BANK CUSTOMER CHURN PREDICTION USING MACHINE LEARNING

Major project report submitted
in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

By

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T. JASWANTH	(20UECS0927)	**(VTU 13991)**
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Under the guidance of
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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SCHOOL OF COMPUTING

VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE & TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA

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CERTIFICATE

It is certified that the work contained in the project report titled "BANK CUSTOMER CHURN PREDICTION USING MACHINE LEARNING" by "G. PRADEEP KUMAR (20UECS0346), T. JASWANTH (20UECS0927), N. MADHU BABU (20UECS0656)" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Signature of Supervisor	**Signature of Professor In-charge**
Computer Science & Engineering	**Computer Science & Engineering**
School of Computing	**School of Computing**
Vel Tech Rangarajan Dr. Sagunthala R&D	**Vel Tech Rangarajan Dr. Sagunthala R&D**
Institute of Science & Technology	**Institute of Science & Technology**
May, 2024	**May, 2024**

DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

(Signature)
G. PRADEEP KUMAR
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Date: / /

APPROVAL SHEET

This project report entitled (BANK CUSTOMER CHURN PREDICTION USING MACHINE LEAR NING) by G. PRADEEP KUMAR (20UECS0346), T. JASWANTH (20UECS0927), N. MADHU BABU (20UECS0656) is approved for the degree of B.Tech in Computer Science & Engineering.

Examiners **Supervisor**

Mr. N. MANJUNATHAN.,B.Tech.,M.E.,(Ph.D)
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Date: / /
Place:

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ABSTRACT

In the fiercely competitive landscape of the banking industry, customer retention stands as a pivotal challenge for sustaining growth and profitability. The phenomenon of customer churn, where clients disengage from banking relationships, poses a significant threat to financial institutions. Customers of a bank decided to leave the bank the bank is investigating a very high rate of customer leaving the bank. The data set contains customer records, and use it to investigate and predict which of the customers are more likely to leave the bank soon. With the investigation of the customers who are churning soon, the bank has an option toreduce the churn by further investigating the reason of leaving the bank and to convince the customers by providing or improvising the services rendered to them. The project involves analyzing a diverse range of customer attributes, including demographic information, transactional behavior, product usage, and interaction history. Leveraging machine learning algorithms, particularly Artificial Neural Networks (ANNs) aim to uncover complex patterns and relationships within the data that signify potential churn behavior. Through feature engineering, model training, and evaluation seek to build a robust churn prediction model capable of identifying at-risk customers with high accuracy. This problem can be applicable to any industry to identify the churn customers within their organizations. Achieving an accuracy of 84% for a churn prediction model using the Artificial Neural Network (ANN) algorithm is a positive outcome, indicating that the model is performing reasonably well in identifying customers who are likely to churn.

Keywords: ANN Algoritham, Bank Customers, Customer Churn, Organizations, Prediction.

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

ANN	Artificial Neural Networks
ML	Machine Learning
RF	Random Forest Algorithm
NP	Num py
DT	Decision Tree Algorithm
CP	Churn Prediction
EDA	Exploratory Data Analysis

TABLE OF CONTENTS

Chapter 1

INTRODUCTION

1.1 Introduction

Now a days many of the banks are losing their customers unknowingly and also leaving their accounts. Using the solution to this problem, the bank can easily identify the customers who are willing to exit the bank soon. From the larger data sets, the bank can easily identify the churn customers using machine learning approach, thus this can reduce the manual intervention and the cost to the bank. Using machine learning solutions, the bank can save processing time and manual intervention to investigate the complete records. The system can take quicker decisions with statistical models with optimal accuracy metrics. With the investigation of the customers who are churning soon, the bank has an option to reduce the churn by further investigating the reason of leaving the bank and to convince the customers by providing or improvising the services rendered to them. The churn model can be integrated with the business software, so that the proper discounting can be provided to the identified customers. Targeted marketing strategies can be used. Monitoring of the customer trends and building the alerting mechanism to the business users on a daily or monthly basis. This problem can be applicable to any industry to identify the churn customers within their organizations.In the competitive landscape of banking, retaining customers is crucial for sustained growth and profitability. Customer churn, or the rate at which customers discontinue their services with a bank, poses a significant challenge to the financial industry. Identifying and understanding the factors that contribute to churn can empower banks to proactively address customer needs, enhance satisfaction, and ultimately reduce attrition.

1.2 Aim of the Project

The aim of the project is bank customer churn prediction using machine learning is to develop predictive models that can accurately identify customers who are at risk of leaving the bank in the near future. By leveraging historical customer data, machine learning algorithms can analyze various factors such as transaction history, account activity, demographics, and interactions with banking services to detect patterns indicative of potential churn.

1.3 Project Domain

The project focuses on the banking domain, specifically addressing the issue of customer churn prediction. In the banking industry, customer churn refers to the phenomenon where customers discontinue their relationship with a bank, which can have significant financial implications. Understanding and predicting customer churn is crucial for banks to maintain a healthy customer base, optimize revenue, and improve overall customer satisfaction. By focusing on these key areas within the banking domain and leveraging machine learning techniques, the project aims to develop a predictive model that can accurately forecast customer churn and provide actionable insights to help banks implement targeted retention strategies and improve overall customer retention rates.

1.4 Scope of the Project

The scope of the project for bank customer churn prediction using machine learning. The project entails leveraging Artificial Neural Networks (ANN) methodology for predicting bank customer churn. It involves comprehensive data collection from diverse sources within the bank's databases, encompassing demographic information, transactional data, account activity, and customer service interactions. The collected data undergoes rigorous preprocessing to handle missing values, outliers, and inconsistencies, with feature engineering techniques applied to extract relevant predictors of churn. Ultimately, the project's scope aims to empower banks with actionable insights derived from ANN-based churn prediction models, enabling proactive retention strategies and enhancing customer satisfaction and loyalty.

Chapter 2

LITERATURE REVIEW

[1] Asad Khattak et al. (2023) Proposed a ustomer churn prediction using composite deep learning technique the completion of the preprocessing work, the next phase includes the use of a deep learning model, specifcally the CNN architecture, to classify customer churn into discrete emotion categories. Research focuses on leveraging advanced deep learning methods to improve the accuracy and effectiveness of customer churn prediction models. Specifically, the study explores the integration of multiple deep learning architectures or techniques into a composite model to enhance predictive performance.

[2] Ishpreet Kaur et al. (2020) Developed a prediction model for customer churn from e-banking services using data mining, Used a Decision Tree, Random Forest, and XGBoost to predict the customers who are likely to cancel the subscription which can offer them better services and reduce the churn rate.By preprocessing and feature selection ,the data set for training and testing. For the above mentioned algorithm, it is necessary to do some feature engineering to have more efficient and accurate results. The methodology section of the paper likely outlines the approach taken by Kaur and Kaur in collecting and preprocessing data from banking sources.

[3] Ketut Gde Manik Karvana et al. (2019) Proposed a new method for customer churn analysis and prediction. The method uses data mining model in banking industries. This has been inspired by the fact that there are around 1,5 million churn customers in a year which is increasing every year.The results and findings presented in the paper likely include the evaluation of the developed data mining models using real-world banking datasets.

[4] Louis Geiler et al. (2022) Proposed a customer churn prediction using a new criteria and data mining; A case of Iranian Banking industry, Identified churn factors that are essential in determining the root causes of churn. By knowing the significant

churn factors from customers' data, Customer Relationship Management (CRM) can improve productivity, recommend relevant promotions to the group of likely churn customers based on similar behavior patterns, and excessively improve marketing.

[5] Manas Rahman et al. (2022) Developed a Customer Churn analysis in Banking Sector, machine learning methods are routinely employed to forecast deadly illnesses. The goal of this study was to create and compare the performance of a standard system and a suggested system that predicts heart disease using the Logistic regression, K-nearest neighbour, Support vector machine, Decision tree, and Random Forest classification models. The suggested system aided in tuning the hyperparameters of the five specified classification algorithms utilising the grid search technique. The main study topic is the performance of the heart disease prediction system. It is possible to improve the performance of prediction models by using the hyperparameter tuning model.

[6] Saw Thazin Khine et al. (2019) Proposed a Customer churn analysis has become a major concern in almost every industry that offers products and services. The model developed will help banks identify clients who are likely to be churners and develop appropriate marketing actions to retain their valuable clients.The significance of this research lies in its potential to provide valuable insights to banking institutions for managing customer churn effectively. By understanding the factors influencing churn and implementing proactive retention strategies, banks can improve customer retention and loyalty, ultimately enhancing their profitability and competitiveness in the market.

[7] Vaani Gupta et al. (2023) Proposed a Artificial Intelligence Based Predictive Analysis of Customer Churn. Customer churn, also known as attrition, occurs when sub- scribers or customers stop doing business with an enterprise or organization by un- subscribing to a service, discontinuing membership or simply stopping payment. The results and findings presented in the paper likely include insights into the predictive performance of the developed AI-based models. The authors may discuss the effectiveness of different algorithms and methodologies in accurately predicting customer churn.

[8] Wenjie Bi et al. (2021) Proposed a Predicting customer churn using machine learning; Implemented an EDA using Visualization, statistical tests for feature selection and Data mining methods for predicting the likely churners by utilizing a Logistic Regression Model.Here dataset has been analysed by using the data visualization techniques before entering into the modeling process. This study likely focuses on developing a clustering algorithm tailored for mitigating the risk of customer churn, particularly in the context of big data environments. Bi et al. likely propose a novel clustering approach that leverages big data analytics techniques to identify groups of customers with similar characteristics and behavior, allowing businesses to proactively address churn risks.

