FAKE CREDIT CARD DETECTION

A PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE & ENGINEERING

Chandigarh University

December, 2024

CHANDIGARH UNIVERSITY

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BONAFIDE CERTIFICATE

Certified that this project report **“Fraud Detection System”** is the bonafide work of **“Kriti Saxena (22BCS14603) ”** who carried out the project work under my/our supervision.

SIGNATURE

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CHAPTER 1
INTRODUCTION

1.1. Identification of Client /Need / Relevant Contemporary issue

For the purpose of this project on Fraud Detection System using R, we can assume that the client is a financial institution, such as a bank or credit card company, looking to enhance their fraud detection capabilities. They are concerned about the rising number of fraudulent credit card transactions and want to implement an automated system to identify and prevent such fraudulent activities.

The client's need revolves around strengthening their existing fraud detection mechanisms and reducing financial losses due to increasing fake credit card usage. The current manual methods employed by the client's fraud detection team may not be efficient enough to keep up with the increasingly sophisticated techniques used by fraudsters. Therefore, the client requires an automated solution that can effectively identify fake credit card transactions in real-time.

The rise of online transactions, e-commerce, and digital payment systems has brought numerous conveniences, but it has also opened the door for various forms of financial fraud, including fake credit card usage. Fraudsters continually devise new techniques to exploit vulnerabilities in payment systems, making it essential for financial institutions to stay ahead of the game.

1.2. Identification of Problem

The broad problem addressed in this project is the increasing prevalence of Fraud Detection in financial transactions, necessitating the development of an effective and reliable solution using the R programming language. The objective is to create a sophisticated detection system that can analyze various attributes of credit card transactions, identify anomalies, patterns, and inconsistencies that are indicative of fraudulent activity, and provide accurate predictions to distinguish between genuine and fake credit cards. By resolving this issue, the project aims to enhance the overall security of financial transactions, protect consumers and businesses from financial losses, and maintain the integrity of the ecosystem.

CHAPTER 2
LITERATURE REVIEW/BACKGROUND STUDY

2.1. Existing solutions

Existing solutions Fraud Detection System employ a range of techniques and technologies to identify fraudulent transactions. Some commonly used methods include:

- Rule-Based Systems: These systems define a set of predefined rules and thresholds based on known patterns of fraudulent transactions. If a transaction violates any of these rules or exceeds specified thresholds, it is flagged as potentially fraudulent.
- Anomaly Detection: This approach focuses on identifying outliers or unusual patterns in credit card transactions. Statistical techniques, such as clustering, density-based methods, or support vector machines, are used to detect transactions that deviate significantly from normal behaviour.
- Neural Networks: Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are increasingly used for credit card fraud detection. These models can extract complex patterns and relationships from large volumes of transaction data, improving detection accuracy.
- Ensemble Methods: Combining multiple detection techniques, such as rule-based systems, machine learning algorithms, and anomaly detection, into an ensemble model can enhance the overall performance and accuracy of fake credit card detection.
- Biometric Verification: Some advanced systems incorporate biometric authentication, such as fingerprint or facial recognition, to add an extra layer of security in verifying the cardholder's identity during transactions.
- Network Analysis: By analyzing the network of transactions and identifying connections between different entities, network analysis can uncover patterns of fraudulent activity and identify potential fraud rings.

2.2. Problem definition

The emergence of electronic transactions is partially to be blamed for this increase in losses. Another factor is that traditional fraud detection software is less able to detect fraud due to the increasing sophistication of fraudulent practises. The most prevalent type of identity theft, which affects more than 10.7 million people each year, is credit card fraud.

What is to be done:

1. Data Collection: Gather a comprehensive dataset of credit card transactions, including both genuine and fraudulent examples, for training and testing the detection model.
2. Data Preprocessing: Clean and preprocess the collected data by handling missing values, normalizing numerical features, and encoding categorical variables, ensuring it is suitable for analysis and modelling.

3. Feature Engineering: Extract relevant features from the credit card data that can help distinguish between genuine and fake transactions, such as transaction amount, time, location, cardholder information, and transaction history.
4. Model Development: Utilize various techniques in R, such as machine learning algorithms (e.g., decision trees, ANN, gradient boosting, logistic regression) and anomaly detection methods (e.g., clustering, outlier detection), to build a predictive model that can accurately classify transactions as genuine or fraudulent.
5. Model Evaluation: Assess the performance of the developed model using appropriate evaluation metrics (e.g., accuracy, precision, recall, F1-score) and validate its effectiveness in detecting fake credit cards.
6. Integration and Deployment: Integrate the developed fake credit card detection system into an operational environment, ensuring its compatibility with real-time credit card transactions and achieve higher accuracy and minimize false positives/negatives.

