Activity diagram for the Proposed System

Explanation:

We use **Activity Diagrams** to illustrate the flow of control in a system and refer to the steps involved in the execution of a use case. We model sequential and concurrent activities using activity diagrams. So, we basically depict workflows visually using an activity diagram. An activity diagram focuses on condition of flow and the sequence in which it happens. We describe or depict what causes a particular event using an activity diagram. UML models basically three types of diagrams, namely, structure diagrams, interaction diagrams, and behavior diagrams. An activity diagram is a **behavioral diagram** i.e., it depicts the behavior of a system. An activity diagram portrays the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed. We can depict both sequential processing and concurrent processing of activities using an activity diagram. They are used in business and process modelling where their primary use is to depict the dynamic aspects of a system. An activity diagram is very **similar to a flowchart**.

5.3.4 Data Flow Diagram:

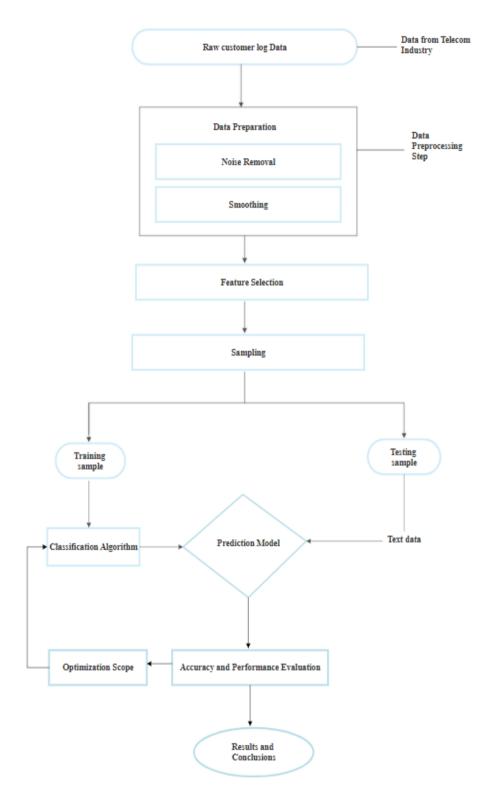


Fig: 5.13 Data Flow Diagram

Explanation:

A data-flow diagram is **a way of representing a flow of data through a process or a system** (usually an information system). The DFD also provides information about the outputs and inputs of each entity and the process itself.

Data Flow Diagrams provide a straightforward, efficient way for organizations to understand, perfect, and implement new processes or systems. They're visual representations of your process or system, so they make it easy to understand and prune. You can either use logical or physical diagrams to describe the same flow of informationor you can use them in conjunction to understand a process or system on a more granularlevel. But, before you can use a DFD to understand your system or process' flow of information, you need to know the standard notations or symbols used to describe it.

5.3 System Architecture:

The original features with customers' consumption and behavior are equidistantly grouped to construct new features. The stacking model consists of two levels with four algorithms: Xgboost (XGB), Logistic regression (LR), Decision tree (DT) and Naive Bayes classifier (NBC) to achieve better prediction accuracy. The third step consists of asoft voting. The results of the stacking model are input to the soft voting.

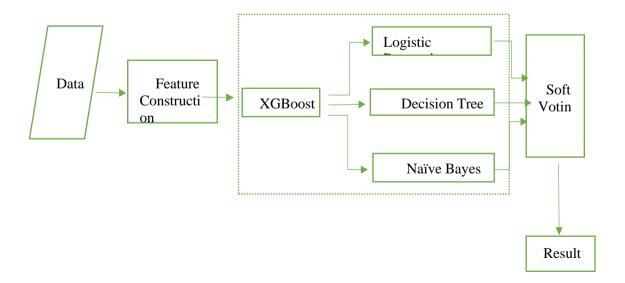


Fig: 5.14 System Architecture

The stacking model is a general method of using a higher-accuracy algorithm to combinelower-accuracy algorithms to achieve greater predictive accuracy. The best results are obtained when the higher-accuracy algorithm is in a first level and lower-accuracy algorithms are in a second level. In this study, the stacking model consists of two layers as shown in, level 1 and level 2. A higher accuracy model is used in the first layer (level 1), while lower-accuracy models are used in the second layer (level 2).

Soft voting estimates the class probability with different algorithms having contrasting approaches to improve the accuracy of prediction. It assigns a larger weight to the important classifier, and the highest category is selected by summing the probabilities predicted by the model. This proposed system can determine important factors affecting customer purchasing behavior in the telecommunications industry.