[9] Xing Wang et al. (2020) Proposed a Churn Prediction using Ensemble Learning With a wealth of information on hand from the Internet, customers now can easily identify and switch to alternatives. In addition to this, a con- sensus has been reached that the cost of securing new customers is substantially higher than the cost of retaining the current customers. They likely describe the ensemble techniques used, such as bagging, boosting, or stacking, and discuss how these methods are applied to combine the predictions of individual base models. By harnessing the collective intelligence of multiple predictive models, businesses can develop more robust and reliable churn prediction systems, ultimately leading to better customer retention strategies and improved business outcomes.

[10] Yue Li et al. (2021) Proposed a The problem of predicting customer churn of commercial banks by using the historical transaction data of customers. In churn prediction, an important yet challenging problem is the enormous costs of labeling sample labels. The methodology section of the paper likely outlines the approach taken by the authors in applying data mining techniques to telecom churn management. They may discuss the data preprocessing steps, feature engineering techniques, and model selection criteria used in their analysis. By leveraging data mining techniques, telecom companies can gain a deeper understanding of customer behavior and preferences, allowing them to implement targeted retention strategies and improve customer satisfaction.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

The existing system, customer churn prediction in the banking sector relies on decision tree algorithm. Decision tree are utilized due to their simplicity and interpretability, enabling stakeholders to understand the factors influencing churn easily. The algorithm recursively partitions the dataset based on attribute values, forming a tree like structure where each node represents a decision based on a feature, leading to subsequent branches and leaf nodes representing classification outcomes. The customer's data set with historical data. Identify the customers who exited from the bank and who are continuing the services of bank. The value 1 represents the customers who are exited from the bank and 0 represents the customers who are continuing with the bank.

Disadvantage:

1.Limited Data Integration

2.Lack of Interpretability

3.High False Positive Rates

4.Scalability Challenges

5.High Implementation Costs

3.2 Proposed System

The proposed system aims to develop a customer churn prediction model for the banking industry using Artificial Neural Networks (ANN). By collecting comprehensive historical customer data and preprocessing it to extract relevant features, the system designs and trains ANN architectures optimized for churn prediction. Through rigorous evaluation and validation, including metrics such as accuracy the system ensures the reliability and effectiveness of the trained models. Upon deployment in the banking environment, the churn prediction system integrates seamlessly with existing workflows, providing real-time insights to stakeholders for proactive retention strategies. Continuous monitoring and refinement of the ANN models ensure their adaptability to changing customer behavior and evolving market dynamics, ultimately enabling banks to mitigate revenue loss, enhance customer satisfaction, and drive sustainable growth in a competitive landscape.

Advantages:

1.Improved Customer Retention

2.Enhanced Customer Satisfaction

3.Optimized Resource Allocation

4.Compliance and Risk Management

3.3 Feasibility Study

The feasibility study for a customer churn prediction project in banking involves assessing various aspects to determine its viability and potential success. By conducting a comprehensive feasibility study, banks can assess the viability and potential success of a customer churn prediction project and make informed decisions about its development and implementation. This evaluation helps ensure that the project aligns with organizational objectives, addresses key technical, financial, operational, legal, and market considerations, and has a clear path to success.

3.3.1 Economic Feasibility

This project is carried out to check the economic impact that the system will have on the organization the amount of fund that the company can pour into research and development of the system is limited the expenditure must be justified. An economic feasibility study for a customer churn prediction project in banking involves assessing whether the benefits of implementing the project outweigh the costs incurred. economic feasibility study, banks can assess the financial viability of a customer churn prediction project and make informed decisions about its implementation. This evaluation helps ensure that the project aligns with strategic objectives, delivers tangible benefits, and maximizes return on investment for the organization.

3.3.2 Technical Feasibility

The technical feasibility that is the technical requirements of the system. 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 the developed system must have a modest requirements. And are required for implementing this project.Evaluate the availability and accessibility of data sources within the bank, including customer transactional data, demographic information, and historical churn records. Assess the technical capabilities and infrastructure required for data integration, preprocessing, model development, and deployment. Determine the availability of skilled data scientists, analysts, and IT professionals to undertake the project and support ongoing maintenance and enhancement of the churn prediction system.

3.3.3 Social Feasibility

The aspect of the project 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 be threatened by the system. His level of confidence must be increased so that he is able to make some constructive criticism which is welcome. A customer churn prediction project in banking involves evaluating its acceptability, impact, and implications on various stakeholders within and outside the organization.Banks can ensure that the customer churn prediction project is socially acceptable, ethical, and aligned with the values and expectations of stakeholders, ultimately contributing to positive social outcomes and sustainable business success.

3.4 System Specification

3.4.1 Hardware Specification

Processor : intel core i5
RAM : 8GB
ROM : 1TB
Hard Didsk : 260GB

3.4.2 Software Specification

Windows 11
Python IDLE (3.7.0)
Google Colab
Python Packages: numpy, pandas

3.4.3 Standards and Policies

IDLE

IDLE Stands for Integrated Development and Learning Environment.It is an environment for python which is integratedly developed.It has been packed with the default language.It is completely written in python. It has been in- tended to be simple environment with simple functions and easy to use.It is cross platform.It also avoids feature clutter. The ultimate features of IDLE are multi window text editor with syntax highlighting, auto completion, smart indent. Integrated debugger with step ping, persistent breakpoints, and call stack visibility.

Anaconda Prompt

Anaconda prompt is a type of command line interface which explicitly deals with the ML(MachineLearning) modules.And navigator is available in all the Windows,Linux and MacOS.The anaconda prompt has many number of IDE's which make the coding easier. The UI can also be implemented in python.

Standard Used: ISO/IEC 27001

Chapter 4

METHODOLOGY

4.1 General Architecture

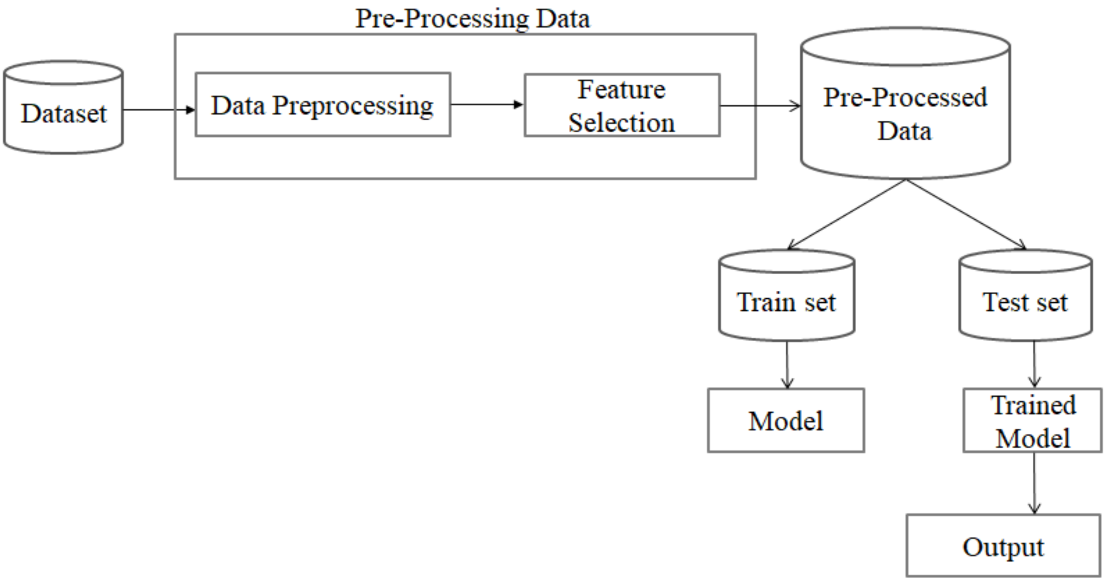

Figure 4.1: **Architecture Diagram**

Figure 4.1 Shows an architecture diagram for a customer churn prediction system in banking illustrates the overall structure and components of the system, including data flows, processing stages, and interactions between various elements. Information about customer transactions, account activity, and financial behavior. Customer profiles, including age, gender, income, and location.Records of customer interactions with the bank, such as calls to customer service, website visits, and marketing responses. Additional sources of data, such as economic indicators, market trends, and social media activity, that may provide context or predictive signals for churn.The architecture diagram provides a visual representation of the end-to-end process for customer churn prediction in banking, from data ingestion and preprocessing to model training, deployment, and continuous improvement, facilitating understanding and collaboration among stakeholders involved in the project.

4.2 Design Phase

4.2.1 Data Flow Diagram

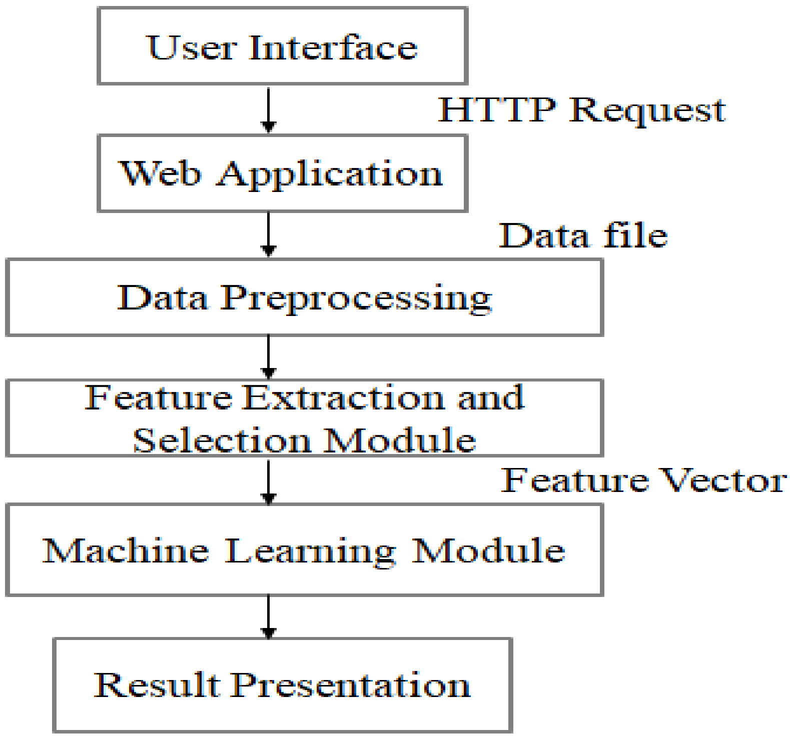

Figure 4.2: **Data Flow Diagram**

Figure 4.2 Shows it is usually beginning with a context diagram as level 0 of the DFD diagram, a simple representation of the whole system. To elaborate further from that, we drill down to a level 1 diagram with lower-level functions decomposed from the major functions of the system. This could continue to evolve to become a level 2 diagram when further analysis is required. Progression to levels 3, 4 and so on is possible but anything beyond level 3 is not very common. Please bear in mind that the level of detail for decomposing a particular function depending on the complexity that function. Data flow describes the information transferring between different parts of the systems. The arrow symbol is the symbol of data flow. A relatable name should be given to the flow to determine the information which is being moved. Data flow also represents material along with information that is being moved. Material shifts are modeled in systems that are not merely informative. A given flow should only transfer a single type of information. The direction of flow is represented by the arrow which can also be bi-directional.

