VIT AP UNIVERSITY, ANDHRA PRADESH

A Project Report On

"Credit Card Fraud Detection project"

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1) Abstract

Credit card fraud has increased dramatically in recent months. It is, in fact, one of the most common threats to the BFSI industry. This R project's goal is to create a classifier that can accurately detect credit card fraud.

Credit card transaction dataset with a mix of non-fraudulent and fraudulent transactions will be used for the research. Decision Trees, Logistic Regression, Artificial Neural Networks, and Gradient Boosting Classifier will all be used in the project.

The system will be able to distinguish between a fraudulent and non-fraudulent call by applying these ML algorithms. This project will show you how to classify data using machine learning techniques in a real-world context.

2) Introduction

Unauthorized credit card transactions are referred to as "fraud." Unauthorised use of a user's account by someone other than the user that account's owner Preventative actions may be required, efforts to stop this exploitation and such deceptive behaviour techniques may be investigated in order to reduce it and safeguard against it.

In other words, Credit Card may have similar events in the future.
Fraud is described as when someone takes advantage of another person.
for personal reasons on someone else's credit card, while the owner and the
The card's issuing authority are completely ignorant of the card's existence.
being put to use. Fraud detection entails keeping track of a company's operations, estimating, perceiving, or avoiding user populations
Fraud, intrusion, and other forms of obnoxious behaviour are examples.
defaulting. This is a very important issue that needs to be addressed.
Machine learning and data science are two examples of communities where
This problem's solution can be automated.
This issue is particularly difficult to solve from the standpoint of education since it is characterised by many elements such as class imbalance. The

number of legitimate transactions considerably outnumbers the number of fraudulent transactions. Furthermore, transaction patterns frequently modify their statistical features over time.

However, these aren't the only difficulties that come with implementing a real-world fraud detection system. In real-world scenarios, automated programmes examine a vast stream of payment requests to identify which transactions should be authorised.

To analyse all permitted transactions and report suspect ones, machine learning techniques are used. Professionals evaluate these complaints and call cardholders to establish if the transaction was legitimate or fraudulent.

The investigators give input to the automated system, which is utilised to train and upgrade the algorithm over time to enhance fraud detection effectiveness.

3) Objective/ Aim

These days, Using technologies such as the phishing method to commit online banking fraud entails transmitting and withdrawing funds from a banker's account without the banker's authorization. Credit card fraud is on the rise, and certain banks and organisations that provide services to banks are experiencing difficulties. Using machine learning methods and neural networks, this study aims to create a model that can accurately identify fraud and no fraud transactions. The project's goal is to predict fraud and fraud-free transactions based on time and amount of transaction using classification machine learning algorithms, statistics, calculus (chain rule, differentiation, etc.) and linear algebra in the construction of complex machine learning models for prediction and data understanding.

4) Proposed idea

To detect fraud in credit card transactions, the proposed system employs an Artificial Neural Network. On the basis of prediction, performance is measured and accuracy is calculated. A credit card fraud detection model is also built using classification techniques such as Decision tree and Logistic regression. We compared all three algorithms employed in the experiment and found that artificial neural networks outperformed the Decision tree and Logistic regression techniques in terms of prediction. The credit card dataset information such as v1,v2 ,v3,v4 and so on, and the fraud feature class has a value of 1 and the regular transaction has a value of 0.

5) Methodology

Loading dataset

• We import datasets containing credit card transactions

```
> df=read.csv("creditcard.csv")
> head(df)
  Time         V1          V2        V3         V4          V5          V6          V7          V8         V9         V10        V11
1    0 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995
2    0  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267
3    1 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015
4    1 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873
5    2 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429
6    2 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620
          V12        V13        V14        V15        V16         V17         V18         V19         V20          V21          V22
1 -0.61780086 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058  0.40399296  0.25141210 -0.018306778  0.277837576
2  1.06523531  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127 -0.14578304 -0.06908314 -0.225775248 -0.638671953
3  0.06608369  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931 -2.26185710  0.52497973  0.247998153  0.771679402
4  0.17822823  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500 -1.23262197 -0.20803778 -0.108300452  0.005273597
5  0.53819555  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479  0.80348692  0.40854236 -0.009430697  0.798278495
6  0.35989384 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315 -0.03319379  0.08496767 -0.208253515 -0.559824796
          V23         V24        V25        V26          V27         V28 Amount Class
1 -0.11047391  0.06692807  0.1285394 -0.1891148  0.133558377 -0.02105305 149.62     0
2  0.10128802 -0.33984648  0.1671704  0.1258945 -0.008983099  0.01472417   2.69     0
3  0.90941226 -0.68928096 -0.3276418 -0.1390966 -0.055352794 -0.05975184 378.66     0
4 -0.19032052 -1.17557533  0.6473760 -0.2219288  0.062722849  0.06145763 123.50     0
5 -0.13745808  0.14126698 -0.2060096  0.5022922  0.219422230  0.21515315  69.99     0
6 -0.02639767 -0.37142658 -0.2327938  0.1059148  0.253844225  0.08108026   3.67     0
```