Chapter - 6 IMPLEMENTATION

CHAPTER – 6 IMPLEMENTATION

6.1 MODEL IMPLEMENTATION:

Implementation of various models to predict churn on the data before and after oversampling the data, after splitting the data into test and train set. The train set includes the values in the churn column which is used to train the model and same model will be applied on test set, to test the quality of the model. Following are the different models used to predict churn with its implementation considering ensemble modeling andboosting methods for best results:

Performance Evaluation Parameters

The following evaluation parameters used

False Positive (FP): refers to the number of negative tuples that were incorrectly labelledas positive.

False Negative (FN): refers to the number of positive tuples that were incorrectly labelled as negative.

True Positive (TP): refers to the positive tuples that were labelled correctly as positive. **True negative (TN):** refers to the number of negative tuples that were labelled correctlyby the classifier.

Precision:

Precision is the number of correct results divided by the number of all returned results.

$$Precision = tp / (tp + fn)$$
 (1)

Recall:

Recall is the number of correct results divided by the number of results that shouldhasbeen returned.

$$Recall = tp / (tp + fn)$$
 (2)

F1-Score:

A measure that combines precision and recall is the harmonic mean of precision and recall.

$$F = (2 * precision * recall) / (precision + recall)$$
 (3)

Measure of evaluation:

The probability of success in recognizing the right class of an instance.

Accuracy =
$$(tp + tn) / (tp + tn + fp + fn)$$
 (4)

	precision	recall	f1-score	support
0	0.96	0.97	0.96	530
1	0.97	0.96	0.97	652
accuracy			0.96	1182
macro avg	0.96	0.96	0.96	1182
weighted avg	0.96	0.96	0.96	1182

6.2 Modules:

NumPy

This article will help you get acquainted with the widely used array-processing libraryin Python, NumPy. What is NumPy? NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays. It is the fundamental package for scientific computing with Python. It is open-source software. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Pandas

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with "relational" or "labelled" data both easy and intuitive. Itaims to be the fundamental high-level building block for doing practical, real-world data analysis in Python.

Additionally, it has the broader goal of becoming the most powerful and flexible open-source data analysis/manipulation tool available in any language.

Here are just a few of the things that pandas do well:

- Easy handling of **missing data** (represented as NaN) in floating point as well as non-floating-point data.
- Size mutability: columns can be **inserted and deleted** from DataFrame and higher dimensional objects.
- Automatic and explicit data alignment: objects can be explicitly aligned to
 a set of labels, or the user can simply ignore the labels and let Series,
 DataFrame, etc. automatically align the data for you in computations.
- Powerful, flexible **group by** functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data.
- Make it easy to convert ragged, differently-indexed data in other Python and NumPy data structures into DataFrame objects.
- Intelligent label-based **slicing**, **fancy indexing**, and **subsetting** of large data sets.
- Intuitive **merging** and **joining** data sets.
- Flexible **reshaping** and pivoting of data sets.
- **Hierarchical** labelling of axes (possible to have multiple labels per tick).
- Robust IO tools for loading data from **flat files** (CSV and delimited), Excel files,databases, and saving / loading data from the ultrafast **HDF5 format**.
- **Time series**-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting, and lagging.

Seaborn

Seaborn is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures. Seaborn helps you explore and understand your data. Its plotting functions operate on dataframes and arrays containing whole datasets and internally perform the necessary semantic mapping and statistical aggregation to produce informative plots. Its dataset-oriented, declarative API lets you focus on what the different elements of your plots mean, rather than on the details of how to draw them.

Matplotlib

Matplotlib is an amazing visualization library in Python for 2D plots of arrays. Matplotlib is a multi-platform data visualization library built on NumPy arrays and designed to work with the broader SciPy stack. It was introduced by John Hunter in the year 2002.

One of the greatest benefits of visualization is that it allows us visual access to huge amounts of data in easily digestible visuals. Matplotlib consists of several plots like line, bar, scatter, histogram etc.It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK. There is also a procedural "pylab" interface based on a state machine (like OpenGL), designed to closely resemble that of MATLAB, though its use is discouraged. SciPy makes use of Matplotlib.

Plotly

The plotly Python library is an interactive, open-source plotting library that supports over 40 unique chart types covering a wide range of statistical, financial, geographic, scientific, and 3-dimensional use-cases.

Built on top of the Plotly JavaScript library (plotly.js), plotly enables Python users to create beautiful interactive web-based visualizations that can be displayed in Jupyter notebooks, saved to standalone HTML files, or served as part of pure Python-built web applications using Dash. The plotly Python library is sometimes referred to as "plotly.py" to differentiate it from the JavaScript library.