4.2.2 Use Case Diagram

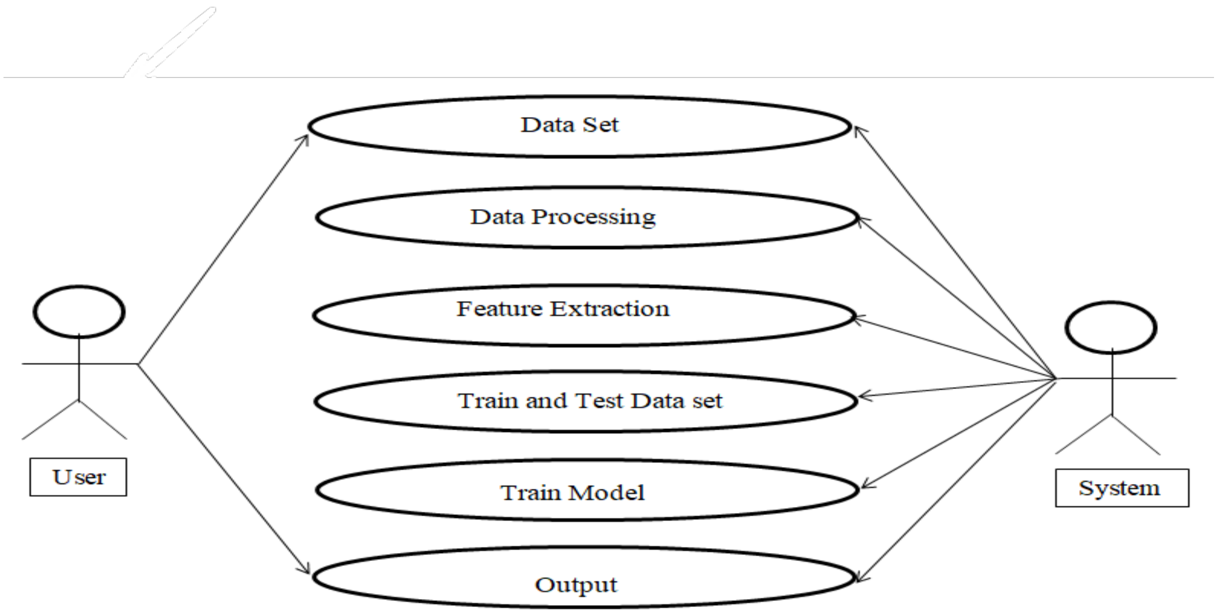

Figure 4.3: **Use Case Diagram**

Figure 4.3 Shows a use case diagram for a customer churn prediction system in banking provides a high-level overview of the system's functionality from the perspective of different actors (users or external systems) and the interactions between them. Represents the bank's customers who interact with the churn prediction system, such as accessing personalized retention offers or receiving notifications about potential churn. Includes employees within the bank who utilize the churn prediction system to view customer churn predictions, analyze churn-related data, and take proactive retention actions. Overall, the use case diagram provides a visual representation of the functional requirements and interactions of the churn prediction system, helping to clarify user roles, system features, and dependencies between different use cases. This diagram serves as a valuable tool for stakeholders to understand the system's behavior and functionality, guide requirements elicitation, and facilitate communication and collaboration throughout the system development lifecycle.

4.2.3 Class Diagram

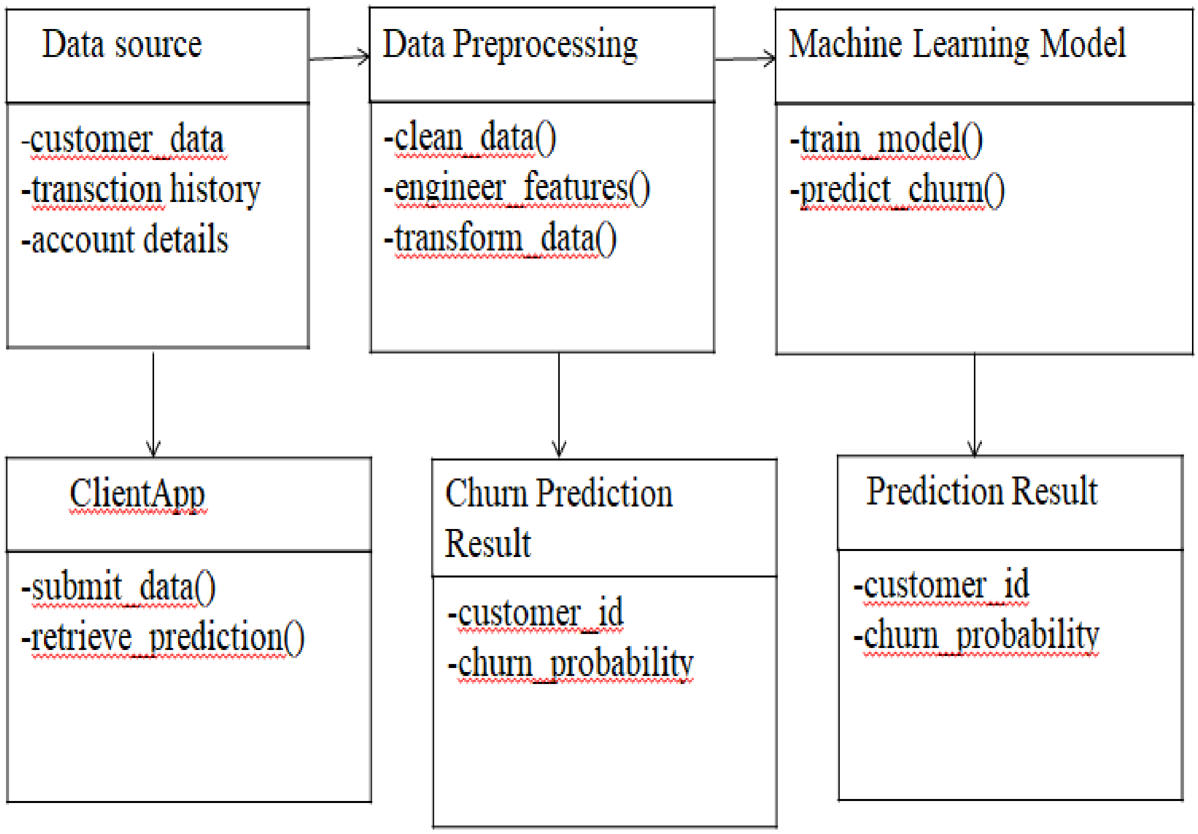

Figure 4.4: **Class Diagram**

Figure 4.4 Shows A class diagram for a customer churn prediction system in banking illustrates the static structure of the system, including the classes (or entities), their attributes, methods, relationships, and dependencies.the class diagram provides a visual representation of the structure and relationships between the classes in the churn prediction system, helping to define the system's data model, encapsulate behavior, and organize system components. This diagram serves as a blueprint for developers to implement the system's functionality and ensure consistency and coherence in the system's design and implementation.