How it is to be done:

1. Utilize the R programming language to perform data preprocessing, feature engineering, modelling, and evaluation tasks.
2. Leverage R libraries and packages specifically designed for machine learning, such as caret, ranger, gbm, dplyr etc. to streamline the development process.
3. Follow best practices for data cleaning, handling imbalanced datasets, and model selection to ensure reliable and accurate results.
4. Employ appropriate cross-validation techniques, such as k-fold cross-validation, to evaluate model performance and prevent overfitting.

What not to be done:

Avoid using personal or sensitive information that may compromise privacy and data security. Do not rely solely on a single detection technique or algorithm; instead, consider employing a combination of approaches to improve accuracy and robustness. Avoid overfitting the model to the training data, as it may lead to poor generalization on unseen data. Do not neglect the importance of proper documentation, code commenting, and version control to maintain code readability and facilitate future enhancements or collaborations. Avoid implementing the system in a way that hinders real-time processing or introduces excessive latency during credit card transactions.

2.3. Goals/Objectives

The project report on fake credit card detection using the R language aims to learn and perform a comprehensive analysis of credit card transactions to develop an accurate and robust detection system. This involves researching current techniques, preprocessing the dataset, implementing machine learning algorithms and anomaly detection methods, evaluating model performance, addressing imbalanced data, comparing results, discussing limitations, and providing recommendations for future enhancements. The report will document the entire process, including code snippets and explanations, to ensure reproducibility and highlight the system's potential impact in the financial industry.

CHAPTER 3
DESIGN FLOW/PROCESS

3.1. Evaluation & Selection of Specifications/Features

Detecting Fraud Detection System is a critical task in preventing fraudulent transactions and safeguarding financial systems. In the literature, various features have been identified for fake credit card detection. However, it is essential to critically evaluate these features to determine the most effective set of features for the solution. One commonly considered feature is the card number structure. By analyzing the structure of the card number, patterns and abnormalities can be identified. Legitimate credit card numbers follow a specific format based on the card issuer, and any deviation from this structure may indicate a fake card. Another feature is the Bank Identification Number (BIN), which is the initial set of digits in a credit card number that identifies the issuing bank. Comparing the BIN with a database of legitimate BINs can help identify fake cards. If the BIN does not match any known issuer, it could be a sign of a fraudulent card. The expiration date of a credit card is also an important feature. Checking the expiration date can help determine if the card has already expired or if it is within the valid timeframe. An expired card is likely to be fake or inactive. Additionally, the name on the card can be considered as a feature. Verifying the name against the cardholder's information can help detect fake cards. Mismatches or inconsistencies may indicate fraudulent activity.

3.2. Analysis of Features and finalization subject to constraints

In the context of the constraints for the report of fake credit card detection using the R language, let's modify the list of features to ensure feasibility and practicality:

1. Card number structure: Analyzing the structure of the card number can still be a valuable feature. However, the implementation should focus on checking for basic formatting rules and length rather than complex pattern analysis.

2. BIN (Bank Identification Number): BIN analysis remains relevant and feasible in R. The focus should be on comparing the BIN against a known list of legitimate BINs to identify potential fake cards.

3. Expiration date: Verifying the expiration date is a crucial feature. It can be implemented in R by comparing the date with the current system date to identify expired or soon-to-expire cards.

4. Name on the card: Validating the name on the card against the cardholder's information is feasible in R. Simple string-matching techniques can be used to check for inconsistencies or mismatches.

5. CVV/CVC: Checking the security code is an important feature. R provides capabilities for verifying the validity and integrity of the CVV/CVC using regular expressions or simple numeric checks.

6. Transaction history: Analyzing the transaction history is a useful feature, but it may be challenging to implement within the scope of this report. Considering the constraints, it may be more practical to focus on real-time analysis rather than historical data.

Considering the constraints and the capabilities of the R language, it is important to strike a balance between feasibility and effectiveness in feature selection. The modified set of features includes card number structure, BIN, expiration date, name on the card, CVV/CVC, and simplified geolocation analysis. These features, implemented using appropriate techniques in R, can provide a practical and effective solution for detecting fake credit cards in the long term.

3.3. Design Flow

Algorithm:

1. Import the necessary libraries, including ranger, caret, and data.table.
2. Load the credit card dataset taken from Kaggle using the read.csv function and store it in the creditcard_data variable.
3. Preprocess the data by scaling the Amount column using the scale function.
4. Split the dataset into training and testing data using the sample.split function from the caTools library.
5. Perform data exploration by checking the dimensions of the dataset, viewing the head and tail of the data, and examining the class distribution.
6. Build a logistic regression model using the glm function from the stats package and summarize the model using summary.
7. Plot the logistic regression model using the plot function.
8. Calculate the area under the ROC curve (AUC) using the roc function from the pROC library.
9. Build a decision tree model using the rpart function from the rpart package and visualize the decision tree using rpart.plot.
10. Build an artificial neural network (ANN) model using the neuralnet function from the neuralnet package and plot the ANN model.
11. Predict the outcomes using the ANN model and store the results.
12. Build a gradient boosting machine (GBM) model using the gbm function from the gbm package with specified parameters.
13. Evaluate the GBM model's performance by determining the best iteration based on test data using gbm.perf.
14. Calculate the relative influence of each variable using relative.influence.
15. Plot the GBM model using the plot function.