Scikit-Learn

Scikit-learn (formerly scikits.learn and also known as sklearn) is

a freesoftware machine learning library

for the Python programming language.

It features various classification, regression and clustering algorithms which including support vector machines, random forests, gradient boosting, *k*-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

<u>Scikit-learn</u> is a library in Python that provides many unsupervised and supervised learning algorithms. It's built upon some of the technology you might already be familiarwith, like NumPy, pandas, and Matplotlib!

The functio	nality that scikit-learn provides include:
\Box R	Regression, including Linear and Logistic Regression
	Classification, including K-Nearest Neighbors
	Clustering, including K-Means and K-Means++
\Box N	Iodel selection
□ P	reprocessing, including Min-Max Normalization
performance are written implemente support vec extending to Scikit-learn such as Ma	is largely written in Python, and uses NumPy extensively for high- e linear algebra and array operations. Furthermore, some core algorithms in Cython to improve performance. Support vector machines are ed bya Cython wrapper around LIBSVM; logistic regression and linear etor machines by a similar wrapper around LIBLINEAR. In such cases, these methods with Python may not be possible. In integrates well with many other Python libraries, tplotlib and plotly for plotting, NumPy for array vectoroization, Pandas a SciPy, and many more.
XGBoo	st
The XGBoo	ost python module is able to load data from many different types of data
format, incl	uding:
\square N	TumPy 2D array
\Box S	ciPy 2D sparse array
□ P	andas data frame
\Box c	uDF DataFrame
\Box c	upy 2D array
\Box d	lpack
\Box d	atatable
\Box X	GBoost binary buffer file.
	IBSVM text format file
	Comma-separated values (CSV) file

Xgboost is a supervised learning library that is used for classification as well as regeneration. It implements ML algorithms under the Gradient Boosting framework, and it provides a parallel tree boosting (also known as GBDT, GBM) which solves manydata science problems in a fast and accurate way. It can run on both single and distributed frameworks like Apache Hadoop, Apache Spark, etc. In this article, we are going to see how to install Xgboost in Anaconda Python.