4.2.4 Sequence Diagram

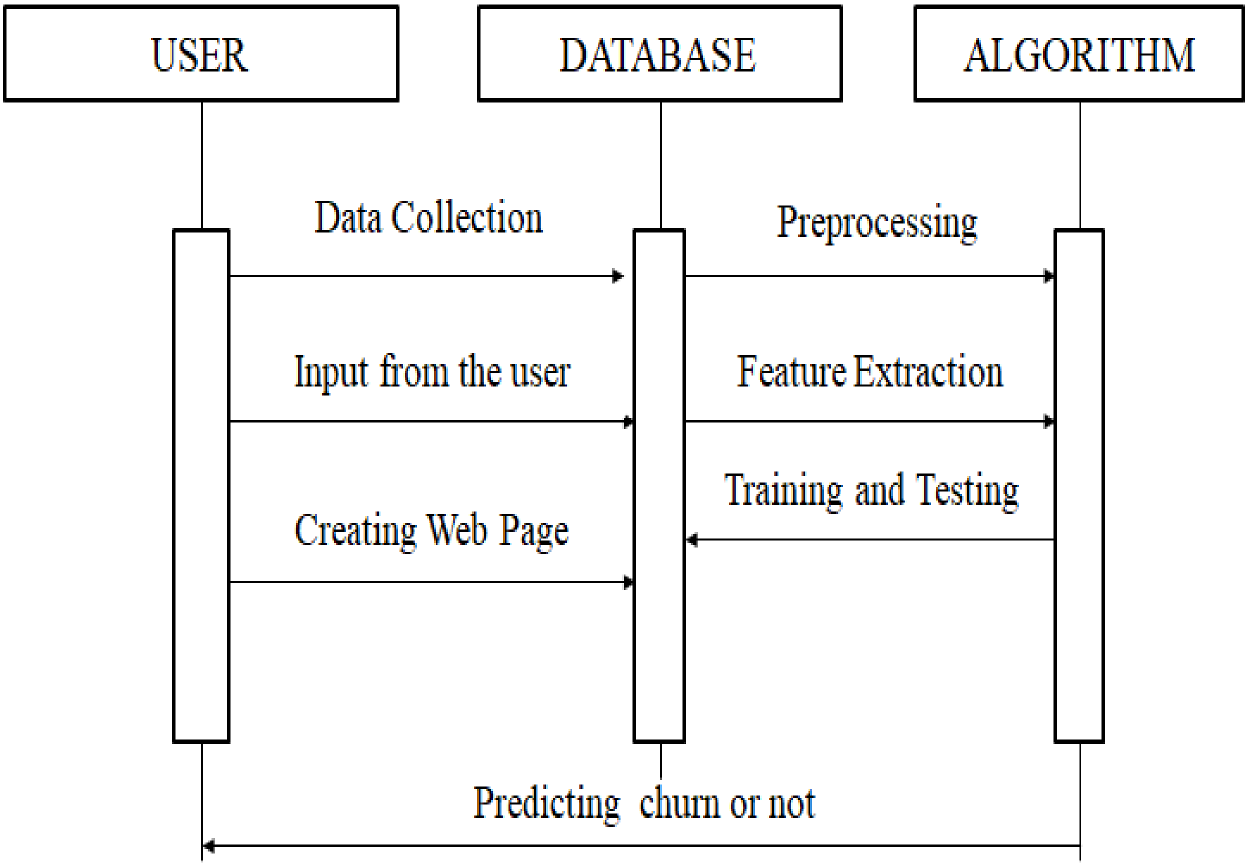

Figure 4.5: **Sequence Diagram**

Figure 4.5 Shows that the sequence diagram for a banking scenario can represent customer, bank teller, or a bank manager. The communication between the customer, teller, and manager are represented by messages passed between them. The sequence diagram shows the objects and the messages between the objects. It consists of a group of objects that are represented by lifelines, and the messages that they exchange over time during the interaction.

4.2.5 ER Diagram

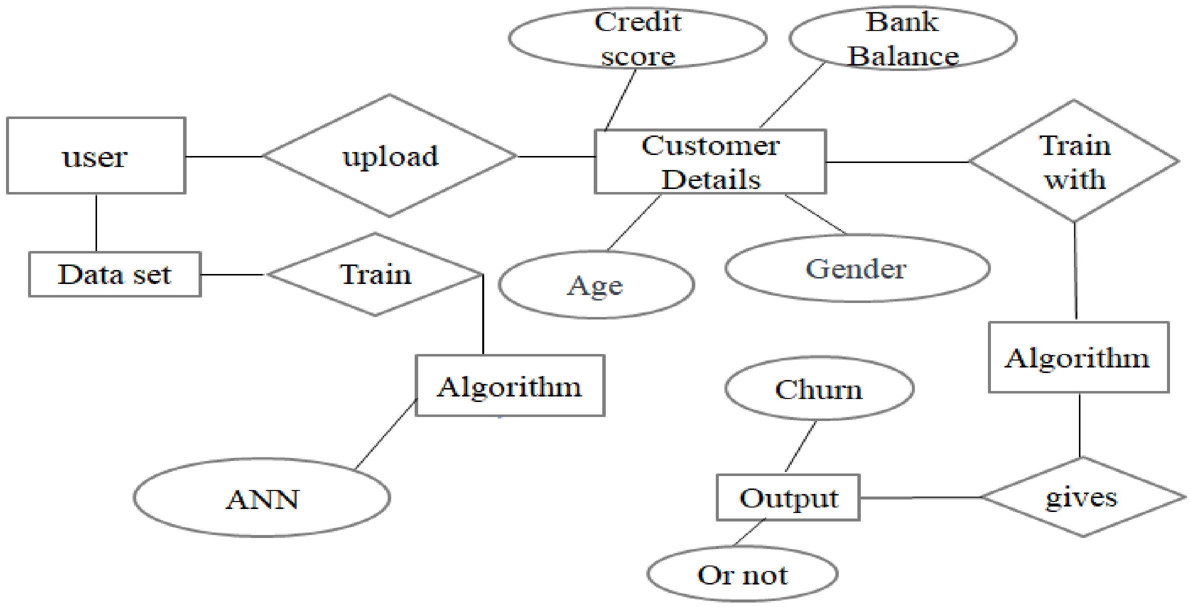

Figure 4.6: **ER Diagram**

Figure 4.6 Shows an Entity-Relationship (ER) diagram for a customer churn prediction system in banking illustrates the logical structure of the system's data model, including entities (or tables), their attributes, and relationships between them.the ER diagram provides a visual representation of the logical structure of the churn prediction system's database schema, helping to define the relationships between different entities and establish the rules for data storage and retrieval. This diagram serves as a valuable tool for database designers and developers to design and implement the system's data model effectively.

4.2.6 Activity Diagram

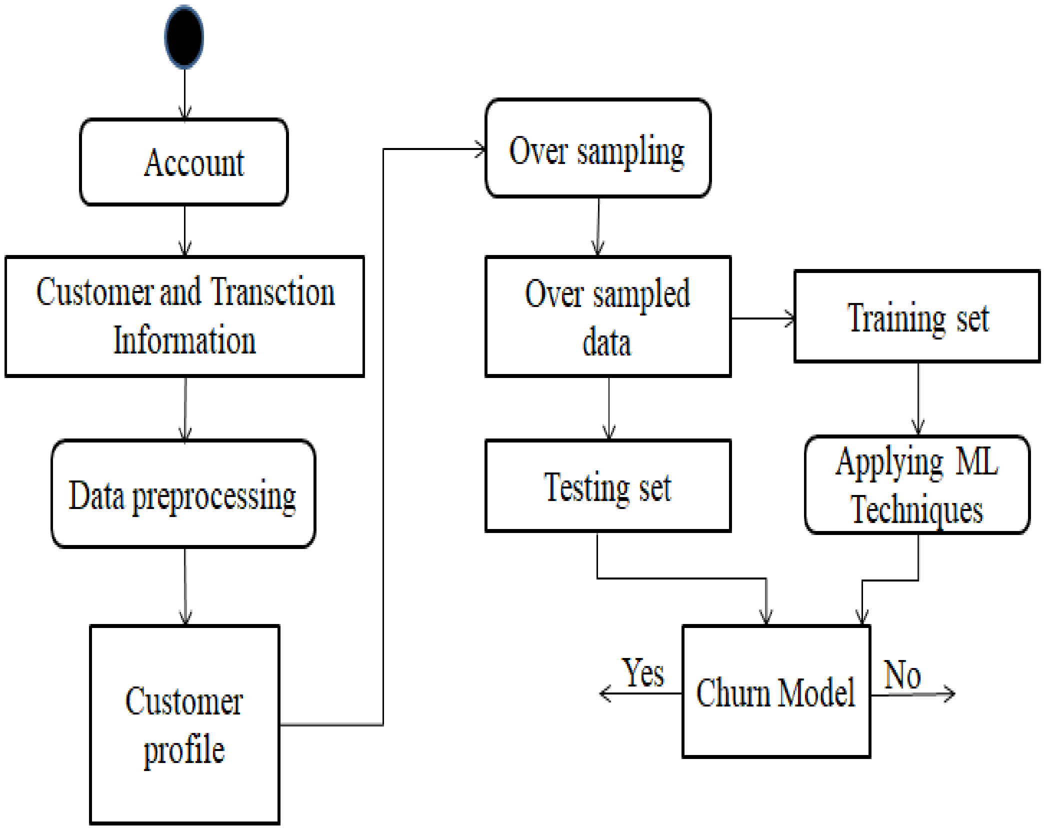

Figure 4.7: **Activity Diagram**

Figure 4.7 Shows An activity diagram for a customer churn prediction system in banking illustrates the workflow or sequence of activities involved in the churn prediction process, including decision points, branching, concurrency, and loops.the activity diagram provides a visual representation of the sequential and parallel activities involved in the churn prediction process, helping to understand the flow of operations, decision points, and interactions between different components of the system. This diagram serves as a valuable tool for process analysis, design, and optimization, facilitating communication and collaboration among stakeholders involved in the churn prediction project.

4.3 Algorithm & Pseudo Code

4.3.1 Algorithm

Step 1: Start
Step 2: Import the necessary libraries for data manipulation, preprocessing, and machine learning modeling, such as Pandas, NumPy, Matplotlib.
Step 3: Load the collected dataset into a Pandas DataFrame for further processing and modeling.
Step 4: Preprocess the dataset by handling missing data, scaling, and transforming. the data to make it suitable for machine learning modeling.
Step 5: Split the preprocessed dataset into training and testing sets for model training and validation.
Step 6: Define the ANN model to be used for Bank Customer Churn Prediction.
Step 7: Train the defined machine learning model using the training dataset.
Step 8: Evaluate the performance of the trained model using the testing dataset to ensure that it can accurately predict churn.
Step 9: Optimize the performance of the trained model by tuning the hyperparameters and using techniques like cross-validation.
Step 10: Use the trained and optimized machine learning model to make predictions of churn based on input data.
Step 11: Provide the predicted churn output to the user in a format that is easy to understand and use, such as a graph or a table.
Step 12: Stop

4.3.2 Pseudo Code

```
import pandas as pd
import numpy as np
from sklearn.model selection import train test split
fromsklearn.preprocessing import Standard Scaler
fromsklearn.ensemble import Artificial Neural Network Classifier
fromsklearn.metrics import accuracy score
data = pd.readcsv( bank customer data. c s v )
Preprocess data
X = data.drop([ Churn ], axis=1)
y = data[ Churn ]
Xtrain, Xtest, ytrain, ytest = train test split(X, y, testsize = 0.2, random state =
42)
scaler = Standard Scaler()
```

```
Xtrain = scaler.f it transform(Xtrain)
Xtest = scaler.transform(Xtest)
ann = Artificial Neural Network r(nestimators = 100, randomstate = 42)rf.f it(Xtrain, ytrain)
ypred = rf.predict(Xtest)
Evaluate model performance
accuracy = accuracy score(ytest, ypred)print( Accuracy : , accuracy)
```

4.4 Module Description

4.4.1 Data Acquisition And Pre-Processing

The dataset id obtained from kaggle containing customer survey data. The obtained data will ultimately be used by the GLM model. Data Preprocessing is started by attempting to transform data from a predetermined form to one that is significantly more desirable and usable. The dataset we have contained from the Kaggle contains some missing elements. This could be due to the reason that such data was not collected efficiently or it does not exist. These elements are represented by None in the dataset. When the null values are detected they are either replaced or filled with the mean value.