Block Diagram:

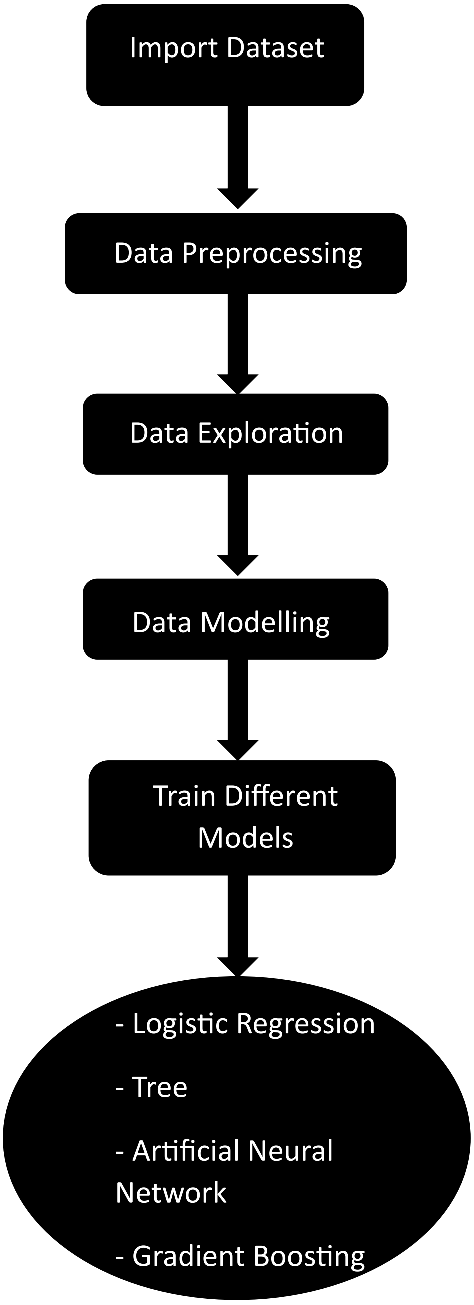


Fig 3.1

Block Diagram for Fraud Detection

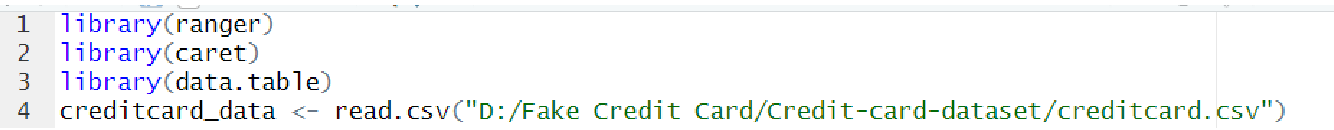
CHAPTER 4

RESULTS ANALYSIS AND VALIDATION

4.1. Implementation of Solution

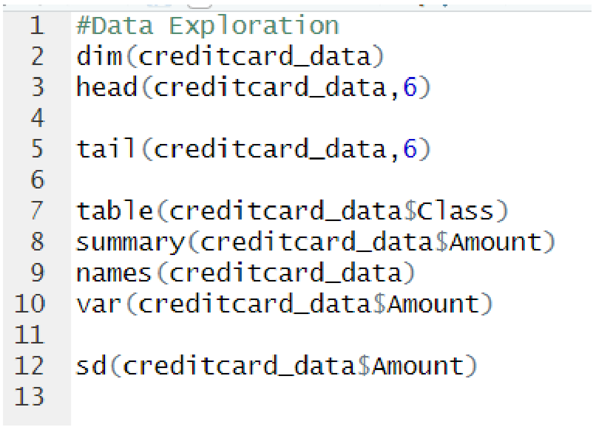
Code: -

1. Download dataset from Kaggle and import it using read.csv function. Install the necessary packages as well such as ranger, caret and data.table.