6.3 Code:

```
import pandas as pd
 import numpy as np
 import pandas as pd
 import seaborn as sns
 import matplotlib.ticker as mtick
 import matplotlib.pyplot as plt
 %matplotlib inlinedf=pd.read_csv('/content/WA_Fn-UseC_-Telco-Customer-
 Churn.csv')
 df.head()
 df.info()
 df.dropna(inplace=True)
 # drop customerID
 df.drop('customerID', axis=1, inplace=True)
 df.info()
 df_cat = df.select_dtypes(include=[object])
 df cat.head()
 for i in df cat.columns:
     print(i, df[i].unique())
 from sklearn.preprocessing import OneHotEncoder
 ohe = OneHotEncoder(handle_unknown='ignore',
 sparse_output=False).set_output(transform='pandas')
 ohetransform = ohe.fit transform(df[df cat.columns])
 ohetransform.head()
 df = pd.concat([df, ohetransform], axis=1)
df.head()
for i in df cat.columns:
   df.drop([i], axis=1, inplace=True)
df.drop('Churn_No', axis=1, inplace=True)
df.rename(columns={'Churn Yes':'Churn'}, inplace=True)
df.head(10)
df.describe()
import matplotlib.pyplot as plt
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))
columns = ['tenure', 'MonthlyCharges', 'TotalCharges']
for i, column in enumerate(columns):
  axes[i].hist(df[column], bins=50, color='skyblue', edgecolor='black')
  axes[i].set_title(f'Distribution of {column}')
```

```
axes[i].set_xlabel(column)
  axes[i].set_ylabel('Frequency')
plt.tight layout()
plt.show()
df['Churn'].value counts().plot(kind='barh', figsize=(8, 6))
plt.xlabel('Count')
plt.vlabel('Churn')
for i, predictor in enumerate(df.drop(columns=['Churn', 'TotalCharges',
'MonthlyCharges', 'tenure'])):
  plt.figure(i, figsize=(5, 3))
  sns.countplot(data=df, x=predictor, hue='Churn')
df[['MonthlyCharges', 'Churn']]
plt.figure(figsize=(10, 5))
sns.kdeplot(data=df, x="MonthlyCharges", hue="Churn", fill=True, alpha=0.5)
plt.title('Density Plot of Monthly Charges by Churn Status')
plt.xlabel('Monthly Charges')
plt.ylabel('Density')
plt.show()
plt.figure(figsize=(20,8))
    df.corr()['Churn'].sort values(ascending = False).plot(kind='bar')
import pandas as pd
from sklearn import metrics
from sklearn.model selection import train test split
from sklearn.metrics import recall_score
from sklearn.metrics import classification report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from imblearn.over sampling import SMOTE
from sklearn.linear model import LogisticRegression
logreg = LogisticRegression(max_iter=10000)
logreg.fit(X train, y train)
y_pred = logreg.predict(X_test)
y_pred
# confusion_matrix
from sklearn import metrics
cnf matrix = metrics.confusion matrix(y test, y pred)
cnf matrix
class_names=[0,1] # name of classes
fig. ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick marks, class names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu",fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred, labels=[0, 1]))
# UpSampling
from imblearn.combine import SMOTEENN
sm = SMOTEENN()
X_{res}, y_{res} = sm.fit_{resample}(X,y)
Y res.value counts()
Xr train, Xr test, yr train, yr test = train test split(X res, y res,test size=0.2)
logreg.fit(Xr_train, yr_train)
yr pred = logreg.predict(Xr test)
print(classification_report(yr_test, yr_pred, labels=[0, 1]))
model dt=DecisionTreeClassifier(criterion = "gini",random state =
100,max_depth=6, min_samples_leaf=8)
model_dt.fit(Xr_train,yr_train)
y pred=model dt.predict(Xr test)
print(classification_report(yr_test, y_pred, labels=[0,1]))
from sklearn.ensemble import RandomForestClassifier
model_rf=RandomForestClassifier(n_estimators=100, criterion='gini', random_state =
100,max depth=6, min samples leaf=8)
model rf.fit(Xr train,yr train)
y_pred=model_rf.predict(Xr_test)
print(classification_report(yr_test, y_pred, labels=[0,1]))
from xgboost import XGBClassifier
model_xg = XGBClassifier()
model_xg.fit(Xr_train, yr_train)
y_pred=model_rf.predict(Xr_test)
print(classification_report(yr_test, y_pred, labels=[0,1]))
from sklearn.model selection import RandomizedSearchCV
from xgboost import XGBClassifier
from scipy.stats import uniform, randint
# Define the model
model xg = XGBClassifier()
param_distributions = {
  'max depth': randint(3, 6),
  'learning_rate': uniform(0.01, 0.2),
  'n_estimators': randint(100, 300),
  'subsample': uniform(0.8, 0.2)
random_search = RandomizedSearchCV(estimator=model_xg,
                     param distributions=param distributions,
                     n_iter=100, cv=3, verbose=2, random_state=42, n_jobs=-1)
random search.fit(Xr train, yr train)
print(random_search.best_params_)
best model = random search.best estimator
y_pred = best_model.predict(Xr_test)
print(classification_report(yr_test, y_pred, labels=[0, 1]))
```

Chapter – 7 SYSTEM TESTING

CHAPTER – 7 SYSTEM TESTING

7.1 Testing:

This section describes the different types of testing that may be used to test a software.

Manual Testing

Manual testing includes testing a software manually, i.e., without using any automated tool orany script. In this type, the tester takes over the role of an end-user and tests the software to identify any unexpected behavior or bug. There are different stages for manual testing such asunit testing, integration testing, system testing, and user acceptance testing.

Automation Testing

Automation testing, which is also known as Test Automation, is when the tester writes scriptsand uses another software to test the product. This process involves automation of a manual process. Automation Testing is used to re-run the test scenarios that were performed manually, quickly, and repeatedly.

What to Automate?

It is not possible to automate everything in a software. The areas at which a user can make transactions such as the login form or registration forms, any area where large number of userscan access the software simultaneously should be automated.

When to Automate?

Test Automation should be used by considering the following aspects of a software –

- Large and critical projects
- Projects that require testing the same areas frequently
- Requirements not changing frequently
- Accessing the application for load and performance with many virtual users
- Stable software with respect to manual testing
- Availability of time

How to Automate?

Automation is done by using a supportive computer language like VB scripting and an automated software application. There are many tools available that can be used to write automation scripts. Before mentioning the tools, let us identify the process that can be used toautomate the testing process –

- Identifying areas within a software for automation
- Selection of appropriate tool for test automation
- Writing test scripts
- Development of test suits
- Execution of scripts
- Create result reports
- Identify any potential bug or performance issues

7.2 Black-Box Testing

The technique of testing without having any knowledge of the interior workings of the application is called black-box testing. The tester is oblivious to the system architecture and does not have access to the source code. Typically, while performing a black-box test, a testerwill interact with the system's user interface by providing inputs and examining outputs withoutknowing how and where the inputs are worked upon.

