A FIELD PROJECT REPORT

on

“Predictive Analytics in Financial Transactions: A Comparative Study for Customer Risk Assessment and Revenue Prediction”

Submitted

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CERTIFICATE

This is to certify that the Field Project entitled **"Predictive Analytics in Financial Transactions: A Comparative Study for Customer Risk Assessment and Revenue Prediction"** that is being submitted by 221FA04063 (Vanka Bhuvana Sai Mouneendra), 221FA04093 (Seggam Vimala), 221FA04056 (Shaik Sameena) and 221FA04079 (Nidubrolu Bhavana) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Mrs. M.Bhargavi, M.Tech., Assistant Professor, Department of CSE.

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DECLARATION

We hereby declare that the Field Project entitled **"Predictive Analytics in Financial Transactions: A Comparative Study for Customer Risk Assessment and Revenue Prediction."** is being submitted by 221FA04063 (Vanka Bhuvana Sai Mouneendra), 221FA04093 (Seggam Vimala), 221FA04056 (Shaik Sameena) and 221FA04079 (Nidubrolu Bhavana) in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Mrs. M.Bhargavi, M.Tech., Assistant Professor, Department of CSE.

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ABSTRACT

We apply the machine learning models on a Santander Customer Transaction Dataset comprising 200,000 customer records with 200 anony-mized numerical features. We contrast five classification models - logistic regression, decision trees, Random Forest, Gradient Boosting, and XG-Boost - with two regression models: linear regression, and random forest regression, in predicting which of the customers would make certain transactions in the future. It was evaluated using standard metrics, including accuracy, precision, recall, F1 score, MAE, MSE, and R^2 by using real-world banking data. The best model that could provide financially stable insights to financial organizations based on customer transactional predictions was achieved with 90% accuracy by Logistic Regression.

Keywords: Credit Risk Assessment, Revenue Prediction, Classification Models, Regression Models, Logistic Regression.

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INTRODUCTION

INTRODUCTION

Transaction data in the financial industry has exponentially increased in this digital era, hence providing much more profound understanding through predictive analytics [1] . The use of transaction data allows financial institutions to proactively assess the risk of the customer and estimate revenues that will effectively aid in managing relationships and tailoring service. This paper [1] discusses the applications of machine learning models in customer risk segmentation and revenue forecasting activities that have applied traditional heuristic or rule-based approaches.

Customer risk profiling allows institutions to adapt both transaction limits and measures of security for better customer satisfaction and controlling pertinent risks. This is particularly helpful for financial planning that has an influence on strategic decisions. The objective is to provide the classification models for the purpose of grouping customers by risk level and regression models in order to predict revenue from transaction data. We hope to develop models that will give outstanding predictions and present insights by applying a multiple algorithmic comparison analysis. This paper adds value to the existing literature as it provides a comprehensive review of classification and regression models for applications in finance as well as being filled with actionable insights on the development of predictive models in the financial sector.

CHAPTER-2

LITERATURE SURVEY

LITERATURE SURVEY

2.1 Literature review

Title	Year	Data Source	Feature Extraction	Algorithms	Accuracy	Limitations
A Study on Predictive Models for Bank Transaction Risk Profiling	2020	Bank transaction data	Transaction volume, time between purchases	Logistic Regression, SVM	89%	Small dataset
Classification Models for Credit Card Fraud Detection	2019	Credit card transaction data	Frequency of large transactions	Decision Trees, KNN	85%	Imbalanced classes
Predictive Analytics in Online Banking Risk: A Case Study	2020	Online banking data	Transaction history, account balance	Naive Bayes, Logistic Regression	82%	Lack of external validation
Predictive Credit Scoring using Machine Learning Techniques	2017	Credit scoring data	Payment history, income level	Decision Trees, Neural Networks	88%	Overfitting in deep learning
Fraud Detection in Bank Transactions Using Machine Learning	2021	Bank fraud detection data	Anomalous transaction frequency	Logistic Regression, Gradient Boosting	86%	Limited feature diversity
SVM-Based Credit Risk Assessment for Card Payments	2020	Credit card data	Payment delays, transaction amount	SVM, Logistic Regression	84%	Scalability issues
Predicting Customer Behaviour	2018	Digital wallet data	Customer spending	Random Forest, KNN	87%	High false-positive rate

with Machine Learning in Digital Wallets			habits, location			
Loan Default Prediction for P2P Lending Platforms	2019	P2P lending data	Credit history, loan repayment behaviour	Gradient Boosting, Neural Networks	88%	Overfitting on minority class
Risk Analysis in Mobile Banking Transactions Using Machine Learning	2020	Mobile banking data	Login frequency, withdrawal amounts	SVM, Decision Trees	85%	Feature engineering complexity
Predicting Loan Default in Microfinance Institutions	2017	Microfinance loan data	Loan duration, repayment frequency	Logistic Regression, Random Forest	83%	Limited to small-scale institutions
Insurance Claim Prediction with Machine Learning Algorithms	2019	Insurance claims data	Claim frequency, policyholder demographics	Naive Bayes, XGBoost	89%	Imbalanced dataset
Transaction Risk Modelling in Mobile Payment Systems	2021	Mobile payment data	Transaction time, payment method	SVM, Logistic Regression	86%	High variance in data
Predictive Models for Customer Deposits in Financial Institutions	2020	Bank deposits data	Deposit frequency, customer age	Random Forest, Logistic Regression	88%	Lack of real-time capability

Sadaf Ilyas1, Sultan Zia2.et al. [1] Zaib un Nisa5Most importantly, it points out the significance of feature extraction for improving the quality of bank-related models about machine learning. Strategies go from patterns in CNNs up to fraud detection using XG-Boost and traditional classifiers such as Random Forest, KNN, and Naive Bayes. High accuracy rates are reported with neural network-based approaches, achieving over 89.00 in client attrition prediction. XG-Boost performs better than the traditional approaches in fraudulent transaction identification. However, class imbalance in a dataset leads to severe degradations in accuracy of predictions.