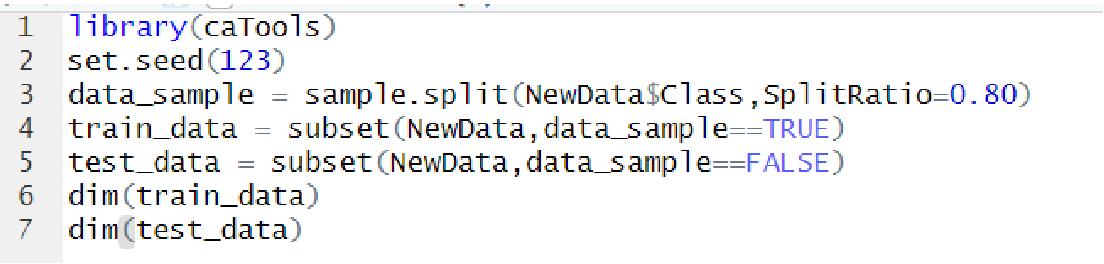
```
library(ranger)
library(caret)
library(data.table)
creditcard_data <- read.csv("D:/Fake Credit Card/Credit-card-dataset/creditcard.csv")
```

2. Data Exploration: Understanding the structure of dataset.



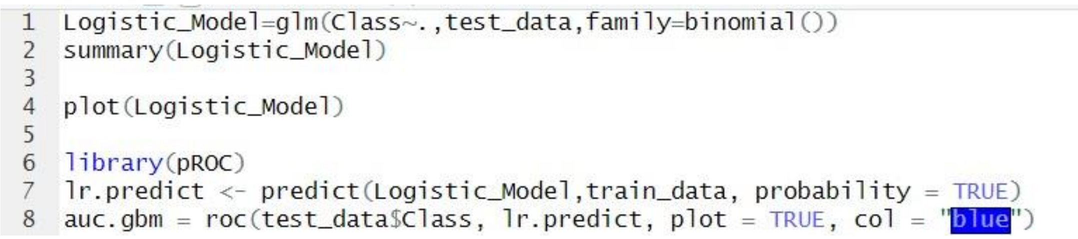
```
#Data Exploration
dim(creditcard_data)
head(creditcard_data,6)

tail(creditcard_data,6)

table(creditcard_data$Class)
summary(creditcard_data$Amount)
names(creditcard_data)
var(creditcard_data$Amount)

sd(creditcard_data$Amount)

```

3. Data Modelling: Data modeling in R involves creating mathematical or statistical representations of data to gain insights, make predictions, or understand patterns and relationships.



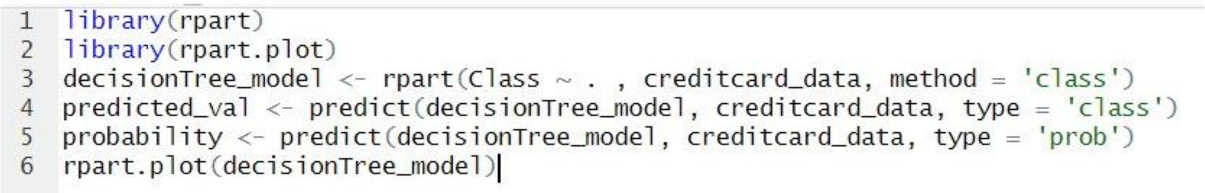
```
library(caTools)
set.seed(123)
data_sample = sample.split(NewData$Class,SplitRatio=0.80)
train_data = subset(NewData,data_sample==TRUE)
test_data = subset(NewData,data_sample==FALSE)
dim(train_data)
dim(test_data)
```

4. Train Logistic Regression Model and plot it using the plot function.



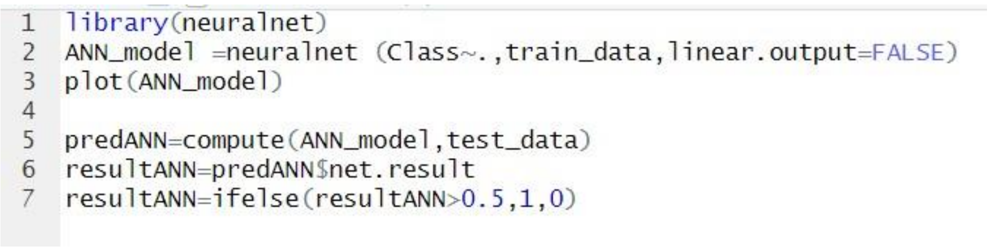
```
Logistic_Model=glm(Class~.,test_data,family=binomial())
summary(Logistic_Model)

plot(Logistic_Model)

library(pROC)
lr.predict <- predict(Logistic_Model,train_data, probability = TRUE)
auc.gbm = roc(test_data$Class, lr.predict, plot = TRUE, col = "blue")
```