The following table lists the advantages and disadvantages of black-box testing.

Advantages	Disadvantages
Well suited and efficient for large code segments.	Limited coverage, since only A selectednumber of test scenariosis actually performed.
Code access is not required.	Inefficient testing, due to the fact That the tester only has limited knowledge about an application.
Clearly separates user's perspective from the developer's perspective through visibly definedroles.	Blind coverage, since the tester cannot target specific code segments or error prone areas.

Large numbers of moderately skilled testers can test	The test cases are difficult to design.	
the application with no knowledge of implementation	,	
programming language, or operating systems.		

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Chapter - 8
RESULTS

CHAPTER - 8

RESULTS

8. Results

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService
0	7590- VHVEG	Female	0	Yes	No	1	No	No phone service	DSL
1	5575- GNVDE	Male	0	No	No	34	Yes	No	DSL
2	3668- QPYBK	Male	0	No	No	2	Yes	No	DSL
3	7795- CFOCW	Male	0	No	No	45	No	No phone service	DSL
4	9237- HQITU	Female	0	No	No	2	Yes	No	Fiber optic

5 rows × 21 columns

> <class 'pandas.core.frame.DataFrame'> Index: 7032 entries, 0 to 7042 Data columns (total 20 columns): Non-Null Count Dtype # Column gender 7032 non-null
> Partner 7032 non-null
> Dependents 7032 non-null
> PhoneService 7032 non-null
> MultipleLines 7032 non-null
> InternetService 7032 non-null
> OnlineSecurity 7032 non-null
> OnlineBackup 7032 non-null
> DeviceProtection 7032 non-null 1 int64 object object object 6 object object 8 object 9 object 10 DeviceProtection 7032 non-null object TechSupport 7032 non-null StreamingTV 7032 non-null 11 object 12 object StreamingMovies 7032 non-null
> Contract 7032 non-null 13 object Contract 14 object PaperlessBilling 7032 non-null 16 PaymentMethod 17 MonthlyCharges 7032 non-null object 7032 non-null float64 TotalCharges 7032 non-null Churn 7032 non-null float64 19 Churn object dtypes: float64(2), int64(2), object(16)

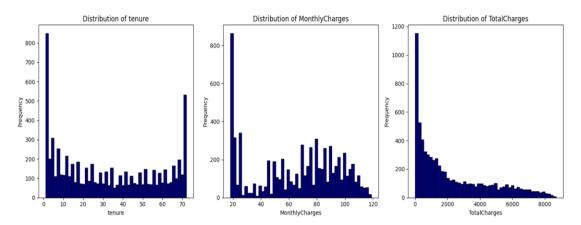
	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMeti
0	Female	Yes	No	No	No phone service	DSL	No	Yes	No	No	No	No	Month-to- month	Yes	Electro ch
1	Male	No	No	Yes	No	DSL	Yes	No	Yes	No	No	No	One year	No	Mailed ch
2	Male	No	No	Yes	No	DSL	Yes	Yes	No	No	No	No	Month-to- month	Yes	Mailed ch
3	Male	No	No	No	No phone service	DSL	Yes	No	Yes	Yes	No	No	One year	No	Bank trans (automa
4	Female	No	No	Yes	No	Fiber optic	No	No	No	No	No	No	Month-to- month	Yes	Electro chi
4															}

```
gender ['Female' 'Male']
Partner ['Yes' 'No']
Dependents ['No' 'Yes']
PhoneService ['No' 'Yes']
MultipleLines ['No phone service' 'No' 'Yes']
InternetService ['DSL' 'Fiber optic' 'No']
OnlineSecurity ['No' 'Yes' 'No internet service']
OnlineBackup ['Yes' 'No' 'No internet service']
DeviceProtection ['No' 'Yes' 'No internet service']
TechSupport ['No' 'Yes' 'No internet service']
StreamingTV ['No' 'Yes' 'No internet service']
StreamingMovies ['No' 'Yes' 'No internet service']
Contract ['Month-to-month' 'One year' 'Two year']
PaperlessBilling ['Yes' 'No']
PaymentMethod ['Electronic check' 'Mailed check' 'Bank transfer (automatic)' 'Credit card (automatic)']
Churn ['No' 'Yes']
```