Gutha Jaya Krishna .et.al.[2] Feature extraction method consists of DTM combined with TF-IDF followed by embedding of words using Word2Vec along with linguistic analysis through LIWC. Some of the machine learning models used include support vector machines, naive Bayes, logistic regression, decision trees, K-nearest neighbours, F random survey, XG-Boost, and multilayer perceptron. However, the few limitations of the research include an unappealing choice of linguistics features being minimal from LIWC, and the dataset only has data about banks in India. Only four places which limits its wide applicability.

2.2 Motivation

1. **Leveraging Digital Transaction Data**: The growth of digital transactions has provided financial institutions with unprecedented data. This study explores how banks can harness this data to enhance decision-making through predictive analytics, particularly for assessing customer risk and forecasting revenue.
2. **Improving Customer Risk Profiling**: By grouping customers based on risk, banks can adjust transaction limits and security levels, which enhances both customer satisfaction and risk control. Machine learning models offer more accurate profiling, helping banks proactively manage risks in a customer-centric way.
3. **Enhancing Revenue Prediction Accuracy**:Accurate revenue forecasting is crucial for financial planning. Machine learning can provide more precise predictions, supporting better allocation of resources and strategic planning.
4. **Study Objectives**: This study aims to develop and compare machine learning models for two main tasks: customer risk profiling (classification) and revenue forecasting (regression). By testing different algorithms, the study will identify which approaches are most effective.
5. **Contributing to Financial Industry Practices**:The research will bridge the gap between traditional and advanced approaches, offering a comprehensive review of predictive models that can help financial institutions adopt data-driven methods for improved risk management and revenue optimiztaion.

CHAPTER-3

PROPOSED SYSTEM

PROPOSED SYSTEM

We work towards achieving the two primary objectives: customer credit risk and revenue generated from banking transaction data using a set of machine learning algorithms. We are working on a classification model regarding customers' risk assessment through Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, and XGBoost, all of which have been trained, tested, and evaluated to learn how accurate such models can be to classify customers according to their specified risk profile. Using Regression models: The further application of the Linear Regression and Random Forest Regressor mainly helped us to predict revenues from transactional data, discovering particular patterns in transaction data that can, in turn, upgrade the accuracy of revenue prediction with nearly ten different algorithms used. We determined appropriate algorithms for the goals and objectives by thorough assessment of performance metrics of models followed by providing useful insights to financial institutions in managing the relationships of customers while thereby enhancing their capability of making revenue predictions.