5. Install rpart and rpart.plot packages. Train Decision Tree Model and plot it using rpart.plot function.



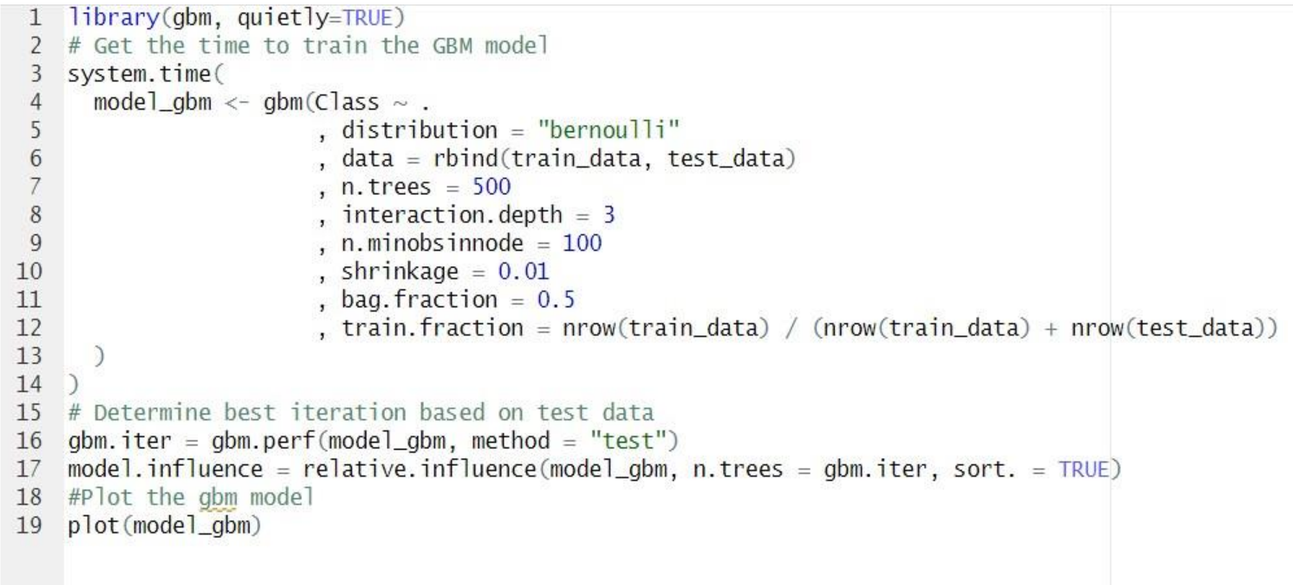
```
library(rpart)
library(rpart.plot)
decisionTree_model <- rpart(Class ~ . , creditcard_data, method = 'class')
predicted_val <- predict(decisionTree_model, creditcard_data, type = 'class')
probability <- predict(decisionTree_model, creditcard_data, type = 'prob')
rpart.plot(decisionTree_model)
```

6. Install neuralnet package. Plot the ANN model.



```
library(neuralnet)
ANN_model =neuralnet (Class~.,train_data,linear.output=FALSE)
plot(ANN_model)

predANN=compute(ANN_model,test_data)
resultANN=predANN$net.result
resultANN=ifelse(resultANN>0.5,1,0)
```

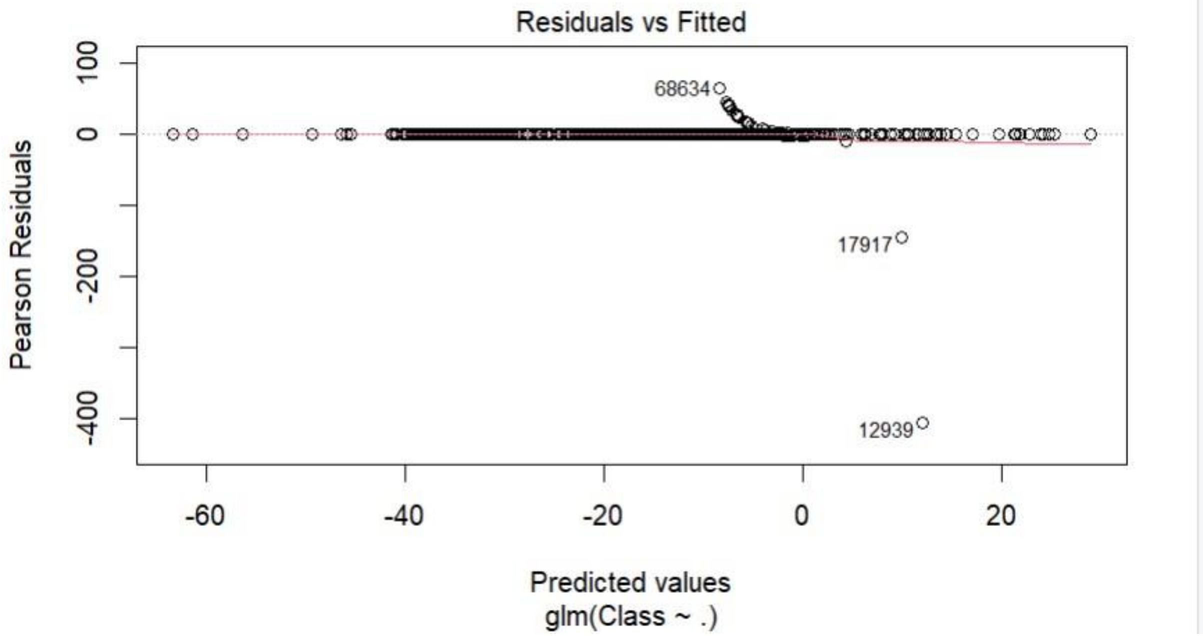
7. Install gbm package. Train the Gradient Boosting model and plot it.