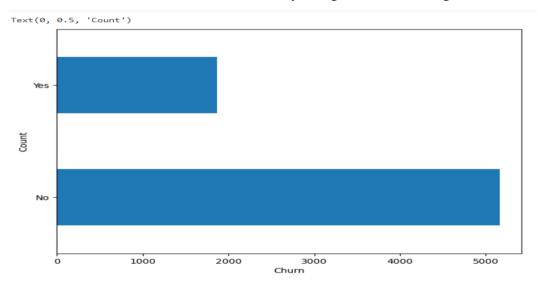
g	ender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	MultipleLines_No	MultipleLines_No phone service	 Contract_One year	Contract_Two year	PaperlessBilling
0	1.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	
1	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	
2	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	
3	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	
4	1.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	
5 rows	s × 43 columns												
4)

ge	nder :	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	 Contract_One year	Contract_Two year	PaperlessBilling_No	PaperlessBilling_Yes
0 Fe	male	0	Yes	No	1	No	No phone service	DSL	No	Yes	0.0	0.0	0.0	1.0
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	1.0	0.0	1.0	0.0
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	0.0	0.0	0.0	1.0
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	1.0	0.0	1.0	0.0
4 Fe	male	0	No	No	2	Yes	No	Fiber optic	No	No	0.0	0.0	0.0	1.0
5 rows	× 63 co	lumns												
4)

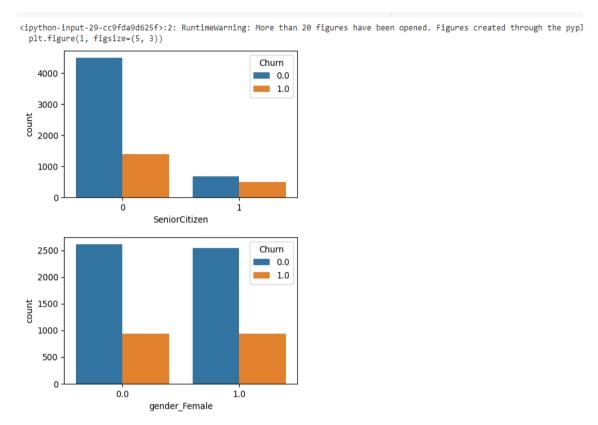
Senio	orCitizen	tenure	MonthlyCharges	TotalCharges	gender_Female	gender_Male	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes		Contract_Month- to-month	Contract_One year	Contract_Two year	PaperlessBilling_f
0	0	1	29.85	29.85	1.0	0.0	0.0	1.0	1.0	0.0)	1.0	0.0	0.0	0
1	0	34	56.95	1889.50	0.0	1.0	1.0	0.0	1.0	0.0)	0.0	1.0	0.0	1
2	0	2	53.85	108.15	0.0	1.0	1.0	0.0	1.0	0.0)	1.0	0.0	0.0	0
3	0	45	42.30	1840.75	0.0	1.0	1.0	0.0	1.0	0.0		0.0	1.0	0.0	1
4	0	2	70.70	151.65	1.0	0.0	1.0	0.0	1.0	0.0)	1.0	0.0	0.0	0
5	0	8	99.65	820.50	1.0	0.0	1.0	0.0	1.0	0.0		1.0	0.0	0.0	0
6	0	22	89.10	1949.40	0.0	1.0	1.0	0.0	0.0	1.0)	1.0	0.0	0.0	0
7	0	10	29.75	301.90	1.0	0.0	1.0	0.0	1.0	0.0		1.0	0.0	0.0	1
8	0	28	104.80	3046.05	1.0	0.0	0.0	1.0	1.0	0.0		1.0	0.0	0.0	0
9	0	62	56.15	3487.95	0.0	1.0	1.0	0.0	0.0	1.0		0.0	1.0	0.0	1
10 rows ×	46 columns														
(•



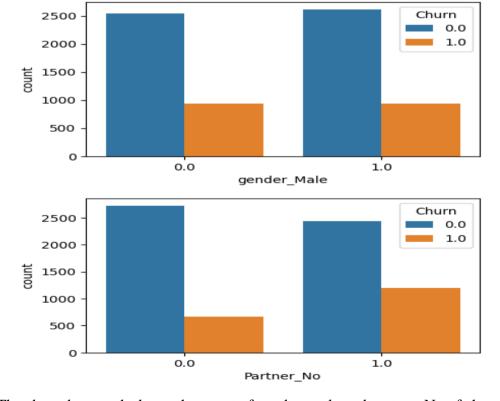
The distribution of tenure, monthly charges and total charges.