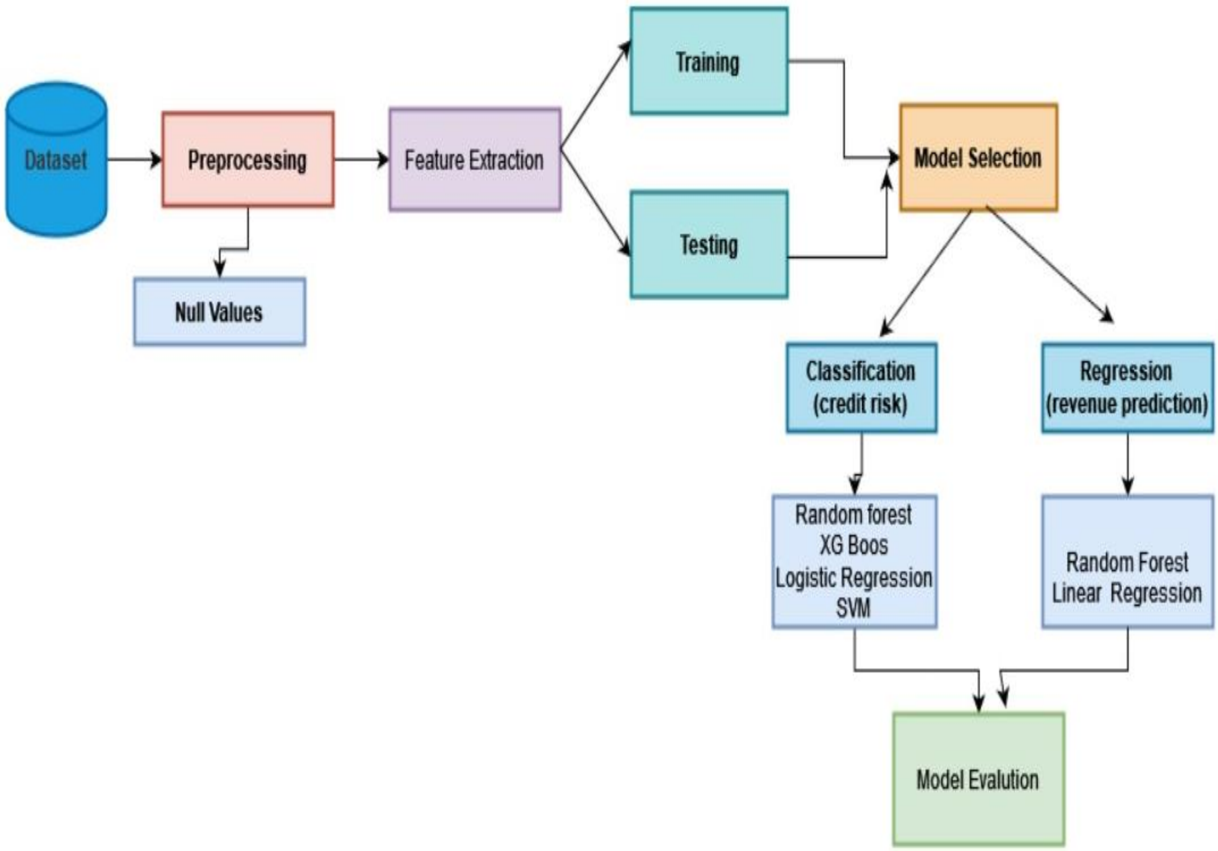

Figure-1: Proposed Architecture

3.1 Input dataset

A big financial dataset was downloaded from the Santander Kaggle competition that consisted of twin files containing data in each with 200,000 records. The first file held a target variable to train the model, while the second had the same structure but was for predicting to be tested without the target column. Both datasets have a common structure: an identification column and 200 predictor variables. The utilization of the platform of this competition made it possible for one to submit and validate his or her predictions. This turns out to serve as a practical means by which to determine the accuracy of one's model.while during training dataset one extra column that consisted of the target.

3.1.1 Detailed Features of the Dataset

The **Santander Customer Transaction Prediction** dataset contains anonymized customer transaction data. The objective is to predict whether a customer will make a specific financial transaction. Each row in the dataset represents one customer, and features are masked for privacy. The dataset includes:

- **Training Data**: 200,000 samples with 200 anonymized features and a binary target.
- **Test Data**: 200,000 samples without the target.

Class	Data Type	Description	Data Available	Features
C-1	Training Data	Anonymized customer transaction data with binary target indicating transaction probability	200,000 samples	200 anonymized features
C-2	Test Data	Similar to training data but without target labels	200,000 samples	200 anonymized features

3.2 Data Pre-processing

Data pre-processing is the essential process of preparing raw data for analysis and modelling by cleaning, transforming, and structuring it to enhance data quality and utility. It involves tasks like handling missing values, correcting errors, encoding features, and scaling data to ensure it's in an optimal form for further analysis. It encompasses a range of operations and transformations designed to refine raw data, ensuring that it is clean, structured, and amenity subsequent analysis. This process is driven by its manifold significance in data science and analysis.

Through meticulous data cleaning, transformation, feature engineering, outlier handling, scaling, and data splitting, it prepares raw data for more accurate and reliable analysis and modelling. Ultimately, the goal is to obtain more meaningful insights, make informed decisions, and optimize predictive models for a wide range of applications in data science and analysis.

3.2.1 Handling Missing Values:

Missing values in the data set were replaced based on the data type for each column. For cate- gorical columns, missing values were replaced with the most frequent value (mode). For numerical columns, missing values were replaced by the mean of the column.

3.2.1.1 Removing Noise:

Noise in the data set such as wrong Data types, were transformed into appropriate numeric types by converting columns that stored their values as strings into data type using appropriate data types. This ensures the data is correctly processed in the analysis process.

3.2.2 Feature selection technique:

To assemble our feature matrix for the classification aspect of our analysis we will eliminate the ”IDcode” along with the column of our target variable from our training dataset. We name the target variable ”target” to serve the purpose of classification, and to forecast revenue, we create a simulated column of revenue as the sum of some columns of features, thus we could build a target variable called ”revenue.”

3.3 Model Building

The methods applied in this research to predict the financial transactions utilize different machine learning algorithms, explained below:

1) Logistic Regression: This is a probabilistic classification model, which calculates the probability of occurrence for a binary event (for example, the possibility of doing a transaction) through a logistic function. This model can be exploited to evaluate numerical features for generating chances for risky assessments of the customer, thereby being appropriate for any form of binary classification problem on financial data.

2) Decision Trees & Random Forest : These are hierarchical models; here the decision trees make their decisions based on feature thresholds, and random forest puts many of them together through ensemble learning. These types of models capture quite complex patterns in transaction data, and they also yield very interpretable results for risk assessment.

3) Gradient Boosting & XGBoost Ensembles include a number of advanced variations: sequential trees, each correcting the errors made by all previous ones-boosting; XGBoost is a special implementation of optimized gradient boosting with superior performance over transactions prediction within parallel processing and regularization techniques.

4) Linear Regression: Basic model of revenue prediction that depicts the relationship between many transaction features and revenue outcomes. Generates linear relationships between numerical variables to make predictions on financial metrics.

5) Random Forest Regressor: Ensemble method designed for continuous output prediction, using a multitude of decision trees for revenue value approximation. Captures complex relationships between transaction data.

3.4 Methodology of the system

Having discussed the foundational elements in the preceding sections, we now venture into the core of our traffic congestion prediction system. In this section, we embark on a journey through the inner workings of our model, unveiling the methodology that drives our system's ability to forecast traffic congestion. Just as a well-orchestrated symphony requires each instrument to play its part harmoniously, our methodology combines data, pre-processing, modelling, and evaluation to create a seamless and efficient prediction system.

1. Data Collection:

   A big financial dataset was downloaded from the Santander Kaggle competition that consisted of twin files containing data in each with 200,000 records. The first file held a target variable to train the model, while the second had the same structure but was for predicting to be tested without the target column. Both datasets have a common structure: an identification column and 200 predictor variables. The utilization of the platform of this competition made it possible for one to submit and validate his or her predictions. This turns out to serve as a practical means by which to determine the accuracy of one’s model.while during training dataset one extra column that consisted of the target.