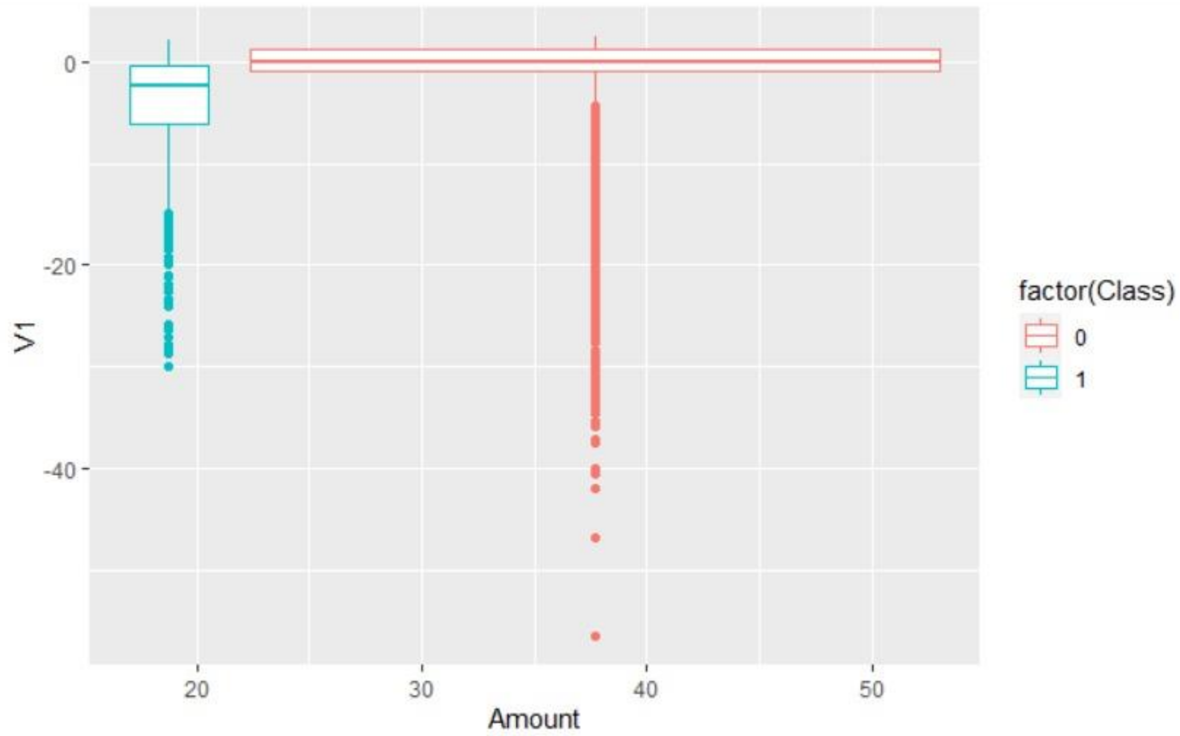
Data Exploration

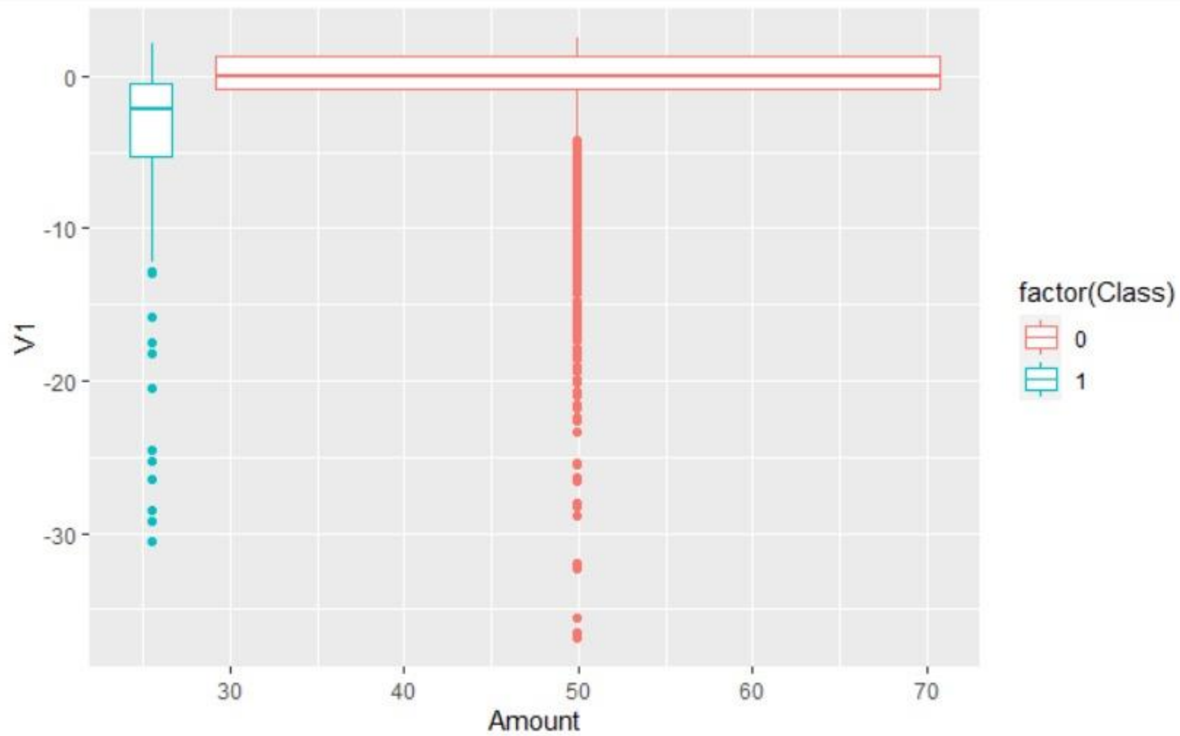
• In this step of the fraud detection ML project, we are able to discover the information this is contained with inside the credit score card information. We will continue through showing the credit score card information the usage of the head() feature in addition to the tail() feature. We will then continue to discover the opposite additives of this data frame.

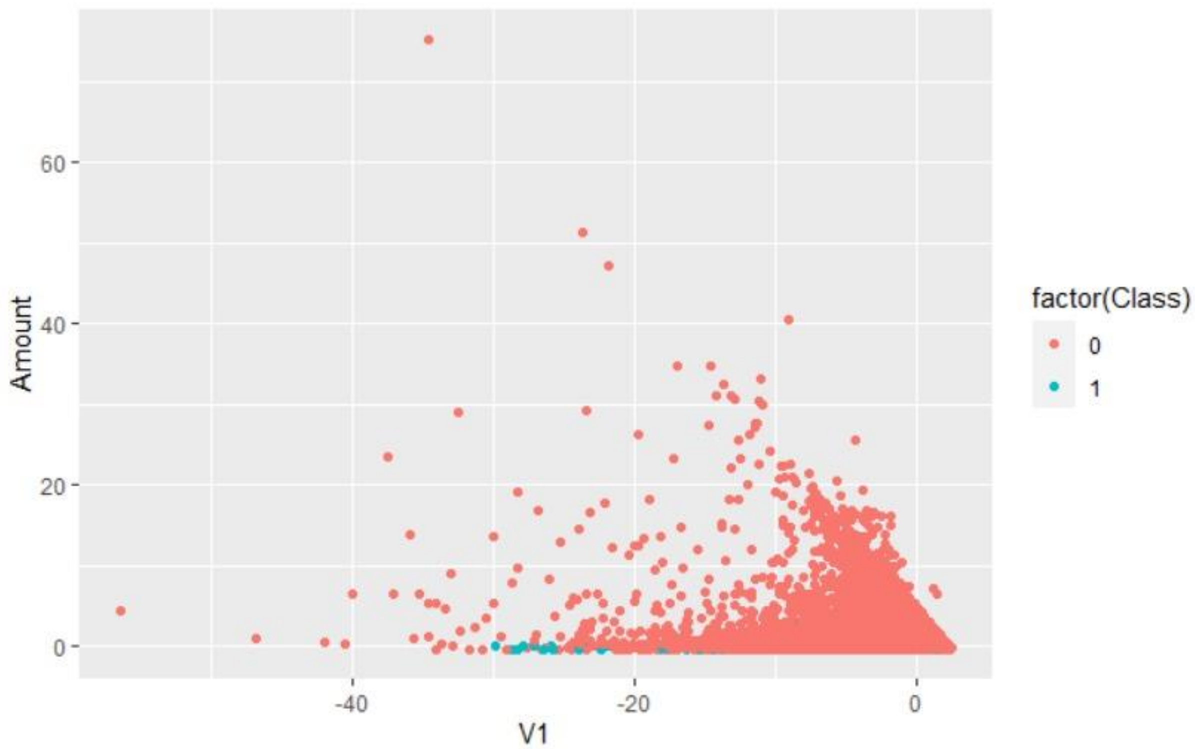
```
> dim(df)
[1] 284807     31
> colnames(df)
 [1] "Time"   "V1"     "V2"     "V3"     "V4"     "V5"     "V6"     "V7"     "V8"     "V9"     "V10"    "V11"    "V12"    "V13"    "V14"    "V15"
[17] "V16"    "V17"    "V18"    "V19"    "V20"    "V21"    "V22"    "V23"    "V24"    "V25"    "V26"    "V27"    "V28"    "Amount" "Class"
> table(df$Class)

     0      1 
284315    492 
> summary(df)
      Time              V1                  V2                  V3                 V4                 V5                   V6          
 Min.   :     0   Min.   :-56.40751   Min.   :-72.71573   Min.   :-48.3256   Min.   :-5.68317   Min.   :-113.74331   Min.   :-26.1605  
 1st Qu.: 54202   1st Qu.: -0.92037   1st Qu.: -0.59855   1st Qu.: -0.8904   1st Qu.:-0.84864   1st Qu.:  -0.69160   1st Qu.: -0.7683  
 Median : 84692   Median :  0.01811   Median :  0.06549   Median :  0.1799   Median :-0.01985   Median :  -0.05434   Median : -0.2742  
 Mean   : 94814   Mean   :  0.00000   Mean   :  0.00000   Mean   :  0.0000   Mean   : 0.00000   Mean   :   0.00000   Mean   :  0.0000  
 3rd Qu.:139321   3rd Qu.:  1.31564   3rd Qu.:  0.80372   3rd Qu.:  1.0272   3rd Qu.: 0.74334   3rd Qu.:   0.61193   3rd Qu.:  0.3986  
 Max.   :172792   Max.   :  2.45493   Max.   : 22.05773   Max.   :  9.3826   Max.   :16.87534   Max.   :  34.80167   Max.   : 73.3016  
       V7                 V8                  V9                 V10                 V11                V12                V13          
 Min.   :-43.5572   Min.   :-73.21672   Min.   :-13.43407   Min.   :-24.58826   Min.   :-4.79747   Min.   :-18.6837   Min.   :-5.79188  
 1st Qu.: -0.5541   1st Qu.: -0.20863   1st Qu.: -0.64310   1st Qu.: -0.53543   1st Qu.:-0.76249   1st Qu.: -0.4056   1st Qu.:-0.64854  
 Median :  0.0401   Median :  0.02236   Median : -0.05143   Median : -0.09292   Median :-0.03276   Median :  0.1400   Median :-0.01357  
 Mean   :  0.0000   Mean   :  0.00000   Mean   :  0.00000   Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.0000   Mean   : 0.00000  
 3rd Qu.:  0.5704   3rd Qu.:  0.32735   3rd Qu.:  0.59714   3rd Qu.:  0.45392   3rd Qu.: 0.73959   3rd Qu.:  0.6182   3rd Qu.: 0.66251  
 Max.   :120.5895   Max.   : 20.00721   Max.   : 15.59500   Max.   : 23.74514   Max.   :12.01891   Max.   :  7.8484   Max.   : 7.12688  
```