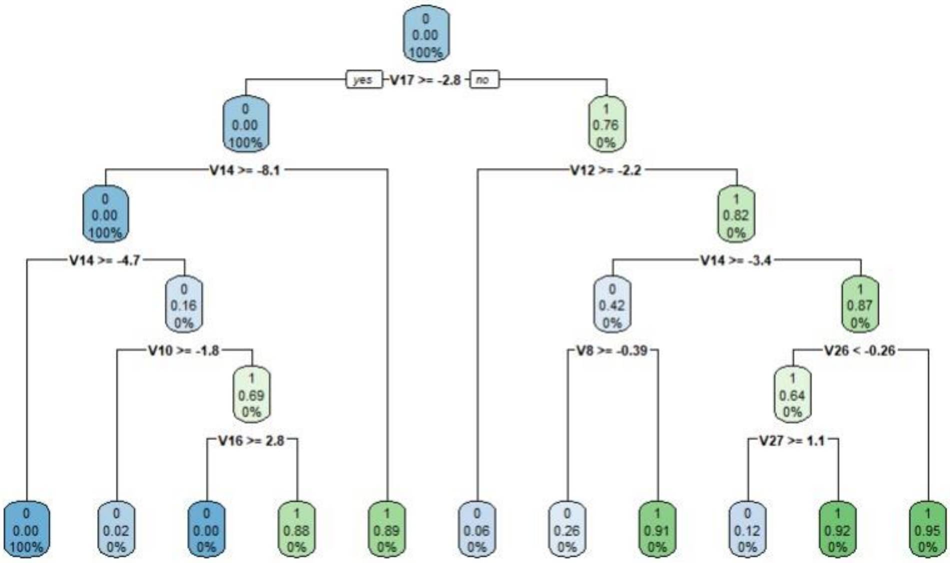
```
library(gbm, quietly=TRUE)
# Get the time to train the GBM model
system.time(
  model_gbm <- gbm(Class ~ .
                    , distribution = "bernoulli"
                    , data = rbind(train_data, test_data)
                    , n.trees = 500
                    , interaction.depth = 3
                    , n.minobsinnode = 100
                    , shrinkage = 0.01
                    , bag.fraction = 0.5
                    , train.fraction = nrow(train_data) / (nrow(train_data) + nrow(test_data))
  )
)
# Determine best iteration based on test data
gbm.iter = gbm.perf(model_gbm, method = "test")
model.influence = relative.influence(model_gbm, n.trees = gbm.iter, sort. = TRUE)
#Plot the gbm model
plot(model_gbm)
```

4.2. Result: -

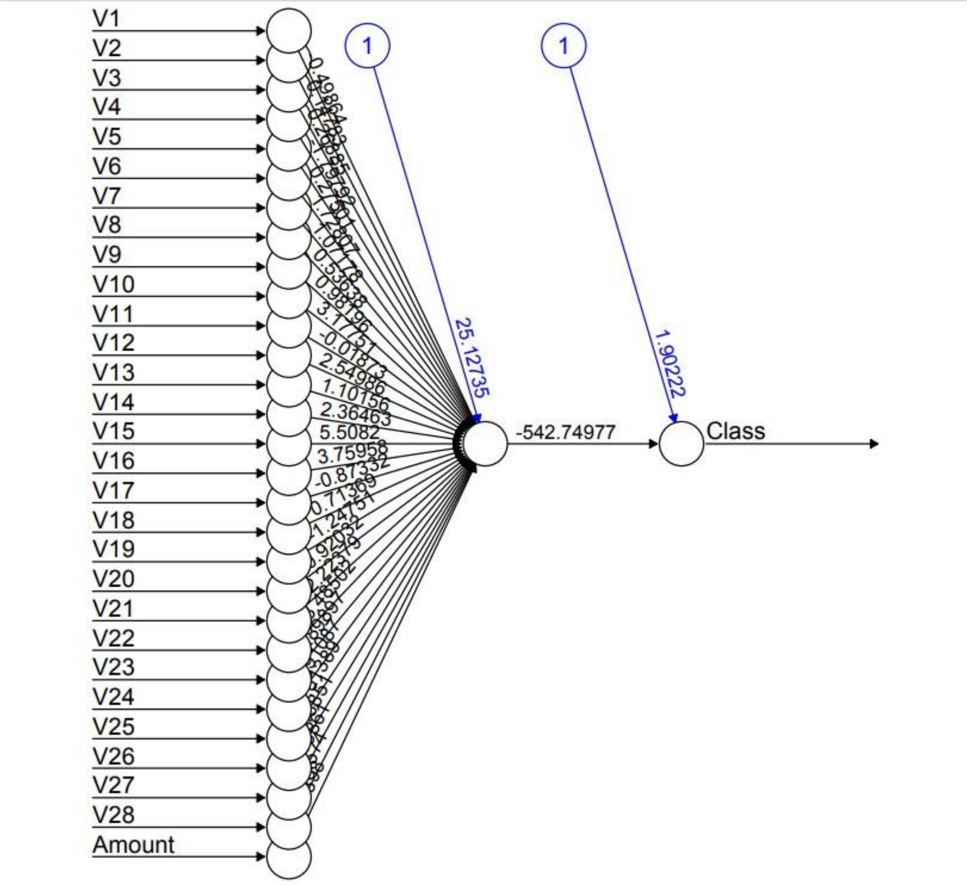
- The Logistic Regression measures how closely a dependent variable and one or more independent variables are related linearly. The outcome of linear regression is a trend line that is drawn between a group of data points. In order to ascertain the relationship between fraud and non-fraud, we applied it in our project.