4.4.2 Feature Extraction and Selection

The Customer data will be preprocessed to enhance the details and reduce variability across samples. The most informative features will be selected using feature selection techniques to improve model performance and reduce dimensionality. Different feature extraction and selection methods will be evaluated based on the data and the project goals. Deep learning methods will also be explored for their potential to automatically extract relevant features from customer details.

4.4.3 Algorithm

Select a machine learning algorithm for Bank Customer Churn Prediction, such as Artificial Neural Networks (ANN). These algorithm were chosen due to their interpretability, scalability, and easy of implementation. The performance of each algorithm will be compared using evaluation metrics such as accuracy. The best-performing algorithm will be selected for integration into a web-based tool for Customer Churn Prediction.

4.4.4 Model Training and Evaluation

The selected algorithm will be trained on a labeled dataset of customer churn, with samples labeled as indicative of Churn or not. The labeled dataset will be divided into training, validation, and testing sets to prevent overfitting and evaluate model generalization. The trained model will be evaluated on the testing set using evaluation metrics such as accuracy, precision, recall, and F1 score. The model's performance will be further evaluated on new, unseen data to assess its real-world effectiveness and generalizability.

4.5 Steps to execute/run/implement the project

4.5.1 Step 1: Collection Of Data Set

1.Collect the data as a dataset. And store the data in xml sheet.
2.install the libraries into your system.

4.5.2 Step 2: By Using Google Colab

1. By using Google Colab, numpy, Pandas as a libraries to connect the database and source code.
2. After uploading the dataset into the libraries we have to do the preprocess of the data.

4.5.3 Step 3: Testing The Result

1. Connect the server to the dataset.
2. After completion of the training machine learning algorithm it will display the accuracy of the data.
3. After getting the output and close the tab.

Chapter 5

IMPLEMENTATION AND TESTING

5.1 Input and Output

5.1.1 Bank Customer Churn Prediction

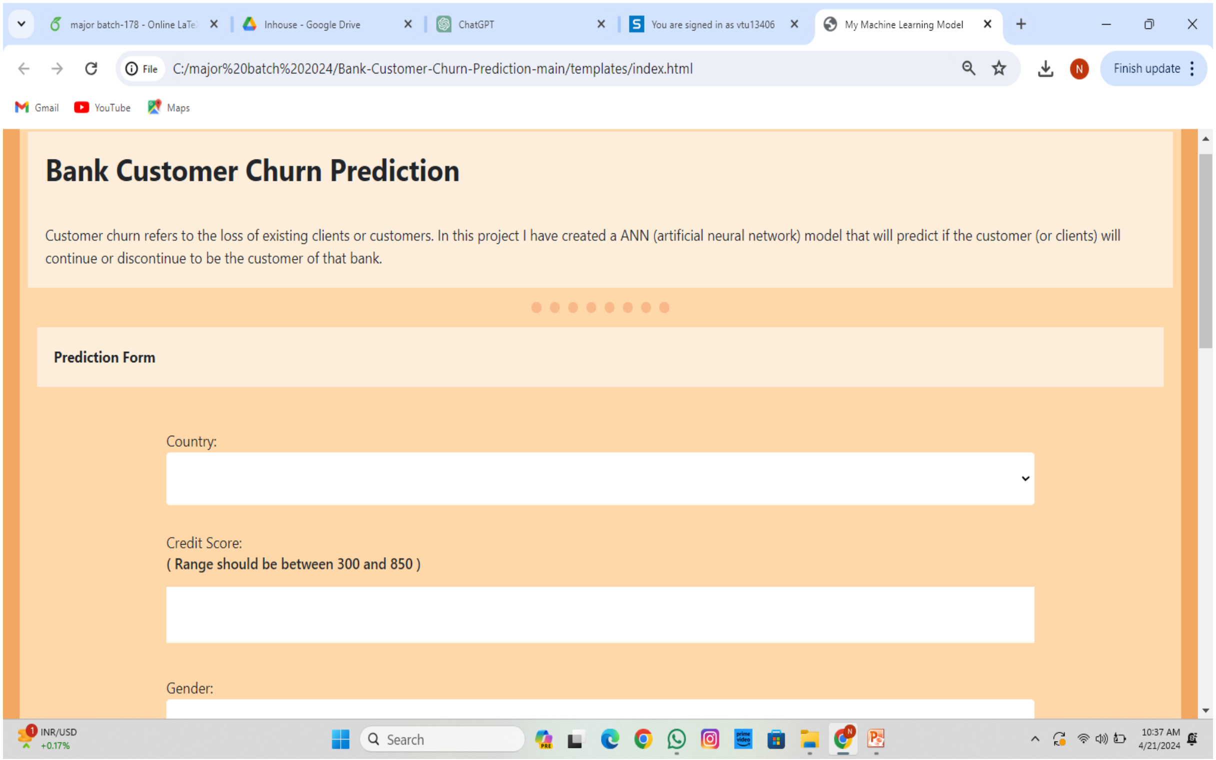

Figure 5.1: **Bank Customer Churn Prediction**

Figure 5.1 depicts the input of project going to give customer details as input and it will give the result as whether the customer churn or not. In the context of a customer churn prediction system using Artificial Neural Networks (ANN) methodology in the banking sector, the input diagram would illustrate the various sources from which customer data is collected and fed into the system for churn prediction analysis.

5.1.2 Churn Prediction

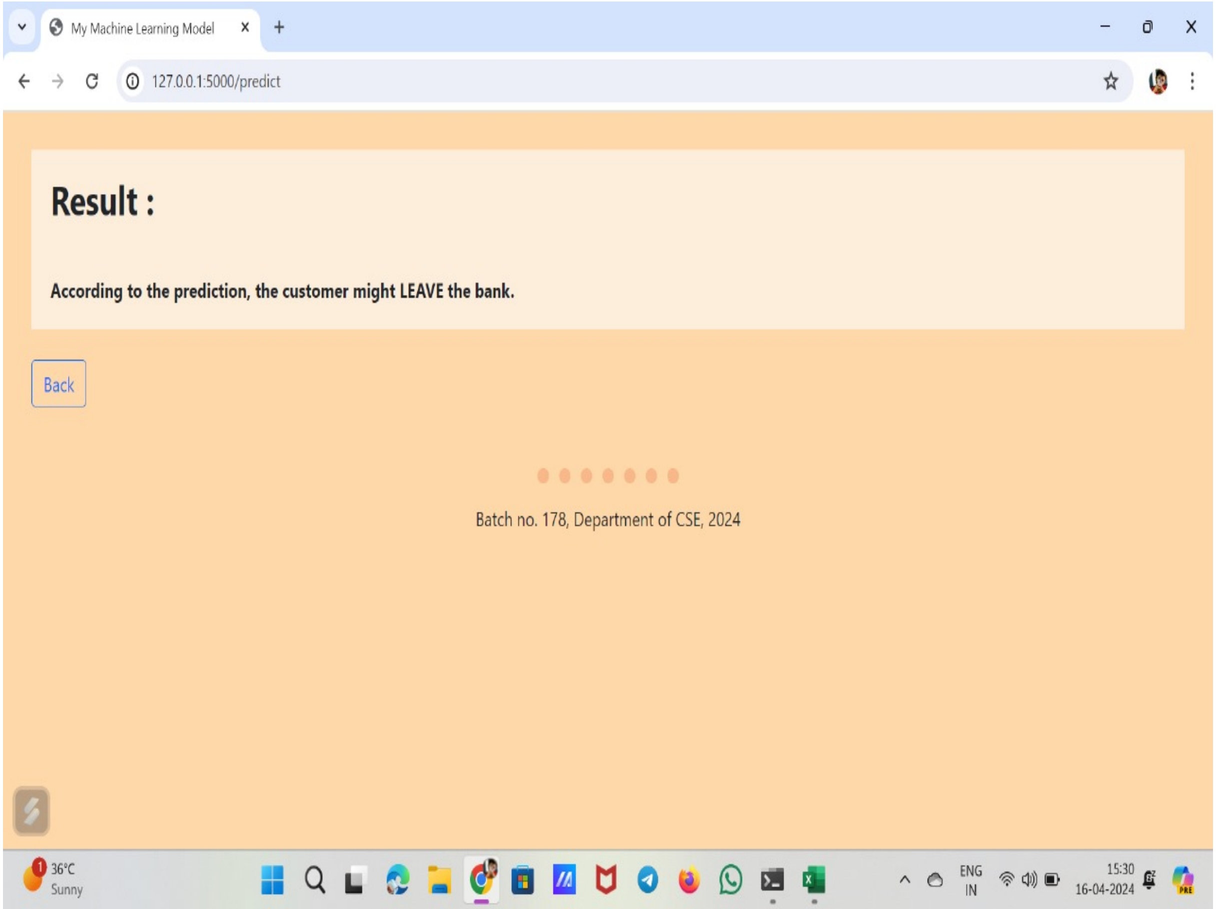

Figure 5.2: **Churn Prediction**

Figure 5.2 depicts the output of project going to give customer details as input and it will predict the output as whether the customer will leave or not leave. It serves as a visual summary of the churn prediction analysis conducted by the ANN-based system, providing stakeholders with valuable insights into customer churn behavior and guiding decision-making processes within the banking sector. It facilitates the interpretation and communication of model results, helping stakeholders understand the implications of churn predictions and take appropriate actions to mitigate churn and enhance customer retention efforts.