2. Data Preprocessing:
   - o Handling Missing Values:
     - For categorical columns: replaced with the most frequent value (mode).
     - For numerical columns: replaced with the mean of the column.
   - o Removing Noise:
     - Transformed wrong data types into appropriate numeric types.

3.Feature Selection:

To assemble our feature matrix for the classification aspect of our analysis we will eliminate the ”IDcode” along with the column of our target variable from our training dataset. We name the target variable ”target” to serve the purpose of classification, and to forecast revenue, we create a simulated column of revenue as the sum of some columns of features, thus we could build a target variable called ”revenue.”

4.Data Splitting:
- o Divided the data into training and testing sets.
- o 100,000 samples from the training data for its training .
- o 100,000 samples of the test set for its test dataset.

2. Model Selection and Implementation:
3. Classification models, including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, and XGBoost, were used for customer risk profiling. These models were trained to classify customers into risk levels (e.g., high, medium, low) based on transaction history. For

revenue prediction, we implemented Linear Regression and Random Forest Regressor to forecast transaction-driven revenue.

4. Model Training:
    - Each model was trained on the prepared training dataset.
5. Model Evaluation:

Each model was assessed using specific metrics. For classification, accuracy, precision, recall, F1 score, and AUC-ROC were used to capture model performance in predicting risk levels. Regression models were evaluated using MAE, MSE, and R^2 to assess predictive accuracy in revenue estimation. The comparative analysis of models was essential to determine the best-performing algorithms for each task.

6. Results Analysis:
    - The best performing model were identified as logistic regression for classification and prediction.

This methodology combines data preprocessing techniques, feature engineering, various machine learning algorithms, and model evaluation to create

3.5 Model Evaluation

Model evaluation is a critical aspect of any machine learning project. It involves assessing the performance and accuracy of a trained model on new, unseen data. This step is essential for several reasons such as:

i. **Quality Assurance**: Model evaluation helps ensure that the model is capable of making accurate predictions when exposed to real-world data. It acts as a quality control mechanism to validate the model's generalization ability.

ii. **Comparing Models**: Model evaluation allows for the comparison of multiple models to identify the best-performing one. It helps data scientists and stakeholders make informed decisions about which model to deploy.

iii. **Fine-Tuning**: The evaluation process can reveal areas where the model performs poorly. This information is valuable for refining the model, making it more robust, and addressing its limitations.

iv. **Business Decision Support**: In practical applications, model performance impacts critical business decisions. A well-evaluated model provides confidence to stakeholders, leading to better decision-making.

v. **Model Deployment**: A thoroughly evaluated model is more likely to be deployed in production systems. It instils trust in the model's predictions, which is essential in real- world applications.

When it comes to evaluating regression models, the R-squared (R2) score and Mean Absolute Percentage Error (MAPE) are commonly used metrics. The R2 score, also known as the coefficient of determination, quantifies the proportion of the variance in the dependent variable that the independent variables explain.

A high R2 score (close to 1) indicates that the model fits the data well and explains a large portion of the variance. Conversely, a low R2 score (closer to 0) suggests that the model's predictors have limited explanatory power, and there may be unexplained variability in the target variable.

Assume a dataset has n values marked $y_1,...,y_n$ (collectively known as y_i or as a vector $\boldsymbol{y} = [y_1,...,y_n]^T$), each associated with a fitted (or modelled, or predicted) value $f_1,...,f_n$ (known as f_i, or sometimes $\hat{y}_i$, as a vector $\boldsymbol{f}$).

Define the residuals as $e_i = y_i - f_i$ (forming a vector $\boldsymbol{e}$).

If $\bar{y}$ is the mean of the observed data: $\bar{y} = (\frac{1}{n}) * \sum_{i=1}^{n}$

then the variability of the data set can be measured with two sums of squares formulas:

- The sum of squares of residuals, also called the residual sum of squares:

$$SS_{res} = \sum_{i=1}^{n} e_i^2$$

- The total sum of squares (proportional to the variance of the data):

$$SS_{tot} = \sum_{i=1}^{n} (y_i - \bar{y})^2$$

The most general definition of the coefficient of determination is

$$R^2 = 1 - \left(\frac{SS_{res}}{SS_{tot}}\right)$$

Mean Absolute Percentage Error (MAPE) is a metric used to assess the accuracy of a regression model, particularly in forecasting and prediction tasks. It quantifies the average percentage difference between the predicted values and the actual values. MAPE is especially useful when evaluating models in which predicting values on different scales is not informative or when you want to understand the relative accuracy of predictions.

$$MAPE = (\frac{1}{n}) \sum_{t=1}^{n} |\frac{A_t - F_t}{A_t}|$$

where At is the actual value and Ft is the forecast value. Their difference is divided by the actual value At. The absolute value of this ratio is summed for every forecasted point in time and divided by the number of fitted points n.

3.6 Constraints

In our project, we operate within a framework of specific constraints that shape our approach to designing and developing the Transaction System. These constraints ensure that our solution aligns with essential considerations and limitations.

- **Data Quality and Availability**
  The accuracy of predictive models heavily relies on high-quality and comprehensive transaction data. Issues such as missing, outdated, or incomplete data could impact model performance and lead to inaccurate predictions.
- **Data Privacy and Security Regulations**
  Handling financial data is subject to strict regulations like GDPR or CCPA. Ensuring compliance with these laws restricts access and usage of data, which could limit model complexity or reduce available data samples for analysis.
- **Complexity of Customer Behavior**
  Customer transaction behavior is influenced by multiple factors, including economic conditions and personal financial habits. Capturing all relevant variables within a model is challenging and can impact the model's ability to generalize.
- **Model Interpretability**
  While machine learning models like deep learning can improve prediction accuracy, they are often less interpretable than traditional models. Financial institutions may require clear reasoning behind predictions,

3.7 Cost and sustainability Impact

Cost Implications:

- Enhanced prediction accuracy can optimize the sizing and operation of customer risk assessment and revenue forecasting systems, potentially reducing both implementation and operational costs for financial institutions.