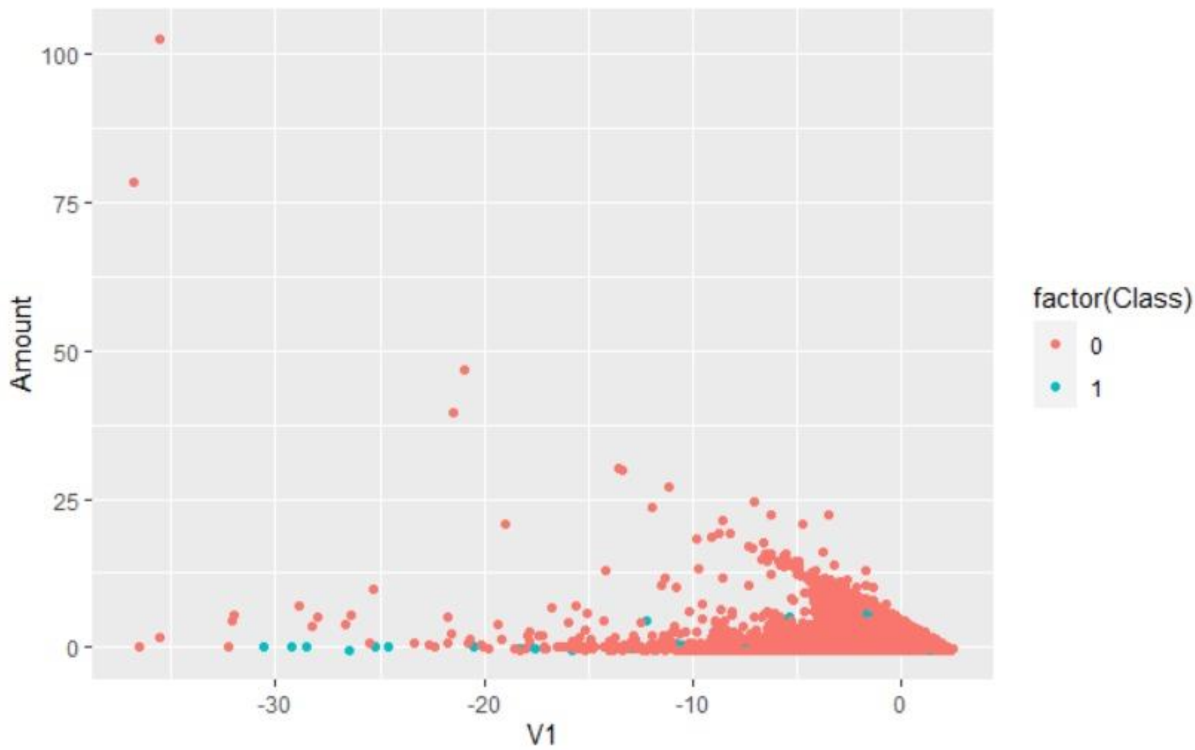
```
      V14               V15                V16                 V17                 V18                  V19                  V20
 Min.   :-19.2143   Min.   :-4.49894   Min.   :-14.12985   Min.   :-25.16280   Min.   :-9.498746   Min.   :-7.213527   Min.   :-54.49772
 1st Qu.: -0.4256   1st Qu.:-0.58288   1st Qu.: -0.46804   1st Qu.: -0.48375   1st Qu.:-0.498850   1st Qu.:-0.456299   1st Qu.: -0.21172
 Median :  0.0506   Median : 0.04807   Median :  0.06641   Median : -0.06568   Median :-0.003636   Median : 0.003735   Median : -0.06248
 Mean   :  0.0000   Mean   : 0.00000   Mean   :  0.00000   Mean   :  0.00000   Mean   : 0.000000   Mean   : 0.000000   Mean   :  0.00000
 3rd Qu.:  0.4931   3rd Qu.: 0.64882   3rd Qu.:  0.52330   3rd Qu.:  0.39968   3rd Qu.: 0.500807   3rd Qu.: 0.458949   3rd Qu.:  0.13304
 Max.   : 10.5268   Max.   : 8.87774   Max.   : 17.31511   Max.   :  9.25353   Max.   : 5.041069   Max.   : 5.591971   Max.   : 39.42090
      V21                 V22                  V23                 V24                V25                 V26                V27
 Min.   :-34.83038   Min.   :-10.933144   Min.   :-44.80774   Min.   :-2.83663   Min.   :-10.29540   Min.   :-2.60455   Min.   :-22.565679
 1st Qu.: -0.22839   1st Qu.: -0.542350   1st Qu.: -0.16185   1st Qu.:-0.35459   1st Qu.: -0.31715   1st Qu.:-0.32698   1st Qu.: -0.070840
 Median : -0.02945   Median :  0.006782   Median : -0.01119   Median : 0.04098   Median :  0.01659   Median :-0.05214   Median :  0.001342
 Mean   :  0.00000   Mean   :  0.000000   Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.000000
 3rd Qu.:  0.18638   3rd Qu.:  0.528554   3rd Qu.:  0.14764   3rd Qu.: 0.43953   3rd Qu.:  0.35072   3rd Qu.: 0.24095   3rd Qu.:  0.091045
 Max.   : 27.20284   Max.   : 10.503090   Max.   : 22.52841   Max.   : 4.58455   Max.   :  7.51959   Max.   : 3.51735   Max.   : 31.612198
      V28                Amount             Class
 Min.   :-15.43008   Min.   :    0.00   Min.   :0.000000
 1st Qu.: -0.05296   1st Qu.:    5.60   1st Qu.:0.000000
 Median :  0.01124   Median :   22.00   Median :0.000000
 Mean   :  0.00000   Mean   :   88.35   Mean   :0.001728
 3rd Qu.:  0.07828   3rd Qu.:   77.17   3rd Qu.:0.000000
 Max.   : 33.84781   Max.   :25691.16   Max.   :1.000000
> var(df$Amount)
[1] 62560.07
> sd(df$Amount)
[1] 250.1201
>
```

```
> names(df)
 [1] "Time"    "V1"      "V2"      "V3"      "V4"      "V5"      "V6"      "V7"      "V8"      "V9"
[11] "V10"     "V11"     "V12"     "V13"     "V14"     "V15"     "V16"     "V17"     "V18"     "V19"
[21] "V20"     "V21"     "V22"     "V23"     "V24"     "V25"     "V26"     "V27"     "V28"     "Amount"
[31] "Class"
> str(df)
'data.frame':	284807 obs. of  31 variables:
 $ Time  : num  0 0 1 1 2 2 4 7 7 9 ...
 $ V1    : num  -1.36 1.192 -1.358 -0.966 -1.158 ...
 $ V2    : num  -0.0728 0.2662 -1.3402 -0.1852 0.8777 ...
 $ V3    : num  2.536 0.166 1.773 1.793 1.549 ...
 $ V4    : num  1.378 0.448 0.38 -0.863 0.403 ...
 $ V5    : num  -0.3383 0.06 -0.5032 -0.0103 -0.4072 ...
 $ V6    : num  0.4624 -0.0824 1.8005 1.2472 0.0959 ...
 $ V7    : num  0.2396 -0.0788 0.7915 0.2376 0.5929 ...
 $ V8    : num  0.0987 0.0851 0.2477 0.3774 -0.2705 ...
 $ V9    : num  0.364 -0.255 -1.515 -1.387 0.818 ...
 $ V10   : num  0.0908 -0.167 0.2076 -0.055 0.7531 ...
 $ V11   : num  -0.552 1.613 0.625 -0.226 -0.823 ...
 $ V12   : num  -0.6178 1.0652 0.0661 0.1782 0.5382 ...
 $ V13   : num  -0.991 0.489 0.717 0.508 1.346 ...
 $ V14   : num  -0.311 -0.144 -0.166 -0.288 -1.12 ...
 $ V15   : num  1.468 0.636 2.346 -0.631 0.175 ...
 $ V16   : num  -0.47 0.464 -2.89 -1.06 -0.451 ...
 $ V17   : num  0.208 -0.115 1.11 -0.684 -0.237 ...
 $ V18   : num  0.0258 -0.1834 -0.1214 1.9658 -0.0382 ...
 $ V19   : num  0.404 -0.146 -2.262 -1.233 0.803 ...
 $ V20   : num  0.2514 -0.0691 0.525 -0.208 0.4085 ...
 $ V21   : num  -0.01831 -0.22578 0.248 -0.1083 -0.00943 ...
 $ V22   : num  0.27784 -0.63867 0.77168 0.00527 0.79828 ...
 $ V23   : num  -0.11 0.101 0.909 -0.19 -0.137 ...
 $ V24   : num  0.0669 -0.3398 -0.6893 -1.1756 0.1413 ...
 $ V25   : num  0.129 0.167 -0.328 0.647 -0.206 ...
 $ V26   : num  -0.189 0.126 -0.139 -0.222 0.502 ...
 $ V27   : num  0.13356 -0.00898 -0.05535 0.06272 0.21942 ...
 $ V28   : num  -0.0211 0.0147 -0.0598 0.0615 0.2152 ...
 $ Amount: num [1:284807, 1] 0.245 -0.3425 1.1607 0.1405 -0.0734 ...
  ..- attr(*, "scaled:center")= num 88.3
  ..- attr(*, "scaled:scale")= num 250
 $ Class : int  0 0 0 0 0 0 0 0 0 0 ...
> class(df)
[1] "data.frame"
> ggplot(test,aes(x=V1,y=Amount))+geom_point(aes(color=factor(Class)))
> ggplot(train,aes(x=V1,y=Amount))+geom_point(aes(color=factor(Class)))
> ggplot(test,aes(x=Amount,y=V1))+geom_boxplot(aes(color=factor(Class)))
> ggplot(train,aes(x=Amount,y=V1))+geom_boxplot(aes(color=factor(Class)))
>
```