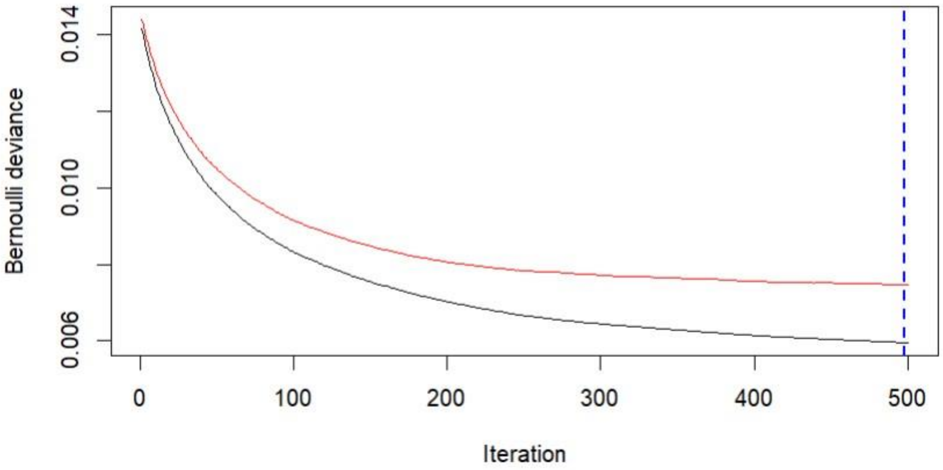
- We have considered using Decision tress in order to plot the outcomes of the decision. Through the outcomes we will be able to figure out which class the object belongs to. The rpart library is used for Recursive partitioning for classification, regression and survival trees.