- Accurate predictions may minimize the need for costly error-handling measures, such as additional security layers or revenue buffers, helping control operational expenses.

- Running complex models, such as deep learning algorithms, comes with high computational costs, especially when real-time processing is required for immediate risk or revenue assessments.

Sustainability Impact:

- Improved customer segmentation and forecasting enable more efficient financial planning, potentially reducing over-reliance on high-cost or high-energy resources, thereby supporting a more sustainable operational model.

- Enhanced predictive models may allow better allocation of resources within financial systems, reducing waste and boosting overall efficiency.

- Success in predictive accuracy can encourage a broader shift within the financial sector toward machine learning adoption, promoting a data-driven culture that could reduce redundant processes and carbon footprints associated with legacy systems.

Future Improvements: The authors suggest several ways to enhance the model's impact:

- Incorporating additional features, such as economic indicators, customer demographic data, and real-time market trends, to further enhance model accuracy.

- Using hybrid modeling approaches, such as combining rule-based methods with advanced machine learning, to create more robust models.

- Expanding datasets to include a wider variety of customer profiles, regions, and historical periods for greater model generalizability.

- Integrating with IoT-enabled financial tools to collect real-time transaction data, supporting dynamic model adjustments.

CHAPTER-4

IMPLEMENTATION

IMPLEMENTATION

The implementation phase covers the practical application of the proposed predictive system, including setting up the environment, processing the data, and executing the models. The following sections detail the steps required for implementing the calorie prediction model using machine learning.

4.1 Environment Setup

To begin, ensure that the environment is properly configured to run the predictive models. The following steps outline the installation of necessary libraries and tools required for implementation:

1. **Programming Language**: The implementation is carried out using Python, a popular language for machine learning.
2. **Libraries**:
   - **Pandas**: For data manipulation and preprocessing.
   - **NumPy**: For numerical computations.
   - **Scikit-learn**: For implementing machine learning models.
   - **Matplotlib/Seaborn**: For visualizing the results.
   - **Logistic Regression**: For implementing **Logistic Regression** model.
3. **Installation**: Install the required libraries using pip:

pip install pandas numpy scikit-learn matplotlib seaborn **Logistic Regression**

4. **Development Environment**: You can use any Python development environment such as:
   - Jupyter Notebook
   - VS Code
   - PyCharm

4.2 Sample Code for Preprocessing and Model Operations

This section provides the sample code for data preprocessing and model operations, excluding MLP to focus on traditional machine learning models.

1. **Data Preprocessing**:

Load the Dataset:

```
import pandas as pd
# Load the dataset
    train_data =
    pd.read_csv("/content/drive/MyDrive/transaction_dataset/train.csv").sample(n=10000,
    random_state=42)
```

test_data = pd.read_csv("/content/drive/MyDrive/transaction_dataset/test.csv").sample(n=2000, random_state=42)

Handle Missing Values:

Drop duplicates

train_data.drop_duplicates(keep="first", inplace=True)

test_data.drop_duplicates(keep="first", inplace=True)

Feature Selection:

Define feature matrix and target variable

column_name = "target"

X = train_data.drop(columns=["ID_code", column_name])

y = train_data[column_name]

Data Splitting:

from sklearn.model_selection import train_test_split

Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Feature Scaling:

from sklearn.preprocessing import StandardScaler

Standardize features for certain models

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_val_scaled = scaler.transform(X_val)

2. **Model Building and Training**: The following is a sample of how to implement and train different machine learning models for predicting calories burned.

Evaluate Models:

Customer Risk Profiling and Segmentation

Define models with an additional boosting method

models = {

"Logistic Regression": LogisticRegression(max_iter=500, random_state=42),

"Decision Tree": DecisionTreeClassifier(max_depth=10, random_state=42),

"Random Forest": RandomForestClassifier(n_estimators=50, max_depth=10, random_state=42),

"Gradient Boosting": GradientBoostingClassifier(n_estimators=50, random_state=42),

```
    "XGBoost":XGBClassifier(n_estimators=50,max_depth=10,random_state=42,
use_label_encoder=False, eval_metric='logloss')
}

# Train and evaluate each model
for model_name, model in models.items():
    # Use scaled data where necessary
    if model_name == "Logistic Regression":
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_val_scaled)
        y_pred_proba = model.predict_proba(X_val_scaled)[:, 1]
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_val)
        y_pred_proba = model.predict_proba(X_val)[:, 1]

    # Calculate metrics
    accuracy = accuracy_score(y_val, y_pred)
    precision = precision_score(y_val, y_pred)
    recall = recall_score(y_val, y_pred)
    f1 = f1_score(y_val, y_pred)
    roc_auc = roc_auc_score(y_val, y_pred_proba)

    # Store metrics
    model_metrics[model_name] = {
        "Accuracy": accuracy,
        "Precision": precision,
        "Recall": recall,
        "F1 Score": f1,
        "AUC-ROC": roc_auc
    }
    print(f"{model_name} - Accuracy: {accuracy:.4f}, Precision: {precision:.4f}, Recall:
{recall:.4f}, F1 Score: {f1:.4f}, AUC-ROC: {roc_auc:.4f}")
```