0
-20
-40
V1
20
30
40
50
Amount
factor(Class)
0
1


0
-10
-20
-30
V1
30
40
50
60
70
Amount
factor(Class)
0
1





Data Manipulation

• In this step, we'll scale our data using the scale () function. We will apply this to the amount component of the amount of our credit card information. Scaling is also known as feature normalization. Using scaling, data is structured according to a specified range. Therefore, there are no extreme values in our dataset that could interfere with the functioning of our model.

```
> df$Amount=scale(df$Amount)
> data=df[,-c(1)]
> head(data)
          V1          V2        V3         V4          V5          V6          V7          V8         V9         V10        V11         V12        V13
1 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086 -0.9913898
2  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531  0.4890950
3 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369  0.7172927
4 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823  0.5077569
5 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555  1.3458516
6 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384 -0.3580907
         V14        V15        V16         V17         V18         V19         V20          V21          V22         V23         V24        V25
1 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391  0.06692807  0.1285394
2 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802 -0.33984648  0.1671704
3 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226 -0.68928096 -0.3276418
4 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052 -1.17557533  0.6473760
5 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808  0.14126698 -0.2060096
6 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767 -0.37142658 -0.2327938
         V26          V27         V28      Amount Class
1 -0.1891148  0.133558377 -0.02105305  0.24496383     0
2  0.1258945 -0.008983099  0.01472417 -0.34247394     0
3 -0.1390966 -0.055352794 -0.05975184  1.16068389     0
4 -0.2219288  0.062722849  0.06145763  0.14053401     0
5  0.5022922  0.219422230  0.21515315 -0.07340321     0
6  0.1059148  0.253844225  0.08108026 -0.33855582     0
```

Data Modeling

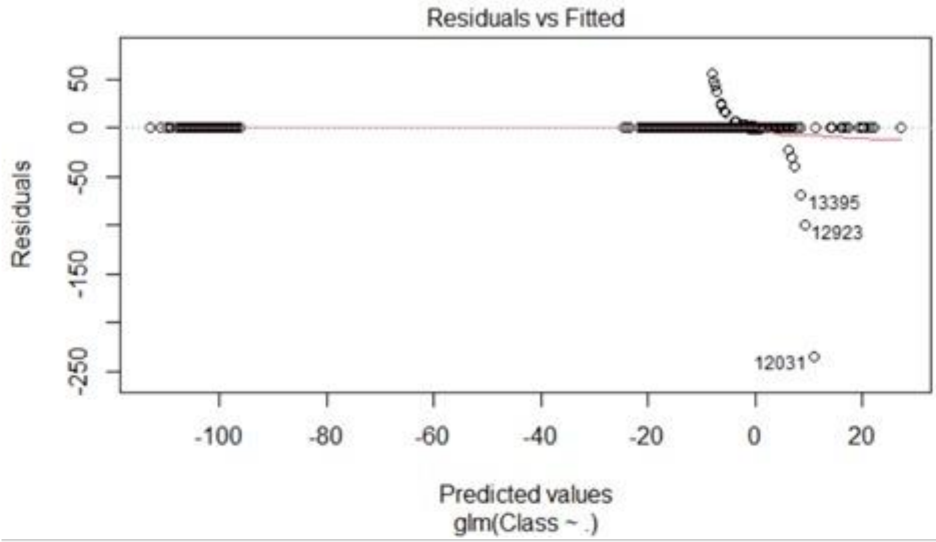
• Once we have standardized the dataset, we will divide our dataset into training sets and test sets with a divide ratio of 0.80. This means that 80% of our data will be attributed to train data while 20% will be attributed to test data.

```
> sample = sample.split(data$Class,SplitRatio=0.80)
> train= subset(data,sample==TRUE)
> test= subset(data,sample==FALSE)
> dim(train)
[1] 227846     30
> dim(test)
[1] 56961    30
> |
```

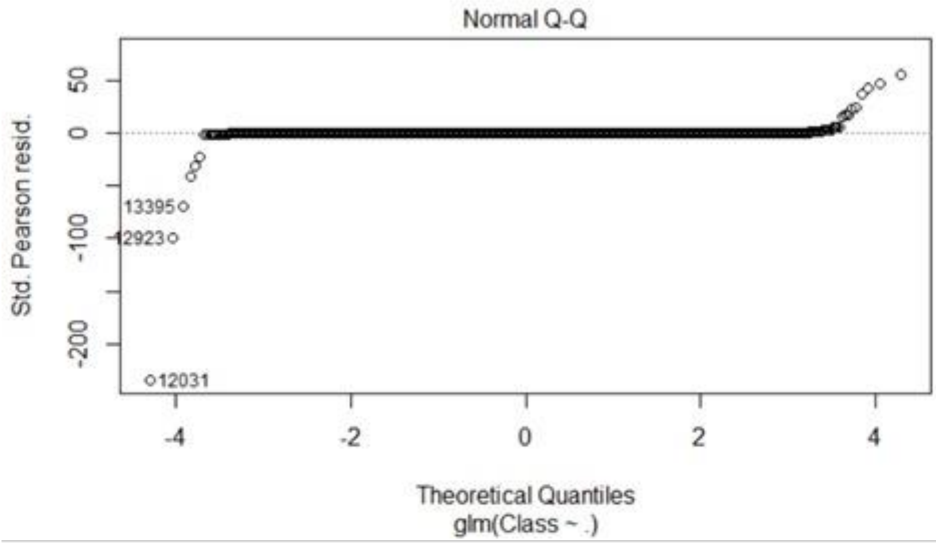
Fitting Logistic Regression Model

• In this section , we will adapt our first model. We will start with the logistic regression. Logistic regression is used to model the probability of a class outcome as pass / fail, pass / fail, and in our case - fraud / non-fraud. We are implementing this model on our test data.

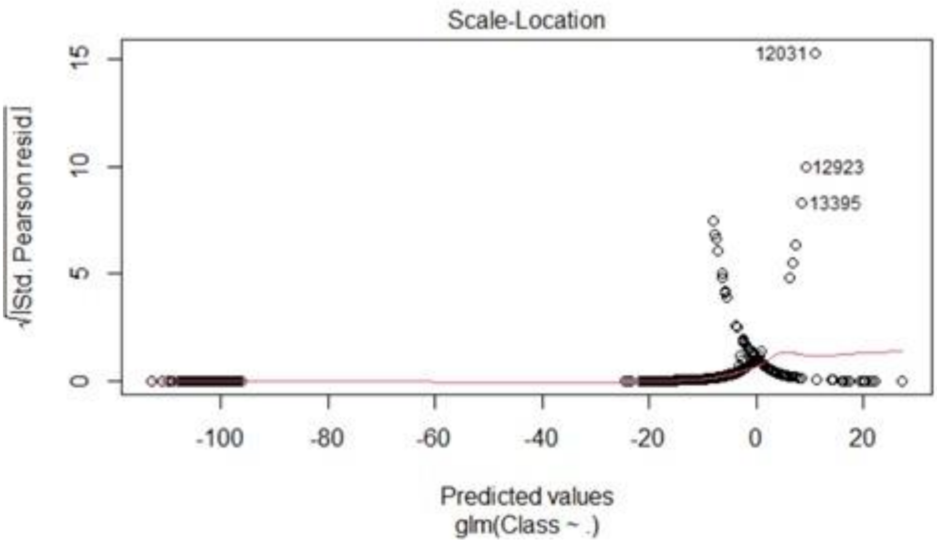
```
> Logistic_regression=glm(Class~.,test,family=binomial())
Warning message:
glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(Logistic_regression)

Call:
glm(formula = Class ~ ., family = binomial(), data = test)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.6721  -0.0243  -0.0138  -0.0059   4.0076

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -23.35723   10.46345  -2.232   0.0256 *
V1           -1.58484    1.27413  -1.244   0.2136
V2            6.08293    4.30739   1.412   0.1579
V3           -0.12974    0.24262  -0.535   0.5928
V4           10.51008    7.24934   1.450   0.1471
V5            5.29508    3.86330   1.371   0.1705
V6           -0.28563    0.27563  -1.036   0.3001
V7            5.47408    4.24678   1.289   0.1974
V8            0.01824    0.19476   0.094   0.9254
V9           11.69057    8.77347   1.332   0.1827
V10          -9.64105    6.71795  -1.435   0.1513
V11          -0.33408    0.29440  -1.135   0.2565
V12           9.30174    6.66803   1.395   0.1630
V13          -2.23434    1.30503  -1.712   0.0869 .
V14           3.75140    3.31695   1.131   0.2581
V15           3.74282    2.94050   1.273   0.2031
V16         -10.46380    7.19279  -1.455   0.1457
V17          -6.73060    5.06457  -1.329   0.1839
V18          11.09331    8.22161   1.349   0.1772
V19          -6.66437    4.83521  -1.378   0.1681
V20          -2.10079    1.19215  -1.762   0.0780 .
V21          -2.50719    2.02720  -1.237   0.2162
V22          -6.48370    5.26233  -1.232   0.2179
V23           0.97618    0.65580   1.489   0.1366
V24           0.74325    0.53334   1.394   0.1634
V25          -2.44598    2.01639  -1.213   0.2251
V26          13.01188    9.42821   1.380   0.1676
V27          -1.78501    0.79534  -2.244   0.0248 *
V28          -0.36543    0.36923  -0.990   0.3223
```