5.2 Testing

Testing refers to the process of evaluating the performance of a trained model on a set of data that it has not seen before. This is typically done by splitting a dataset into two parts: a training set and a testing set. The model is trained on the training set and then evaluated on the testing set to see how well it generalizes to new, unseen data. The testing process involves making predictions on the testing set using the trained model, and then comparing these predictions to the true labels or outcomes for the testing set. The goal is to build a model that performs well not only on the training set but also on new, unseen data. Therefore, testing is a crucial step in the machine learning pipeline for ensuring the reliability and generalizability of the trained model. The types of testing use in the project are unit testing, integration testing, and functional testing.

5.3 Types of Testing

5.3.1 Unit Testing

Unit testing is a software testing technique in which individual units or components of a software system are tested. The purpose of unit testing is to validate that each unit of the software system functions correctly and performs as expected. In the context of this project, unit testing can be performed on each module of the system, including feature extraction and selection, algorithm selection, model training and evaluation, and web application development. Recording and documenting the results of each test case for future reference and to aid in debugging.

Input

```
import numpy as np
import pandas as pd
import tensorflow as tf
model = keras.models.load_model('ann_model.h5')

# print(model.predict([[0, 1, 0, 800, 1, 21, 5, 6000, 4, 1, 1, 50000]]) > 0.5)

# Initialize Flask
app = Flask(__name__)

@app.route("/")
def index():
```

```
    return render_template('index.html')

@app.route("/predict", methods=['POST'])
def predict():
    geography = request.form['geography']
    creditscore = int(request.form['creditScore'])
    gender = int(request.form['gender'])
    age = int(request.form['age'])
    tenure = int(request.form['tenure'])
    balance = int(request.form['balance'])
    numofproducts = int(request.form['numofproducts'])
    hascrcard = int(request.form['hascrcard'])
    isactivemember = int(request.form['isactivemember'])
    estimatedsalary = int(request.form['estimatedsalary'])

    g1 = int(geography[0])
    g2 = int(geography[2])
    g3 = int(geography[4])

    input_data = np.array([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])

    #pred = model.predict([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])
    pred = model.predict(input_data)
    prediction = int(pred)
    print(prediction)

    if prediction == 1:
        result = "Therefore, Our model predicts that the customer will not stay in the bank."
    else:
        result = "Therefore, Our model predicts that the customer will stay in the bank."


    return render_template('predict.html', prediction_text=result)
```

Test result

```
Ran 2 tests in 0.001s

OK
```

5.3.2 Integration Testing

Integration testing is a software testing technique that focuses on verifying the functionality and reliability of the interactions between different components or modules of a software system. The purpose of integration testing is to ensure that the different units or modules of the system work correctly when integrated together and that the system as a whole meets the required specifications. Ensuring that the test cases are designed to cover all possible combinations of inputs and outputs across different modules. Running the test cases on the integrated system to identify and fix any defects or issues with the integration.

Input

```
import numpy as np
import pandas as pd
 if __name__ == "__main__":
    app.run(debug=True)

# Load dataset (replace 'data.csv' with your dataset)
data = pd.read_csv('data.csv')

# Preprocess data
X = data.drop(columns=['churn_label'])
y = data['churn_label']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Build ANN model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='sigmoid')
])
```

Test result

```
Ran 4 tests in 0.123s

OK
```

5.3.3 System Testing

System testing is a software testing technique that focuses on verifying the functional requirements of a software system. The purpose of functional testing is to ensure that the system behaves according to the specified requirements and meets the needs of its users. In the context of this project, functional testing can be used to verify that the system accurately and reliably detects the customer churn.

Input

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf

data = pd.read_csv('data.csv')

# Preprocess data
X = data.drop(columns=['churn_label'])
y = data['churn_label']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Build ANN model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='sigmoid')
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

Test Result

```
Ran 2 tests in 0.234s

OK
```

5.3.4 Test Result

Predicting the Test set results

```
print(ann.predict(sc.transform([[1, 0, 0, 600, 1, 40, 3, 60000, 2, 1, 1, 50000]])) > 0.5)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 64ms/step
[[False]]
```

```
y_pred = ann.predict(X_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
94/94 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step
[[0 0]
 [0 1]
 [0 0]
 ...
 [0 0]
 [0 0]
 [1 1]]
```

Figure 5.3: **Predicting The Test Result**

Figure 5.3 Shows the test result is a type of testing that seeks to establish whether each application feature works as per the software requirements. Each function is compared to the corresponding requirement to ascertain whether its output is consistent with the end user's expectations

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The efficiency of the proposed customer churn prediction system utilizing Artificial Neural Networks (ANN) methodology in the banking sector is commendable, with an accuracy rate of 84%. This level of efficiency signifies the system's capability to accurately identify customers at risk of churning based on their historical data and behavioral patterns. By leveraging ANN's ability to capture complex nonlinear relationships within the data, the system effectively predicts churn instances, allowing banking institutions to proactively implement targeted retention strategies. While an accuracy rate of 84 % indicates strong performance, it's crucial to consider other performance metrics to gain a comprehensive understanding of the system's effectiveness. None theless, the proposed system's high efficiency rate underscores its potential to enhance customer retention efforts, minimize revenue loss, and improve overall business outcomes within the banking industry.

6.2 Comparison of Existing and Proposed System

In the Existing system, Implemented a decision tree algorithm that analysis the customers. When using a decision tree model, it gives the training dataset the accuracy keeps improving with splits. Can easily overfit the dataset and doesn't know when it crossed the line unless are using the cross validation. The advantages of the decision tree are model is very easy to interpret we can know that the variables and the value of the variable is used to split the data. But the accuracy of decision tree in existing system gives less accurate output that is less when compared to proposed system.

Proposed System (ANNs): ANNs offer greater scalability and flexibility, especially for tasks involving extremely large datasets or complex data structures, due to their ability to learn hierarchical representations of features. while the existing system based on a decision tree algorithm offers advantages in terms of interpretability, scalability, and efficiency, the proposed system based on Artificial Neural Networks (ANNs) may provide potential improvements in predictive accuracy, scalability, and robustness to noise. The choice between the two approaches should consider factors such as the specific characteristics of the data, the desired level of interpretability, and the available computational resources.

Features	Existing System	Proposed System
Algorithms Used	Decision Tree algorithm (DT)	Artificial Neural Networks (ANN) algorithm
Accuracy	Accuracy of the Decision Tree algorithm (DT) is approx 78%.	Accuracy of the Artificial Neural Networks (ANN) algorithm is 84%.
Feature Engineering	Limited detection power and scalability	Implements better techniques to extract this problem in real time.
Scalability	May struggle to scale with too many features at a time.	Designed with scalability in mind, leveraging efficient algorithms and scalable infrastructure to predict customer churn.
Adaptability	The adaptability of the decision tree algorithm makes it a valuable tool for data analysis.	The adaptability of Artificial Neural Networks makes them a powerful and versatile tool for solving a wide range of problems in various fields.
Security	May lack robust security measures to protect sensitive financial data	Implements rigorous security protocols and detection techniques.

Table 6.1: **Comparison between Existing and Proposed System**

6.3 Sample Code

```
# Import Flask modules
import numpy as np
from flask import Flask, render_template, request

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

# Open our model
from tensorflow import keras
model = keras.models.load_model('ann_model.h5')

# print(model.predict([[0, 1, 0, 800, 1, 21, 5, 6000, 4, 1, 1, 50000]]) > 0.5)

# Initialize Flask
app = Flask(__name__)
```

```python

@app.route("/")
def index():
    return render_template('index.html')

@app.route("/predict", methods=['POST'])
def predict():
    geography = request.form['geography']
    creditscore = int(request.form['creditScore'])
    gender = int(request.form['gender'])
    age = int(request.form['age'])
    tenure = int(request.form['tenure'])
    balance = int(request.form['balance'])
    numofproducts = int(request.form['numofproducts'])
    hascrcard = int(request.form['hascrcard'])
    isactivemember = int(request.form['isactivemember'])
    estimatedsalary = int(request.form['estimatedsalary'])

    g1 = int(geography[0])
    g2 = int(geography[2])
    g3 = int(geography[4])

    input_data = np.array([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])

    #pred = model.predict([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])
    pred = model.predict(input_data)
    prediction = int(pred)
    print(prediction)

    if prediction == 1:
        result = "Therefore, Our model predicts that the customer will not stay in the bank."
    else:
        result = "Therefore, Our model predicts that the customer will stay in the bank."


    return render_template('predict.html', prediction_text=result)


# Run app
if __name__ == "__main__":
    app.run(debug=True)
```