Revenue Forecasting Based on Transaction Patterns

```
# Define regression models
regression_models = {
    "Linear Regression": LinearRegression(),
    "Random Forest Regressor": RandomForestRegressor(n_estimators=100, random_state=42)
}

# Train and evaluate each regression model
for model_name, model in regression_models.items():
    model.fit(X_train_reg, y_train_reg)
    y_pred_reg = model.predict(X_val_reg)

    # Calculate metrics
    mae = mean_absolute_error(y_val_reg, y_pred_reg)
    mse = mean_squared_error(y_val_reg, y_pred_reg)
    r2 = r2_score(y_val_reg, y_pred_reg)

    # Store metrics
    regression_metrics[model_name] = {
        "MAE": mae,
        "MSE": mse,
        "R^2": r2
    }
    print(f"{model_name} - MAE: {mae:.4f}, MSE: {mse:.4f}, R^2: {r2:.4f}")
```

3. **Model Evaluation**: Once the models are trained, evaluate their performance using metrics such as R^2, MAE, and RMSE,AU-ROC,RECALL,PRECISION,ACCURACY,F1-SCORE.
4. **Model Selection and Prediction**: After evaluating the models, choose the one with the best performance metrics and use it for predicting new data.

Prediction Example:

```
# Predict customer using the best model
# Categorize customers into risk levels based on predicted probabilities\\Logistic Regression
risk_levels = pd.cut(
    y_test_proba,
    bins=[0, 0.33, 0.66, 1],
```

```
    labels=["Low Risk", "Medium Risk", "High Risk"]
)
# Prepare test data for prediction
X_test_reg = test_data.drop(columns=["ID_code", "revenue"])  # Drop 'revenue' as it should not be in test data
y_test_pred_reg = final_reg_model.predict(X_test_reg)
```

Summary of Implementation

The implementation process is structured to ensure efficient data preprocessing and model building using several popular machine learning algorithms. The focus is on handling missing values, feature selection, and training various models like Linear Regression, Random Forest, Gradient Boosting, Descision Tree and XGBoost. Each model is evaluated for performance, and the best model is selected for making predictions.