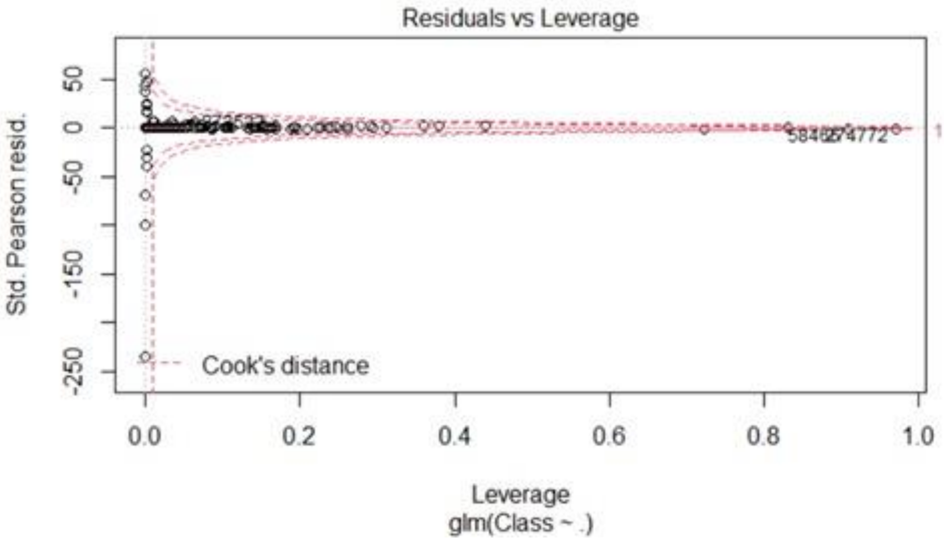
Residuals vs Fitted
Residuals
Predicted values
glm(Class ~ .)
13395
12923
12031

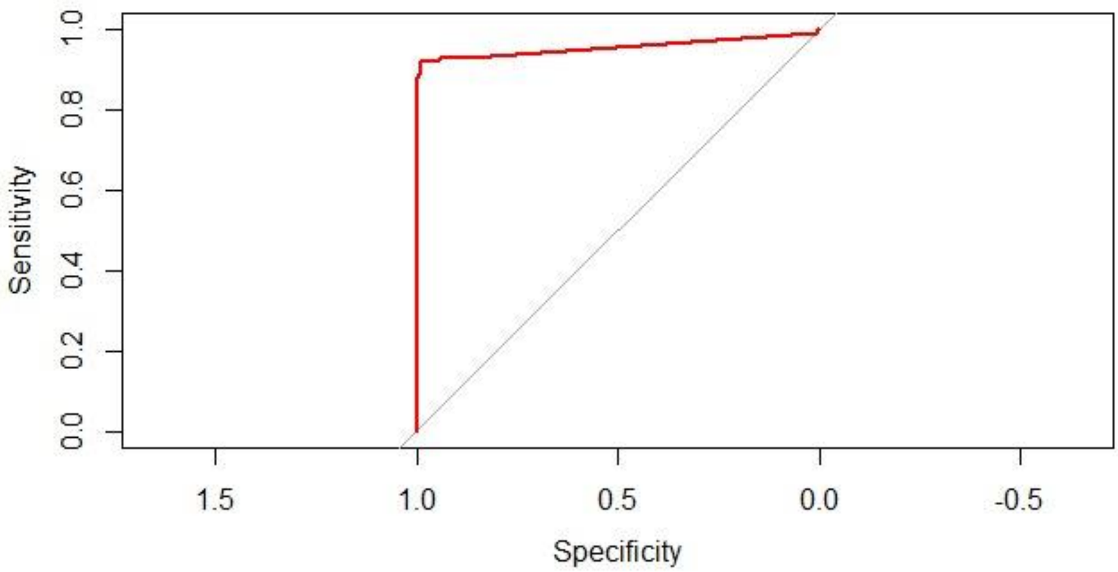


Normal Q-Q
Std. Pearson resid.
Theoretical Quantiles
glm(Class ~ .)
13395
12923
12031



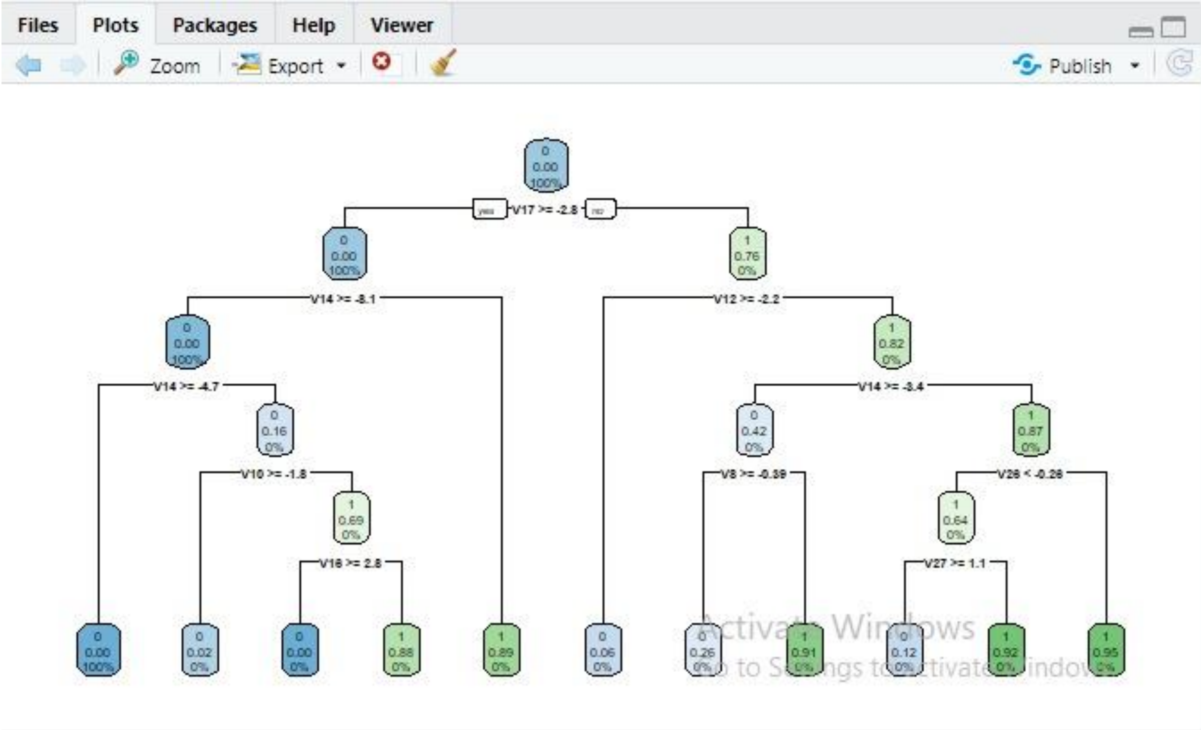
Scale-Location
√|Std. Pearson resid.|
Predicted values
glm(Class ~ .)
12031
12923
13395