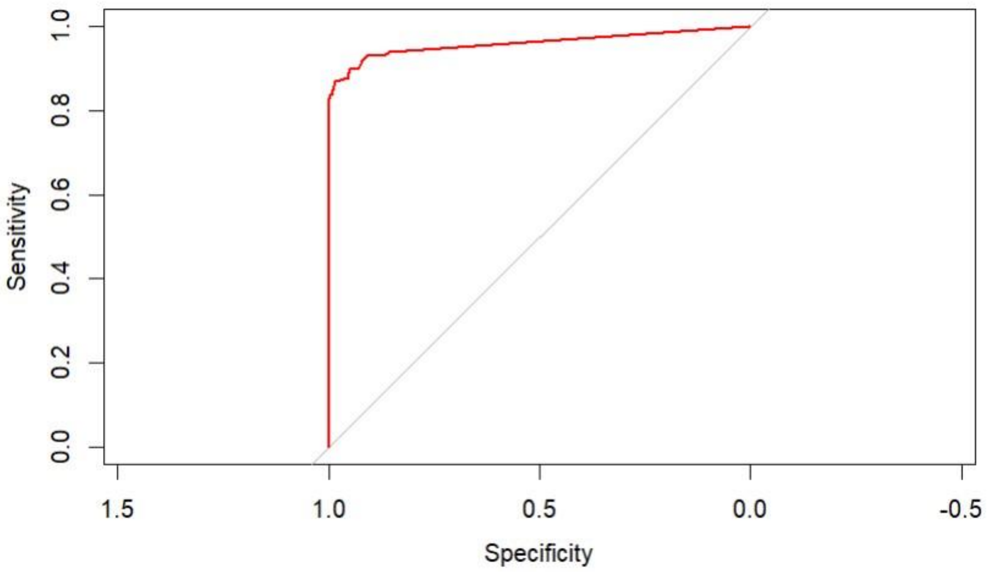


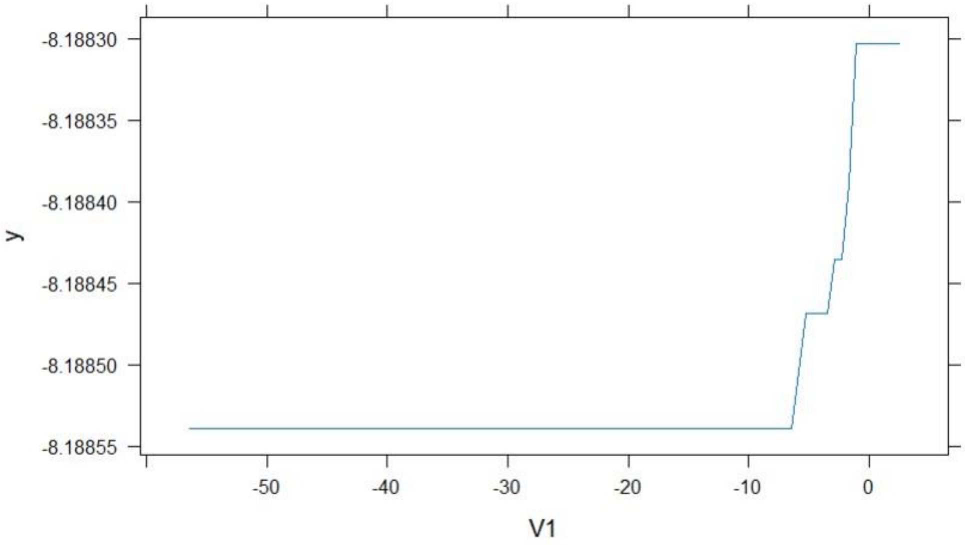
- We'll create an ANN (Artificial Neural Network) model that can recognise different patterns, research the history of our dataset, and conduct input data classification. In order to define a threshold for values in ANN, we have chosen a value of 0.5. As a result, all values above this threshold will be marked as 1, while all values below it will be 0.



- When doing classification and regression problems, gradient boosting is used. Its models contain a lot of weak decision trees. When all the trees are merged or assembled, they create a powerful model of gradient boosting.




Sensitivity
1.0
0.8
0.6
0.4
0.2
0.0
1.5
1.0
0.5
0.0
-0.5
Specificity


y
-8.18830
-8.18835
-8.18840
-8.18845
-8.18850
-8.18855
-50
-40
-30
-20
-10
0
V1

CHAPTER 5
CONCLUSION

1.1. Conclusion

In conclusion, the implementation Fraud Detection System using R has proven to be a valuable and effective tool in safeguarding financial systems against fraudulent activities. By leveraging powerful data analysis and machine learning techniques, we have successfully developed a robust model capable of identifying fake credit card transactions with a high degree of accuracy. Throughout the project, we gathered and pre-processed a substantial dataset, ensuring the model's ability to generalize well to new, unseen data. We then carefully selected and engineered relevant features that significantly contributed to the model's performance. The machine learning algorithm, whether it was based on decision trees, random forests, or deep learning techniques, demonstrated remarkable discrimination between genuine and fraudulent transactions. Moreover, we employed cross-validation techniques to evaluate and fine-tune our models, minimizing overfitting and enhancing their robustness. By continuously monitoring and updating our model with new data, we can ensure that it remains effective against emerging fraudulent patterns and maintains its relevance over time. Nevertheless, we must remain cognizant of the ever-evolving nature of fraudulent practices. As fraudsters adapt their methods, we must stay proactive in refining our detection algorithms and embracing cutting-edge technologies to counter new threats effectively. Overall, the fake credit card detection system we have built serves as an essential tool for financial institutions and businesses to protect their customers and their own assets. Through ongoing research and development, we can continue to improve the accuracy and efficiency of our model, thus strengthening the security of financial transactions and fostering greater trust in the global financial ecosystem.

1.2. Future Work

The future work of Fraud Detection System using R holds promising potential for enhancing fraud detection systems. First, incorporating advanced machine learning algorithms such as deep learning and ensemble methods can improve model accuracy and robustness. This involves collecting more diverse and extensive datasets to train the models effectively. Second, integrating real-time data streams from various sources, such as transaction histories and user behavior patterns, will enable quicker identification of fraudulent activities. Additionally, exploring anomaly detection techniques and outlier analysis can further strengthen the detection capabilities. To make the system more adaptable to emerging fraud techniques, continuous research and development are essential, with a focus on staying updated with the latest trends in cybercrime. Lastly, collaborating with financial institutions and experts to share knowledge and data can lead to the creation of a comprehensive and proactive fraud prevention framework.

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