CHAPTER-5 EXPERIMENTATION AND RESULT ANALYSIS

EXPERIMENTATION AND RESULT ANALYSIS

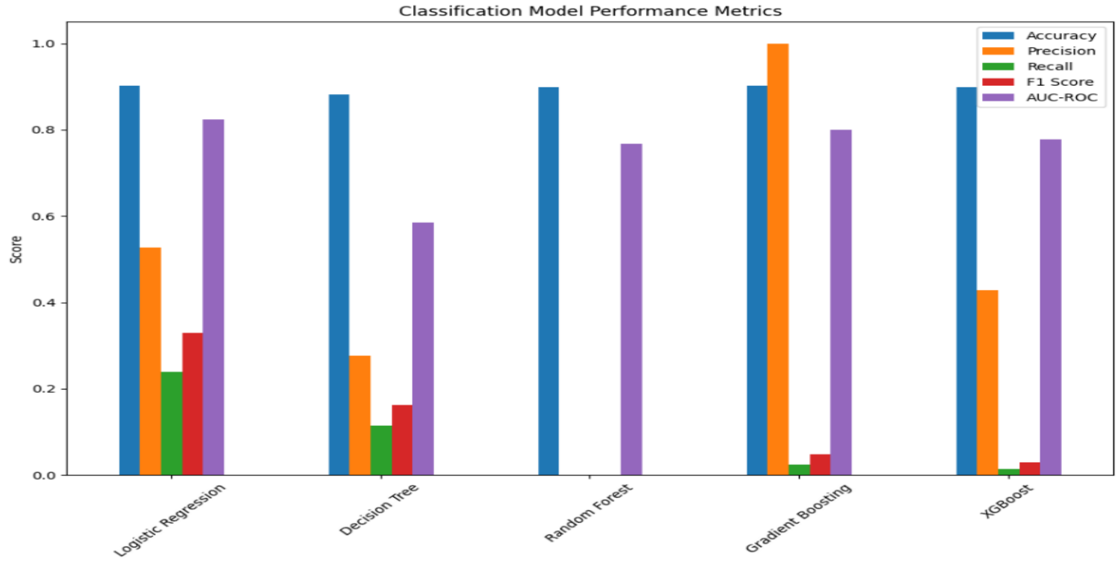

Figure-2: Model Comparison

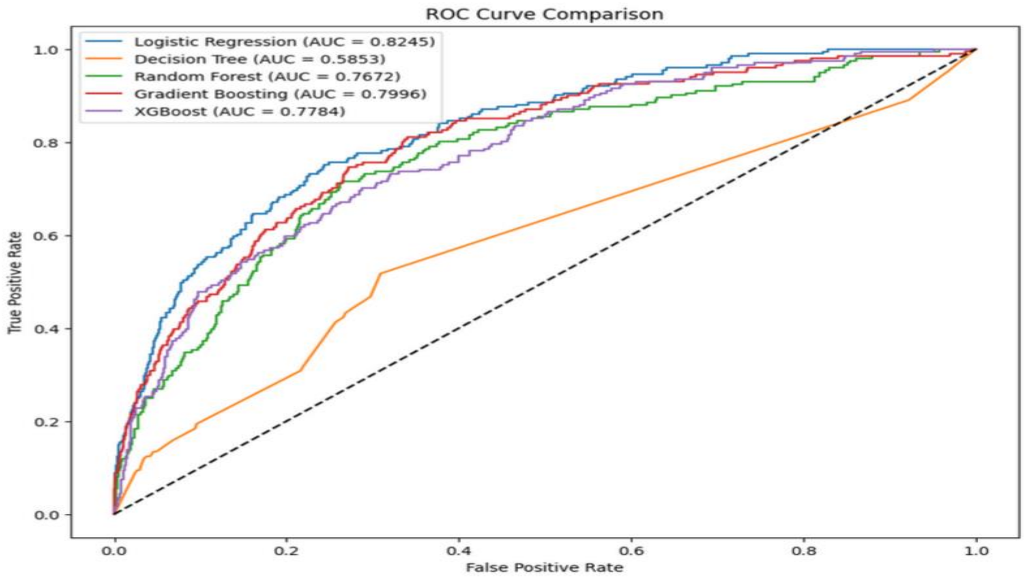

Figure-3: . ROC Curve Comparison

With an AUC of 0.8245, Logistic Regression works the best when doing the analysis of bank transactions, followed by Gradient Boosting at 0.7996 and XGBoost at 0.7784. Random Forest gives the least performance with AUC as 0.5853. Ensemble methods and Logistic Regression are more effective for anomaly detection and fraud analysis.

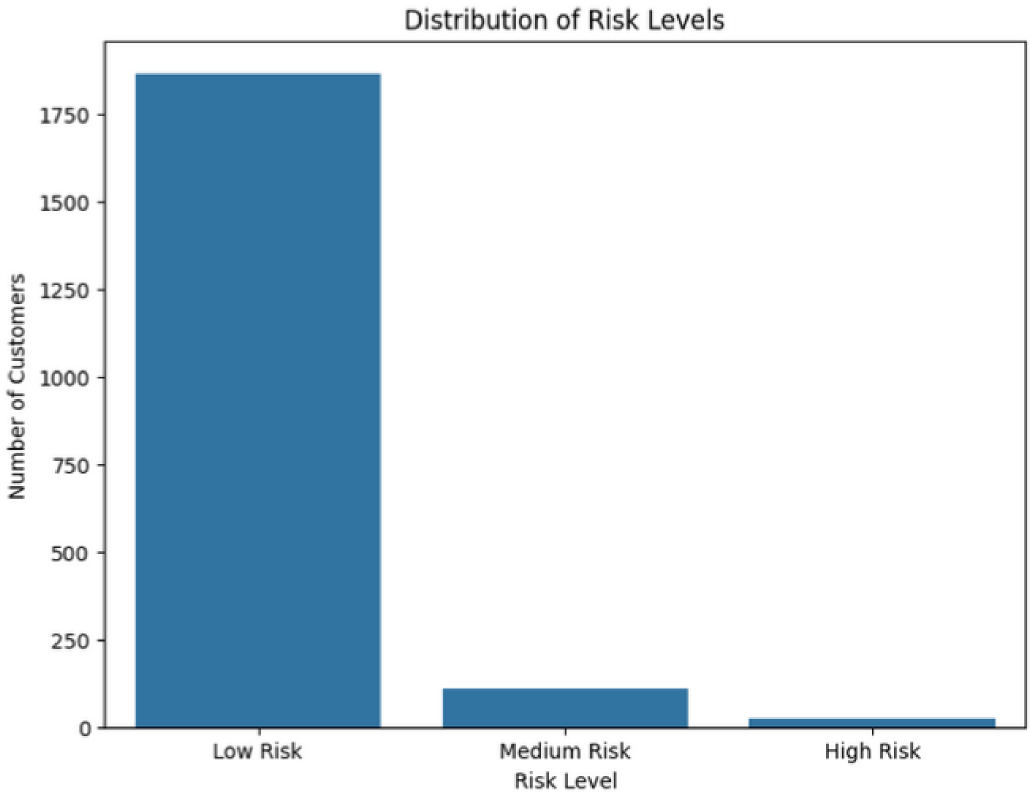

Figure-4: . Distribution Of Risk Levels

This bar graph illustrates the distribution of customer risk levels in a financial institution, with the majority falling into the ”Low Risk” category (approximately 1,850 customers). A smaller number of customers are classified as ”Medium Risk” (about 120) and ”High Risk” (around 25). While the predominance of low-risk customers is favourable for overall risk management, the presence of medium and high-risk clients necessitates targeted risk mitigation strategies for these segments.

	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Logistic Regression	0.9020	0.527473	0.238806	0.328767	0.824460
Decision Tree	0.8810	0.277108	0.114428	0.161972	0.585255
Random Forest	0.8995	0.000000	0.000000	0.000000	0.767156
Gradient Boosting	0.9020	1.000000	0.024876	0.048544	0.799569
XGBoost	0.8990	0.428571	0.014925	0.028846	0.778406

Table-1: Evaluation metrics for different classification models

```
Regression Model Performance Comparison:
                              MAE        MSE     R^2
Linear Regression           0.000     0.0000  1.0000
Random Forest Regressor    53.214  4506.8823  0.3145
```