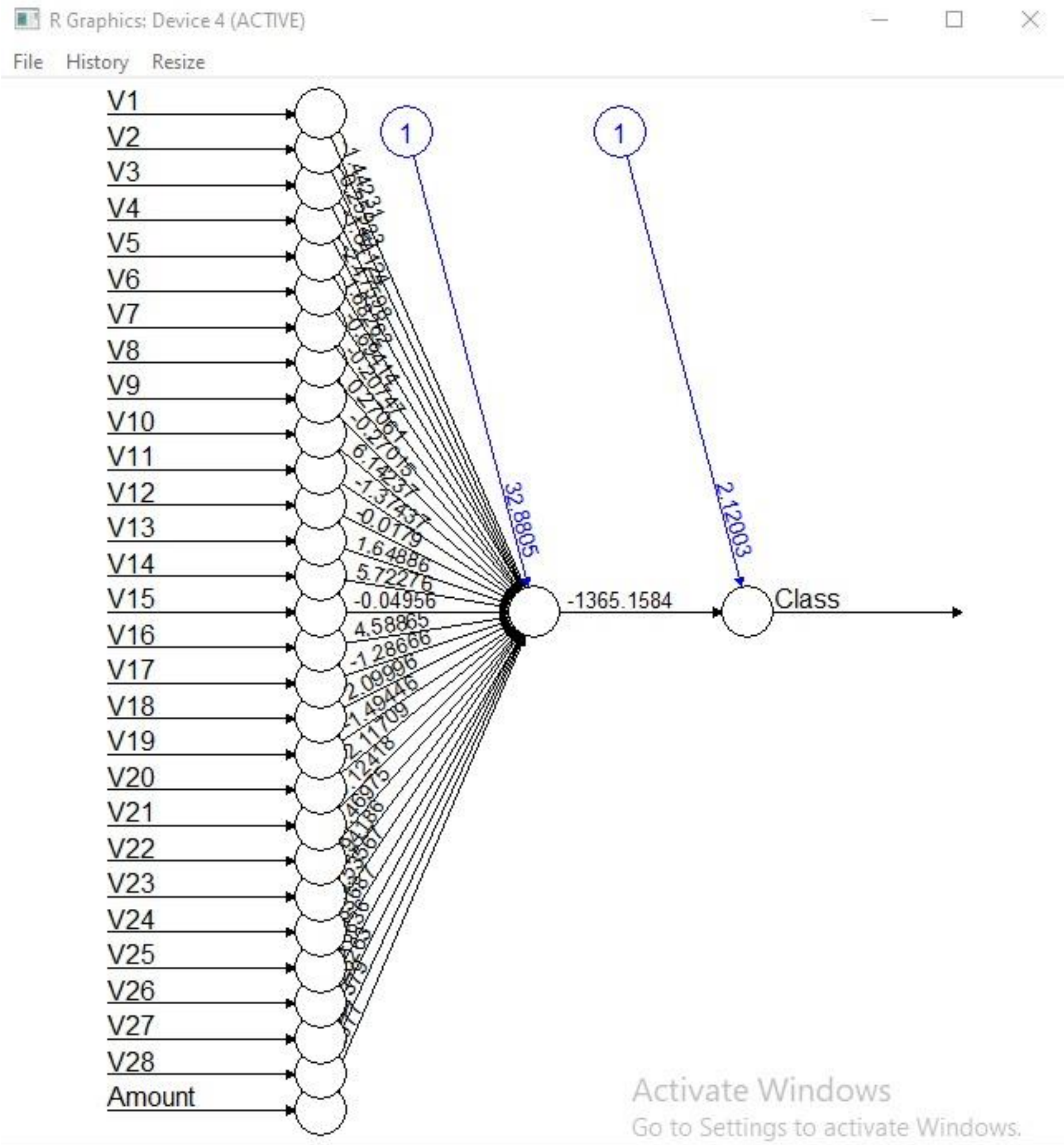
Fitting a Decision Tree Model

• In this section, we will implement a decision tree algorithm. Decision trees to track the results of a decision. These results are essentially a consequence by which we can conclude to which class the object belongs. We will now implement our decision tree model and plot it using the rpart.plot () function. We will specifically use recursive division to plot the decision tree.



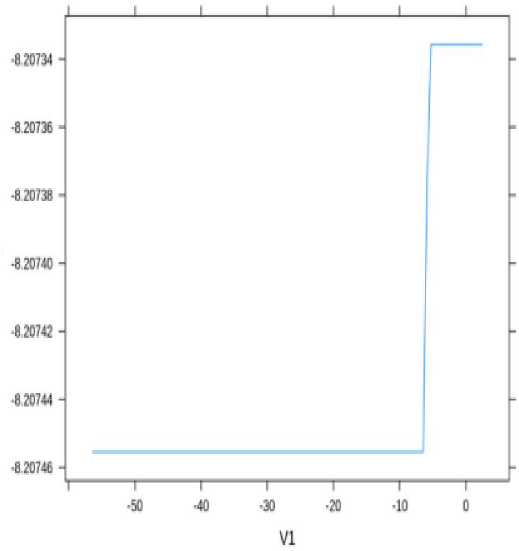
Fitting a Artificial Neural Network Model

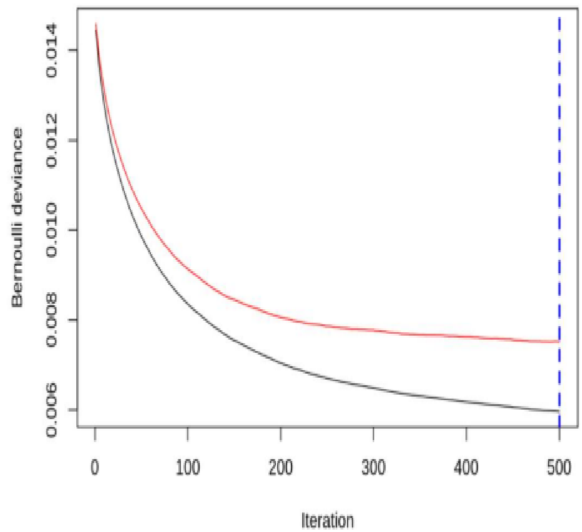
• We import the neuralnet package that would allow us to implement our ANNs. We therefore proceeded to plot it using the plot () function. Now, in the case of artificial neural networks, there is a range of values between 1 and 0. We set a threshold at 0.5, that is, values greater than 0.5 will correspond to 1 and the rest will be 0.



Fitting a Gradient Boosting Model

• Gradient Boosting is a popular machine learning algorithm used to perform classification and regression tasks. This model includes several underlying ensemble models such as weak decision trees. These decision trees combine to form a strong gradient augmentation model. We will implement the gradient descent algorithm in our model





6) Experimental Framework

• Implementation Details

Understanding the issue statement and data, doing statistical analysis and visualisation, and finally assessing whether the data is balanced were the steps we used to forecast the outcome. The data in this collection is unbalanced so, the objective of the project is to train a machine learning algorithm on the dataset to successfully predict fraudulent transactions.

Given the class imbalance ratio, we will be using measuring the accuracy using the Area Under the Precision-Recall Curve (AUC). Confusion matrix accuracy is not meaningful for unbalanced classification.

We will also use different sampling techniques (details below) on the train dataset in order to address the issue of imbalanced classes while training our models.

A. Machine learning algorithms

- **Logistic Regression:**

Logistic regression works with sigmoid function because the sigmoid function can be used to classify the output that is dependent feature and it uses the probability for classification of the dependent feature.
This algorithm works well with less amount of data set because of the use of sigmoid function if value the of sigmoid function is greater than 0.5 the output will 1 if the output the sigmoid function is less than 0.5 then the output is considered as the 0. But this sigmoid function is not suitable for deep learning because the if deep learning when we back tracking from the output to input we have to update the weights to minimize the error in weight update. we have to do differentiation of sigmoid activation function in middle layer neuron then results in the value of 0.25 this will affect the accuracy of the module in deep learning.

- **Decision Tree:**

Decision tree can be used for the classification and regression problems working for both is same but some formulas will change. Classification problem uses the entropy and information gain for the building of the decision tree model. entropy tell about how the data is random and information gain tells about how much information we can get from this feature.
Regression problem uses the gini and gini index for the building of the decision tree model. In classification problems the root node is selected by using information gain that the root node t id selected by using is having the high information again and low entropy. In Regression problems the root node is selected by using gini , the feature which is having the less gini is selected as the root here Depth of the tree can be determined
by using hyper parameter optimization, this can be achieved by Using grid search cv algorithm.

- **ANN Model:**

Artificial neural networks in deeps learning can be used to replace the machine learning algorithms for better prediction, ANN is having different types of layers such as input layer, number middle layers having activation function for the action of neurons and the output layer having some kind of activation function like sigmoid and weight initialization and initialization in backward propagation for reducing the error between actual and predicted values.

• Gradient Boosting

Gradient boosting algorithm is one of the most powerful algorithms in the field of machine learning. As we know that the errors in machine learning algorithms are broadly classified into two categories i.e. Bias Error and Variance Error. As gradient boosting is one of the boosting algorithms it is used to minimize bias error of the model.

Gradient boosting algorithm can be used for predicting not only continuous target variable (as a Regressor) but also categorical target variable (as a Classifier). When it is used as a regressor, the cost function is Mean Square Error (MSE) and when it is used as a classifier then the cost function is Log loss.