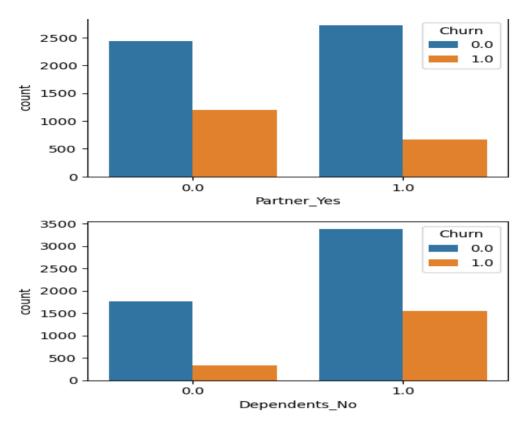
The count of churn and non- churn in the format of bar graph.



The above bar graph shows the count of senior citizen and gender_female of churn.



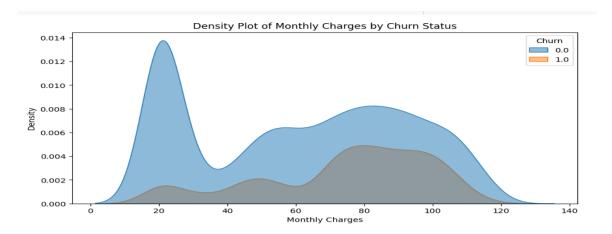
The above bar graph shows the count of gender_male and partner_No of churn.



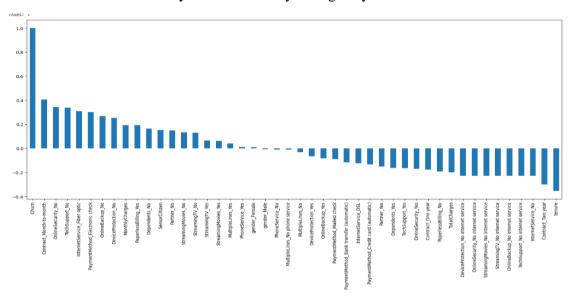
The above bar graph shows the count of partner_Yes and Dependents_No of churn.

	MonthlyCharges	Churn
0	29.85	0.0
1	56.95	0.0
2	53.85	1.0
3	42.30	0.0
4	70.70	1.0
7038	84.80	0.0
7039	103.20	0.0
7040	29.60	0.0
7041	74.40	1.0
7042	105.65	0.0
7032 rd	ows × 2 columns	

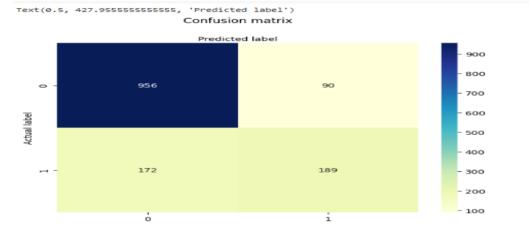
The above shows the monthly charges of patron.



Density Plot of Monthly Charges by Churn Status



Water fall graph



Confusion Matix of actual and predicted label.

	precision	recall	f1-score	support
0 1	0.85 0.68	0.91 0.52	0.88 0.59	1046 361
accuracy macro avg weighted avg	0.76 0.80	0.72 0.81	0.81 0.74 0.81	1407 1407 1407

Classification report of existing model.

Churn 1.0 3201 0.0 2626

Name: count, dtype: int64

The count of churn and non-churn.

	precision	recall	f1-score	support
0 1	0.92 0.95	0.94 0.93	0.93 0.94	512 654
accuracy macro avg weighted avg	0.94 0.94	0.94 0.94	0.94 0.94 0.94	1166 1166 1166

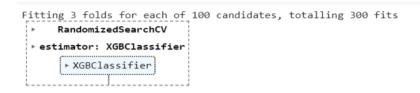
The above screenshot shows metrics of Random forest.

	precision	recall	f1-score	support
0 1	0.94 0.93	0.91 0.96	0.92 0.94	512 654
accuracy macro avg weighted avg	0.94 0.93	0.93 0.93	0.93 0.93 0.93	1166 1166 1166

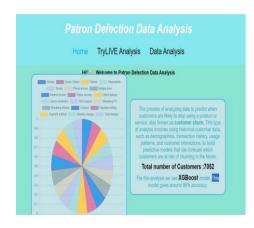
The above screenshot shows metrics of Decision tree.

	precision	recall	f1-score	support
0 1	0.94 0.93	0.91 0.96	0.92 0.94	512 654
accuracy			0.93	1166
macro avg weighted avg	0.94 0.93	0.93 0.93	0.93 0.93	1166 1166

The above screenshot shows metrics of XGBoost.