Table-2: . Evaluation metrics for different prediction models

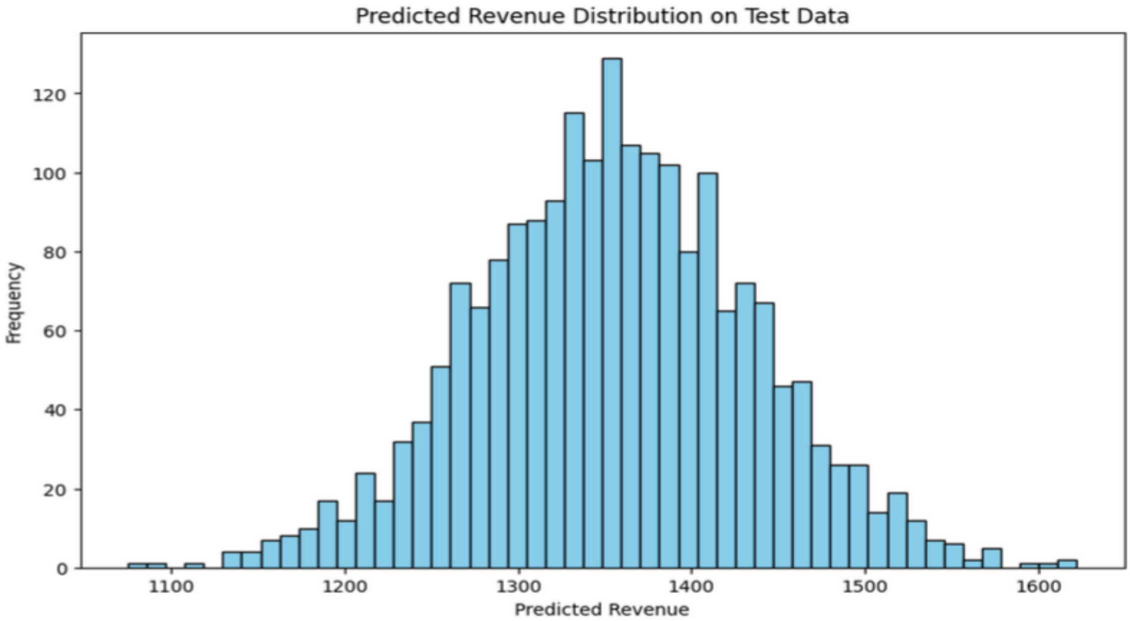

Figure-5: Predicted Revenue Distribution on Test Data

The histogram of the projected revenue is close to normal, peaked around 1350-1400 units with most between 1250 and 1500. Therefore, there is central tendency, wide range, and a few outliers in the revenue outcomes. This distribution helps in understanding model behaviour as well as the revenue pattern.

1	Model	Accuracy	Precision	Recall	F1 Score	ACU-ROC	MAE	MSE	R^2
2	--------------	-------------	-------------	------------	-------------	-------------	------------	--------------	------------
3	Linear Regression	_	_	_	_	_	0.000	0.0000	1.0000
4	Logistic Regression	0.9020	0.527473	0.238806	0.328767	0.824460	_	_	_
5	Decision Tree	0.8810	0.277108	0.114428	0.161972	0.585255	_	_	_
6	Random Forest	0.8995	0.000000	0.000000	0.000000	0.767156	_	_	_
7	Random Forest Regressor	_	_	_	_	_	53.214	4506.8823	0.3145
8	Gradient Boosting	0.9020	1.000000	0.024876	0.048544	0.799569	_	_	_
9	XG Boost	0.8990	0.428571	0.014925	0.028846	0.778406	_	_	_

Table-3 : Both credit risk and revenue prediction

The table compares various classification metrics (Accuracy, Precision, Recall, F1 Score, AUC-ROC) and regression metrics (MAE, MSE, R^2) of different models with the goal of analysis of bank transactions. Both Logistic Regression and Gradient Boosting showed the highest classification accuracy, 0.9020. For the regression metrics, Linear Regression could stand out. With multivariate metrics, more detailed evaluation can be done to select the best model for given financial tasks of banking.

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Logistic Regression (Reference)	0.9156	0.6876	0.2681	0.3857	0.6316
Logistic Regression (Your Model)	0.9020	0.5275	0.2388	0.3288	0.8245
Decision Tree (Reference)	0.8372	0.2024	0.2199	0.2108	0.5624
Decision Tree (Your Model)	0.8810	0.2771	0.1144	0.1620	0.5853
Random Forest (Reference)	0.9011	0.5000	0.0150	0.0291	0.5067
Random Forest (Your Model)	0.8995	0.0000	0.0000	0.0000	0.7672
Gradient Boosting (Reference)	0.9038	0.8526	0.0328	0.0631	0.5161
Gradient Boosting (Your Model)	0.9020	1.0000	0.0249	0.0485	0.7996
XGBoost (Reference)	0.9026	0.9205	0.0164	0.0322	0.5081
XGBoost (Your Model)	0.8990	0.4286	0.0149	0.0288	0.7784

Table-4: Comparision Between Base Model And New Model

The table compares various classification metrics (Accuracy, Precision, Recall, F1 Score, AUC-ROC) and regression metrics (MAE, MSE, R^2) of different models with the goal of analysis of bank transactions. Both Logistic Regression and Gradient Boosting showed the highest classification accuracy, 0.9020. For the regression metrics, Linear Regression could stand out. With multivariate metrics, more detailed evaluation can be done to select the best model for given financial tasks of banking

CHAPTER-6

CONCLUSION

CONCLUSION

This work is found to be viable as far as application of multiple models of machine learning is concerned in predicting customer risk and revenue for banking transaction data. The best model for the task came out to be logistic regression, as it could classify the risk with an accuracy of 90 percent. Some promise has been made by ensemble methods like Random Forest in capturing some of the complexities and details present in the given data. Revenue prediction was found to be best fit for a model where the complexity in the data needed to be captured, as shown by Random Forest Regressor. These results provide very valuable insights regarding how classification and regression models are used in financial predictive analytics. Future work includes increasing model interpretability, adding analysis on time series, and adoption of deep learning approaches. More areas which require investigation are class imbalance for fraud detection, real-time prediction system testing, and cross-institutional validations as well. Finally, ethical matters such as fairness and bias in assessments related to risk should assume priority also. These approaches are pursued to increase the accuracy, reliability, and practical applicability of machine learning on banking transactions for better decisions and quality provision of financial services.

CHAPTER-7

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