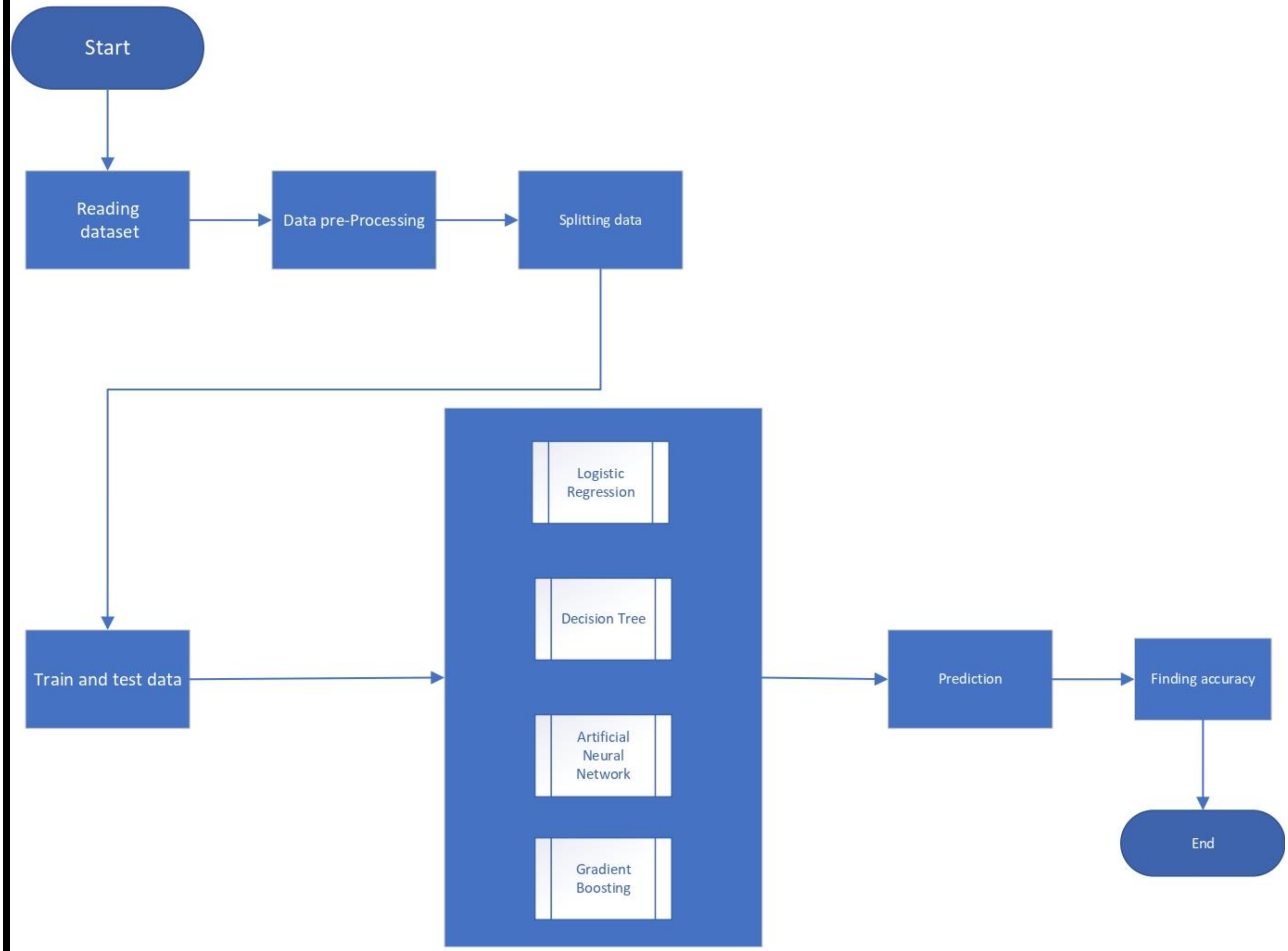
• Dataset Description

The transactions from Europe cardholders in September 2013 are included in this dataset. There are 492 scam transactions out of 2,84,807 total. Because there are fewer fraud cases than there are transactions, the data is unbalanced. The data set has been transformed to a PCA transformation and solely comprises numeric values. Due to privacy and confidentiality concerns, numerous background details are withheld, leaving simply PCA converted data. Only time and money are not PCA converted; all other supplied values (v1, v2, v3, v4, v5, v6, v7, v8, etc.) are PCA transformed numeric values. The fraud feature class has a value of 1 and the regular transaction has a value of 0.