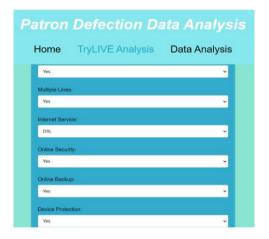


Screenshots of Frontend output:



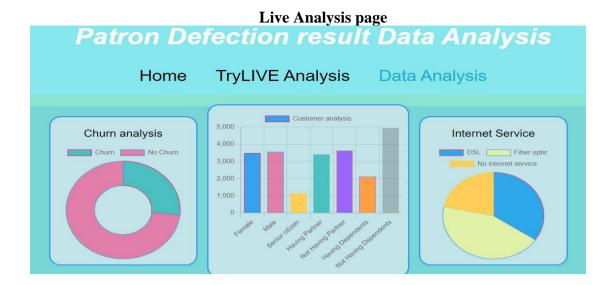
Home Page

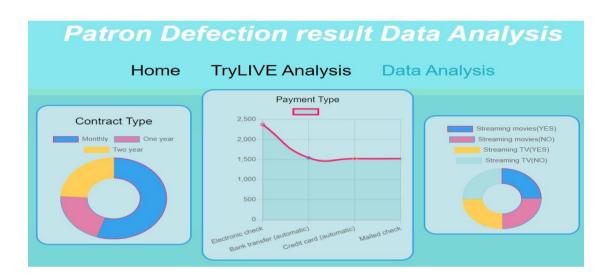














Data Analysis Page

Chapter – 9 CONCLUSION

CHAPTER – 9 CONCLUSION

8. CONCLUSION:

The Patron Defection Data Analysis project provided valuable insights into the patterns and trends surrounding patron defection within the organization. Through rigorous data analysis, several key findings emerged. Firstly, it became evident that certain fluctuations in patron behavior preceded defection, indicating potential warning signs that could be monitored and addressed proactively. These patterns varied across different segments of patrons, highlighting the importance of segmentation in understanding defection dynamics.

Delving deeper into the root causes of defection, it became apparent that dissatisfaction with service quality, changes in personal circumstances, and increased competition were among the primary drivers. Understanding these underlying reasons is crucial for devising effective retention strategies tailored to address the specific needs and concerns of at-risk patrons.

Segmentation analysis further reinforced the notion that not all patrons are equally prone to defection. By leveraging historical data and identifying key predictors, such as frequency of interactions, satisfaction ratings, and tenure, the models demonstrated promising results in anticipating future churn. However, it's essential to continuously refine these models and incorporate additional variables to enhance predictive accuracy over time.

In conclusion, the Patron Defection Data Analysis project has provided valuable insights into the factors driving patron defection and laid the groundwork for implementing proactive retention strategies. By leveraging these insights and recommendations, the organization can strengthen its relationships with patrons, foster loyalty, and ultimately drive sustainable growth and success.

Future Scope

In the future, the Patron Defection Data Analysis project could focus on real-time monitoring for early defection signs, advanced predictive modeling with machine learning, optimizing loyalty programs through experimentation, and integrating data from multiple channels for a holistic view of customer behavior. Additionally, efforts could be directed towards comprehensive customer journey mapping and implementing closed-loop feedback systems. These advancements could result in a more proactive and personalized approach to retaining patrons, driving sustained growth and fostering strong customer relationships.

Chapter – 10 BIBLIOGRAPHY

CHAPTER - 10

BIBLIOGRAPHY

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CHAPTER – 11 INTERNSHIP CERTIFICATES

CHAPTER - 11 INTERNSHIP CERTIFICATES



Fig: 10.1 Internship Certificate of Member 1



Fig: 10.2 Internship Certificate of Member 2

		Smart Interna
ANDHR.	A PRADESH STATE COUNCIL OF HIGHE (A Statutory Body of the Government of A.P) CERTIFICATE OF COMPLETION	
20NN1A05B1 under Vig	Singh Vijayalakshmi of Computer Science And Engman's Nirula Institute Of Technology & Science For Women is months) on Data Analytics with Tableau Organized by State Council of Higher Education. Certificate ID: EXT-APSCHE_DA-16928	of JNTUK has successfully completed
Date: 20-Apr-2024 Place: Virtual		Amarendar Katkam Founder & CEO

Fig: 10.3 Internship Certificate of Member 3



Fig: 10.4 Internship Certificate of Member 4