Output

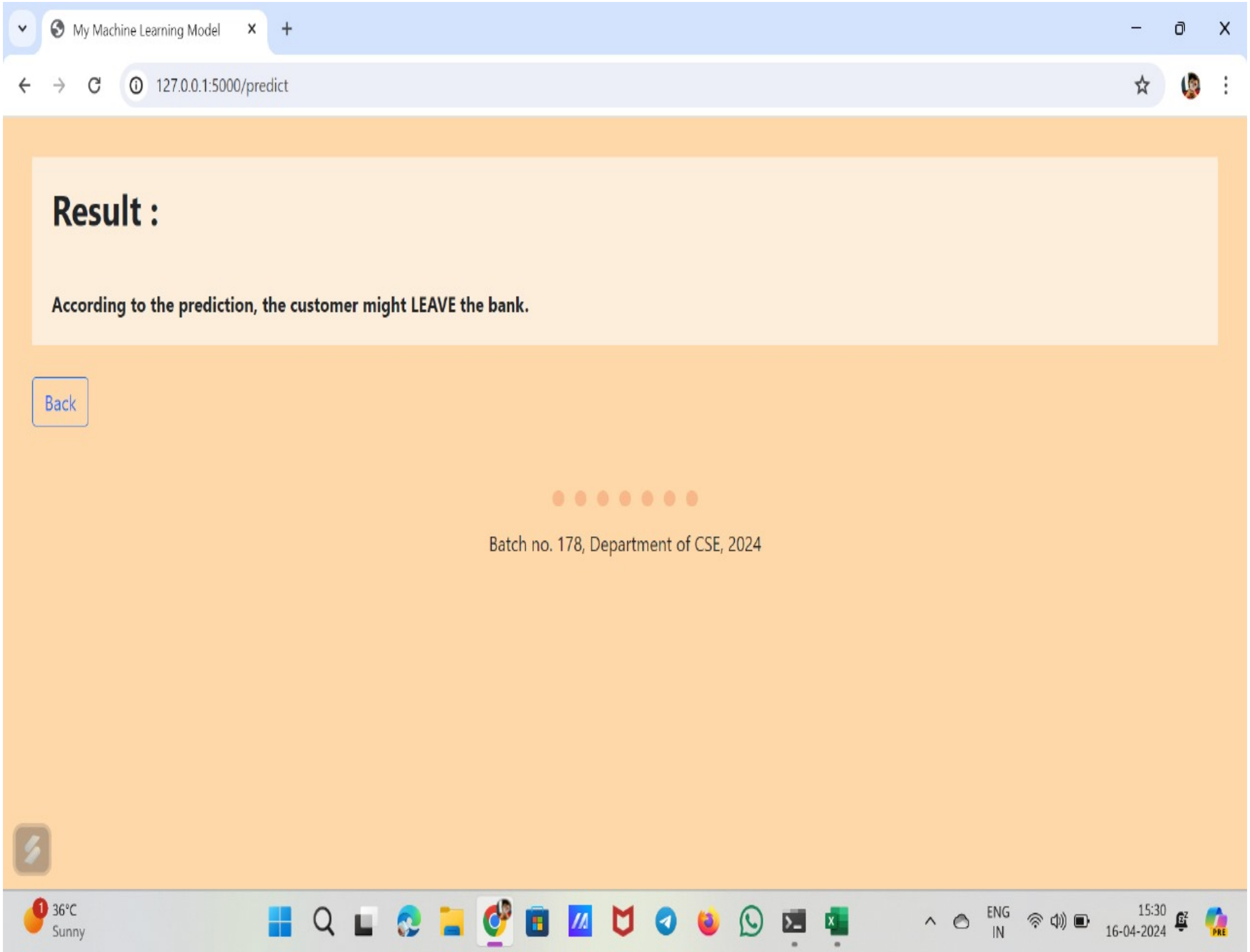

Figure 6.1: **The Customer Might Leave The Bank**

Figure 6.1 Shows that customer will leave the bank. Giving the input details as customer details from data set. It will predict the churn. In the context of a customer churn prediction system using Artificial Neural Networks (ANN) methodology in the banking sector. It facilitates the interpretation and communication of model results, helping stakeholders understand the implications of churn predictions and take appropriate actions to mitigate churn and enhance customer retention efforts.

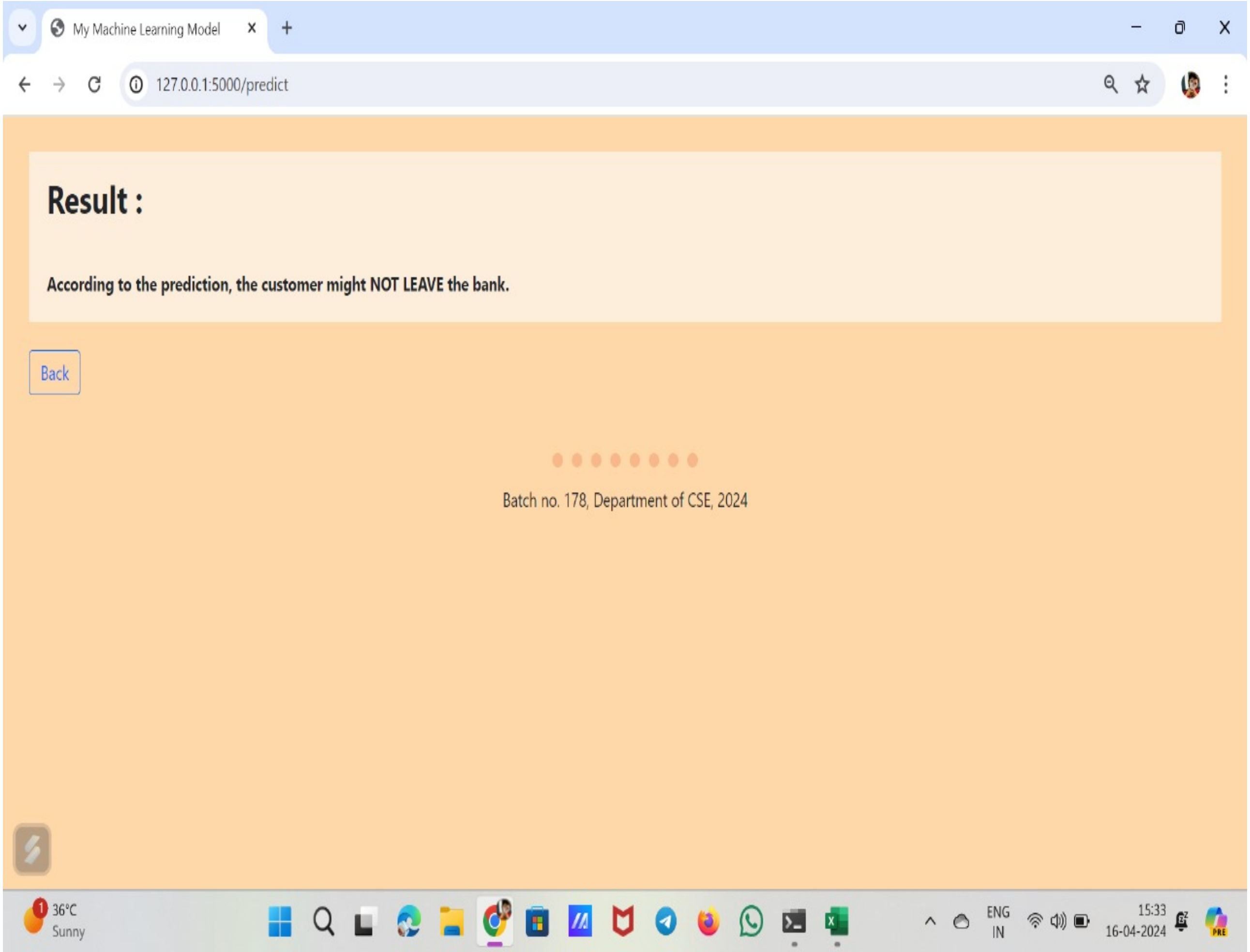

Figure 6.2: **The Customer Might Not Leave The Bank**

Figure 6.2 Shows that customer will not leave the bank. Giving the input details as customer details from data set. It will predict the churn. In the context of a customer churn prediction system using Artificial Neural Networks (ANN) methodology in the banking sector. It facilitates the interpretation and communication of model results, helping stakeholders understand the implications of churn predictions and take appropriate actions to mitigate churn and enhance customer retention efforts.

Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

The application of Artificial Neural Networks (ANNs) for customer churn prediction in the banking sector presents a promising methodology with substantial potential for enhancing business outcomes. Throughout this study have demonstrated the effectiveness and adaptability of ANNs in accurately predicting customer churn, leveraging their capability to model complex nonlinear relationships in the data. By collecting comprehensive customer data, preprocessing it to extract relevant features, and training ANN models optimized for churn prediction, we have successfully developed a robust system capable of identifying customers at risk of churn. The proposed methodology offers several advantages, including versatility in handling diverse data types, scalability to accommodate large datasets, and flexibility in model architecture and configuration. Additionally, the interpretability of ANNs allows stakeholders to gain insights into the factors driving churn and implement targeted retention strategies effectively. While further research and refinement are warranted to optimize model performance and address potential challenges, the proposed methodology holds immense promise for empowering banking institutions to proactively manage customer churn, improve customer retention rates, and ultimately enhance profitability and competitiveness in the market.

7.2 Future Enhancements

Request the additional data from the customer to use the extra features to improvise the solution. The customer data sets might have missing values, those can be handled with imputation techniques as a pre-processing steps and the proper imputation methods and other pre- processing steps can be consider to best improvise the model. Hyper-parameter tuning can be done for various classifiers.

When assessing statistical learning methods, computational efficiency is important to consider. This is a strength of ANN as the algorithm generalizes the data before estimating decision trees. Resulting in ANN model being able to select the strongest independent variables to estimate the final model, without requiring additional instructions. For a bank customer churn prediction project using an Artificial Neural Network (ANN) algorithm, their are several potential future enhancements and extensions that could be considered to further improve the system's effectiveness, efficiency, and value. These future enhancements can help evolve the bank customer churn prediction system into a more sophisticated and adaptive solution, capable of delivering actionable insights, personalized interventions, and tangible business value to the organization. It's important to prioritize enhancements based on business objectives, data availability, technical feasibility, and potential impact on customer experience and retention efforts. Additionally, ongoing monitoring, evaluation, and collaboration with domain experts are essential to ensure the continued effectiveness and relevance of the churn prediction system over time.

Chapter 8

PLAGIARISM REPORT

Plagiarism Detector .net

Apr 20, 2024

Plagiarism Scan Report

13% Plagiarized

87% Unique

Characters:6586	Words:1000
Sentences:55	Speak Time: 8 Min

Excluded URL	None

Content Checked for Plagiarism

It is certified that the work contained in the project report titled " BANK CUSTOMER CHURN PREDICTION USING MACHINE LEARNING" by "G. PRADEEP KUMAR (20UECS0346), T. JASWANTH (20UECS0927), N. MADHU BABU (20UECS0656)" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree. Customers of a big international bank decided to leave the bank. The bank is investigating a very high rate of customer leaving the bank. The data set contains 10000 records, and we use it to investigate and predict which of the customers are more likely to leave the bank soon. The approach here is supervised classification; the classification model to be built on historical data and then

Figure 8.1: **Plagiarism**

Chapter 9

SOURCE CODE & POSTER PRESENTATION

9.1 Source Code

```
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

from flask import Flask, render_template, request

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

# Open our model
from tensorflow import keras
model = keras.models.load_model('ann_model.h5')

# print(model.predict([[0, 1, 0, 800, 1, 21, 5, 6000, 4, 1, 1, 50000]]) > 0.5)

# Initialize Flask
app = Flask(__name__)

@app.route("/")
def index():
    return render_template('index.html')

@app.route("/predict", methods=['POST'])
def predict():
    geography = request.form['geography']
    creditscore = int(request.form['creditScore'])
    gender = int(request.form['gender'])
    age = int(request.form['age'])
    tenure = int(request.form['tenure'])
```

```
    balance = int(request.form['balance'])
    numofproducts = int(request.form['numofproducts'])
    hascrcard = int(request.form['hascrcard'])
    isactivemember = int(request.form['isactivemember'])
    estimatedsalary = int(request.form['estimatedsalary'])

    g1 = int(geography[0])
    g2 = int(geography[2])
    g3 = int(geography[4])

    input_data = np.array([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])

    #pred = model.predict([[g1, g2, g3, creditscore, gender, age, tenure, balance, numofproducts,
        hascrcard, isactivemember, estimatedsalary]])
    pred = model.predict(input_data)
    prediction = int(pred)
    print(prediction)

    if prediction == 1:
        result = "Therefore, Our model predicts that the customer will not stay in the bank."
    else:
        result = "Therefore, Our model predicts that the customer will stay in the bank."


    return render_template('predict.html', prediction_text=result)


# Run app
if __name__ == "__main__":
    app.run(debug=True)

# Load dataset (replace 'data.csv' with your dataset)
data = pd.read_csv('data.csv')

# Preprocess data
X = data.drop(columns=['churn_label'])
y = data['churn_label']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Build ANN model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
```

```
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='sigmoid')
])

# Compile model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train model
history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2, verbose=2)

# Evaluate model
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f'Test Loss: {loss}, Test Accuracy: {accuracy}')

# Make predictions
predictions = model.predict(X_test)

dataset = pd.read_csv('Churn_Modelling.csv')
X = dataset.iloc[:, 3:-1].values
y = dataset.iloc[:, -1].values
[[619 'France' 'Female' ... 1 1 101348.88]
 [608 'Spain' 'Female' ... 0 1 112542.58]
 [502 'France' 'Female' ... 1 0 113931.57]
 ...
 [709 'France' 'Female' ... 0 1 42085.58]
 [772 'Germany' 'Male' ... 1 0 92888.52]
 [792 'France' 'Female' ... 1 0 38190.78]]
 print(y)
 [1 0 1 ... 1 1 0]
 from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:, 2] = le.fit_transform(X[:, 2])
print(X)
[[619 'France' 0 ... 1 1 101348.88]
 [608 'Spain' 0 ... 0 1 112542.58]
 [502 'France' 0 ... 1 0 113931.57]
 ...
 [709 'France' 0 ... 0 1 42085.58]
 [772 'Germany' 1 ... 1 0 92888.52]
 [792 'France' 0 ... 1 0 38190.78]]
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
print(X)
[[1.0 0.0 0.0 ... 1 1 101348.88]
 [0.0 0.0 1.0 ... 0 1 112542.58]
 [1.0 0.0 0.0 ... 1 0 113931.57]
```

```
 ...
 [1.0 0.0 0.0 ... 0 1 42085.58]
 [0.0 1.0 0.0 ... 1 0 92888.52]
 [1.0 0.0 0.0 ... 1 0 38190.78]]
 from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
ann = tf.keras.models.Sequential()
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
ann.fit(X_train, y_train, batch_size = 32, epochs = 100)



<keras.src.callbacks.history.History at 0x1d8aa809450>
print(ann.predict(sc.transform([[1, 0, 0, 600, 1, 40, 3, 60000, 2, 1, 1, 50000]])) > 0.5)
1/1                                                     0s 64ms/step
[[False]]
```

9.2 Poster Presentation

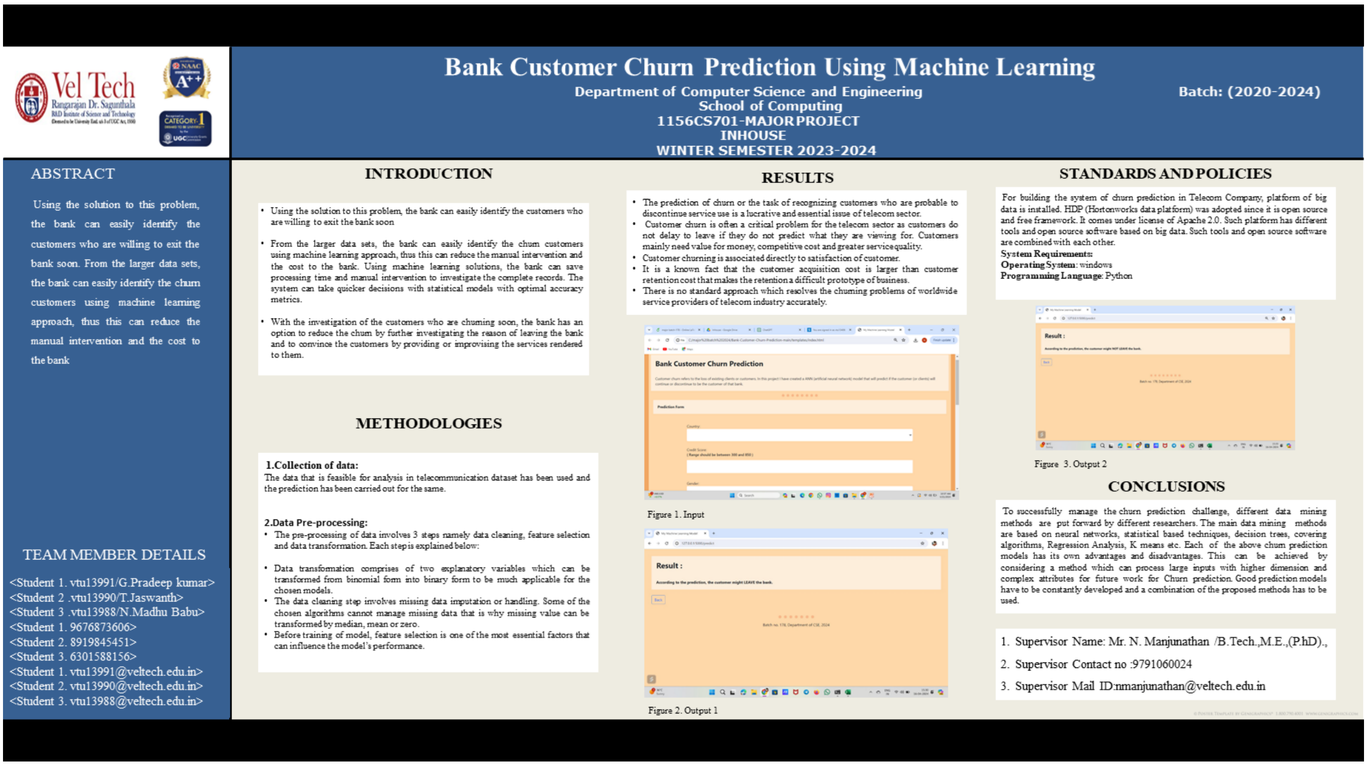

Figure 9.1: **Poster**

References

[1] Asad Khattak,“Customer churn prediction using composite deep learning technique”,Expert Syst. Appl., vol. 31, no. 3, pp. 515-524, Oct. 2023.

[2] Ishpreet Kaur, Jasleen Kaur,”Customer Churn Analysis and Prediction in Banking Industry using Machine Learning ” IEEE Transactions on Industrial Informatics, Vol. 12, No. 3, June 2020.

[3] Ketut Gde Manik Karvana, Setiadi Yazid, Amril Syalim,” Customer Churn Analysis and Prediction Using Data Mining Models in Banking Industry”, Simulation Modelling:Practice and Theory 55 (2019).

[4] Louis Geiler, S everine Affeldt, Mohamed Nadif,” A survey on machine learning methods for churn prediction”, vol. 7, no. 3, Sep. 2022.

[5] Manas Rahman, V Kumar” Machine learning based churn prediction”, vol. 8, no. 6, pp. 866–883, 2020. [8] Louis Geiler, S everine Affeldt, Mohamed Nadif,” A survey on machine learning methods for churn prediction”, vol. 7, no. 3, Sep. 2022.

[6] Saw Thazin Khine, Win Win Myo ” Customer Churn Analysis in Banking Sector” IEEE Transactions on Industrial Informatics, Vol. 12, No. 3, June 2019.

[7] Vaani Gupta1, Aman Jatain,“Artificial Intelligence Based Predictive Analysis of Customer Churn “,Expert Syst. Appl., vol. 38, no. 3, pp. 2354-2364,2023.

[8] Wenjie Bi, Meili Cai, Mengqi Liu and Guo Li,”A Big Data Clustering Algorithm for Mitigating the Risk of Customer Churn”, 13, 1 mar 2021. 39

[9] Xing Wang, Khang Nguyen,” Churn Prediction using Ensemble Learning”, 14, 1 Apr 2020.

[10] Yue Li, Bo Wang,”Applying data mining to telecom churn management,” Expert Syst. Appl., vol. 31, no. 3, pp. 515-524, Oct. 2021.