Credit Card Dataset

Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
0	-1.3598	-0.0728	2.53635	1.37816	-0.3383	0.46239	0.2396	0.0987	0.36379	0.09079	-0.5516	-0.6178	-0.9914	-0.3112	1.46818	-0.4704	0.20797	0.02579	0.40399	0.25141	-0.0183	0.27784	-0.1105	0.06693	0.12854	-0.1891	0.13356	-0.0211	149.62	0
0	1.19186	0.26615	0.16648	0.44815	0.06002	-0.0824	-0.0788	0.0851	-0.2554	-0.167	1.61273	1.06524	0.4891	-0.1438	0.63556	0.46392	-0.1148	-0.1834	-0.1458	-0.0691	-0.2258	-0.6387	0.10129	-0.3398	0.16717	0.12589	-0.009	0.01472	2.69	0
1	-1.3584	-1.3402	1.77321	0.37978	-0.5032	1.8005	0.79146	0.24768	-1.5147	0.20764	0.6245	0.06608	0.71729	-0.1659	2.34586	-2.8901	1.10997	-0.1214	-2.2619	0.52498	0.248	0.77168	0.90941	-0.6893	-0.3276	-0.1391	-0.0554	-0.0598	378.66	0
1	-0.9663	-0.1852	1.79299	-0.8633	-0.0103	1.2472	0.23761	0.37744	-1.387	-0.055	-0.2265	0.17823	0.50776	-0.2879	-0.6314	-1.0596	-0.6841	1.96578	-1.2326	-0.208	-0.1083	0.00527	-0.1903	-1.1756	0.64738	-0.2219	0.06272	0.06146	123.5	0
2	-1.1582	0.87774	1.54872	0.40303	-0.4072	0.09592	0.59294	-0.2705	0.81774	0.75307	-0.8228	0.5382	1.34585	-1.1197	0.17512	-0.4514	-0.237	-0.0382	0.80349	0.40854	-0.0094	0.79828	-0.1375	0.14127	-0.206	0.50229	0.21942	0.21515	69.99	0
2	-0.426	0.96052	1.14111	-0.1683	0.42099	-0.0297	0.4762	0.26031	-0.5687	-0.3714	1.34126	0.35989	-0.3581	-0.1371	0.51762	0.40173	-0.0581	0.06865	-0.0332	0.08497	-0.2083	-0.5598	-0.0264	-0.3714	-0.2328	0.10591	0.25384	0.08108	3.67	0
4	1.22966	0.141	0.04537	1.20261	0.19188	0.27271	-0.0052	0.08121	0.46496	-0.0993	-1.4169	-0.1538	-0.7511	0.16737	0.05014	-0.4436	0.00282	-0.612	-0.0456	-0.2196	-0.1677	-0.2707	-0.1541	-0.7801	0.75014	-0.2572	0.03451	0.00517	4.99	0
7	-0.6443	1.41796	1.07438	-0.4922	0.94893	0.42812	1.12063	-3.8079	0.61537	1.24938	-0.6195	0.29147	1.75796	-1.3239	0.68613	-0.0761	-1.2221	-0.3582	0.3245	-0.1567	1.94347	-1.0155	0.0575	-0.6497	-0.4153	-0.0516	-1.2069	-1.0853	40.8	0
7	-0.8943	0.28616	-0.1132	-0.2715	2.6696	3.72182	0.37015	0.85108	-0.392	-0.4104	-0.7051	-0.1105	-0.2863	0.07436	-0.3288	-0.2101	-0.4998	0.11876	0.57033	0.05274	-0.0734	-0.2681	-0.2042	1.01159	0.3732	-0.3842	0.01175	0.1424	93.2	0
9	-0.3383	1.11959	1.04437	-0.2222	0.49936	-0.2468	0.65158	0.06954	-0.7367	-0.3668	1.01761	0.83639	1.00684	-0.4435	0.15022	0.73945	-0.541	0.47668	0.45177	0.20371	-0.2469	-0.6338	-0.1208	-0.385	-0.0697	0.0942	0.24622	0.08308	3.68	0
10	1.44904	-1.1763	0.91386	-1.3757	-1.9714	-0.6292	-1.4232	0.04846	-1.7204	1.62666	1.19964	-0.6714	-0.5139	-0.095	0.23093	0.03197	0.25341	0.85434	-0.2214	-0.3872	-0.0093	0.31389	0.02774	0.50051	0.25137	-0.1295	0.04285	0.01625	7.8	0
10	0.38498	0.61611	-0.8743	-0.094	2.92458	3.31703	0.47045	0.53825	-0.5589	0.30976	-0.2591	-0.3261	-0.09	0.36283	0.9289	-0.1295	-0.81	0.35999	0.70766	0.12599	0.04992	0.23842	0.00913	0.99671	-0.7673	-0.4922	0.04247	-0.0543	9.99	0
10	1.25	-1.2216	0.38393	-1.2349	-1.4854	-0.7532	-0.6894	-0.2275	-2.094	1.32373	0.22767	-0.2427	1.20542	-0.3176	0.72567	-0.8156	0.87394	-0.8478	-0.6832	-0.1028	-0.2318	-0.4833	0.08467	0.39283	0.16113	-0.355	0.02642	0.04242	121.5	0
11	1.06937	0.28772	0.82861	2.71252	-0.1784	0.33754	-0.0967	0.11598	-0.2211	0.46023	-0.7737	0.32339	-0.0111	-0.1785	-0.6556	-0.1999	0.12401	-0.9805	-0.9829	-0.1532	-0.0369	0.07441	-0.0714	0.10474	0.54826	0.10409	0.02149	0.02129	27.5	0
12	-2.7919	-0.3278	1.64175	1.76747	-0.1366	0.8076	-0.4229	-1.9071	0.75571	1.15109	0.84456	0.79294	0.37045	-0.735	0.4068	-0.3031	-0.1559	0.77827	2.22187	-1.5821	1.15166	0.22218	1.02059	0.02832	-0.2327	-0.2356	-0.1648	-0.0302	58.8	0
12	-0.7524	0.34549	2.05732	-1.4686	-1.1584	-0.0778	-0.6086	0.0036	-0.4362	0.74775	-0.794	-0.7704	1.04763	-1.0666	1.10695	1.66011	-0.2793	-0.42	0.43254	0.26345	0.49962	1.35365	-0.2566	-0.0651	-0.0391	-0.0871	-0.181	0.12939	15.99	0
12	1.10322	-0.0403	1.26733	1.28909	-0.736	0.28807	-0.5861	0.18938	0.78233	-0.268	-0.4503	0.93671	0.70838	-0.4686	0.35457	-0.2466	-0.0092	-0.5959	-0.5757	-0.1139	-0.0246	0.196	0.0138	0.10376	0.3643	-0.3823	0.09281	0.03705	12.99	0
13	-0.4369	0.91897	0.92459	-0.7272	0.91568	-0.1279	0.70764	0.08796	-0.6653	-0.738	0.3241	0.27719	0.25262	-0.2919	-0.1845	1.14317	-0.9287	0.68047	0.02544	-0.047	-0.1948	-0.6726	-0.1569	-0.8884	-0.3424	-0.049	0.07969	0.13102	0.89	0
14	-5.4013	-5.4501	1.1863	1.73624	3.04911	-1.7634	-1.5597	0.16084	1.23309	0.34517	0.91723	0.97012	-0.2666	-0.4791	-0.5266	0.472	-0.7255	0.07508	-0.4069	-2.1968	-0.5036	0.98446	2.45859	0.04212	-0.4816	-0.6213	0.39205	0.94959	46.8	0
15	1.49294	-1.0293	0.45479	-1.438	-1.5554	-0.721	-1.0807	-0.0531	-1.9787	1.63808	1.07754	-0.632	-0.417	0.05201	-0.043	-0.1664	0.30424	0.55443	0.05423	-0.3879	-0.1776	-0.1751	0.04	0.29581	0.33293	-0.2204	0.0223	0.0076	5	0
16	0.69488	-1.3618	1.02922	0.83416	-1.1912	1.30911	-0.8786	0.44529	-0.4462	0.56852	1.01915	1.29833	0.42048	-0.3727	-0.808	-2.0446	0.51566	0.62585	-1.3004	-0.1383	-0.2956	-0.572	-0.0509	-0.3042	0.072	-0.4222	0.08655	0.0635	231.71	0
17	0.9625	0.32846	-0.1715	2.1092	1.12957	1.69604	0.10771	0.5215	-1.1913	0.7244	1.69033	0.40677	-0.9364	0.98374	0.71091	-0.6022	0.40248	-1.7372	-2.0276	-0.2693	0.144	0.40249	-0.0485	-1.3719	0.39081	0.19996	0.01637	-0.0146	34.09	0
18	1.16662	0.50212	-0.0673	2.26157	0.4288	0.08947	0.24115	0.13808	-0.9892	0.92217	0.74479	-0.5314	-2.1053	1.12687	0.00308	0.42442	-0.4545	-0.0989	-0.8166	-0.3072	0.0187	-0.062	-0.1039	-0.3704	0.6032	0.10856	-0.0405	-0.0114	2.28	0
18	0.24749	0.27767	1.18547	-0.0926	-1.3144	-0.1501	-0.9464	-1.6179	1.54407	-0.8299	-0.5832	0.52493	-0.4534	0.08139	1.5552	-1.3969	0.78313	0.43662	2.17781	-0.231	1.65018	0.20045	-0.1854	0.42307	0.82059	-0.2276	0.33663	0.25048	22.75	0
22	-1.9465	-0.0449	-0.4056	-1.0131	2.94197	2.95505	-0.0631	0.85555	0.04997	0.57374	-0.0813	-0.2157	0.04416	0.0339	1.19072	0.57884	-0.9757	0.04406	0.4886	-0.2167	-0.5795	-0.7992	0.8703	0.98342	0.3212	0.14965	0.70752	0.0146	0.89	0
22	-2.0743	-0.1215	1.32202	0.41001	0.2952	-0.9595	0.54399	-0.1046	0.47566	0.14945	-0.8566	-0.1805	-0.6552	-0.2798	-0.2117	-0.3333	0.01075	-0.4885	0.50575	-0.3867	-0.4036	-0.2274	0.74243	0.39853	0.24921	0.2744	0.35997	0.24323	26.43	0
23	1.17328	0.3535	0.28391	1.13356	-0.1726	-0.9161	0.36902	-0.3273	-0.2467	-0.0461	-0.1434	0.97935	1.49229	0.10142	0.76148	-0.0146	-0.5116	-0.3251	-0.3909	0.02788	0.067	0.22781	-0.1505	0.43505	0.72482	-0.3371	0.01637	0.03004	41.88	0
23	1.32271	-0.174	0.43456	0.57604	-0.8368	-0.8311	-0.2649	-0.221	-1.0714	0.86856	-0.6415	-0.1113	0.36149	0.17195	0.78217	-1.3559	-0.2169	1.27177	-1.2406	-0.523	-0.2844	-0.3234	-0.0377	0.34715	0.55964	-0.2802	0.04234	0.02882	16	0
23	-0.4143	0.90544	1.72745	1.47347	0.00744	-0.2003	0.74023	-0.0292	-0.5934	-0.3462	-0.0121	0.7868	0.63595	-0.0863	0.0768	-1.4059	0.77559	-0.9429	0.54397	0.09731	0.07724	0.45733	-0.0385	0.64252	-0.1839	-0.2775	0.18269	0.15266	33	0
23	1.05939	-0.1753	1.26613	1.18611	-0.786	0.57844	-0.7671	0.40105	0.6995	-0.0647	1.04829	1.00562	-0.542	-0.0399	-0.2187	0.00448	-0.1936	0.04239	-0.2778	-0.178	0.01368	0.21373	0.01446	0.00295	0.29464	-0.3951	0.08146	0.02422	12.99	0
24	1.23743	0.06104	0.38053	0.76156	-0.3598	-0.4941	0.00649	-0.1339	0.43881	-0.2074	-0.9292	0.52711	0.34868	-0.1525	-0.2184	-0.1916	-0.1166	-0.6338	0.34842	-0.0664	-0.2457	-0.5309	-0.0443	0.07917	0.50914	0.28886	-0.0227	0.01184	17.28	0
25	1.11401	0.08555	0.4937	1.33576	-0.3002	-0.0108	-0.1188	0.18862	0.20569	0.08226	1.13356	0.6267	-1.4928	0.52079	-0.6746	-0.5291	0.15826	-0.3988	-0.1457	-0.2738	-0.0532	-0.0048	-0.0315	0.19805	0.56501	-0.3377	0.02906	0.00445	4.45	0
26	-0.5299	0.87389	1.34725	0.14546	0.41421	0.10022	0.71121	0.17607	-0.2867	-0.4847	0.87249	0.85164	-0.5717	0.10097	-1.5198	-0.2844	-0.3105	-0.4042	-0.8234	-0.2903	0.04695	0.2081	-0.1855	0.00103	0.09882	-0.5529	-0.0733	0.02331	6.14	0
26	-0.5299	0.87389	1.34725	0.14546	0.41421	0.10022	0.71121	0.17607	-0.2867	-0.4847	0.87249	0.85164	-0.5717	0.10097	-1.5198	-0.2844	-0.3105	-0.4042	-0.8234	-0.2903	0.04695	0.2081	-0.1855	0.00103	0.09882	-0.5529	-0.0733	0.02331	6.14	0

7) Flowchart / Schematic representation of your project



8) Conclusion

Credit card fraud is unquestionably a kind of criminal deception. This article evaluated current results in this subject and outlined the most prevalent types of fraud, as well as how to identify them. This paper also includes a detailed description of how machine learning may be used to improve fraud detection findings, as well as the method, pseudocode, explanation, and experimentation results.

While the method achieves a precision of over 99.6%, when only a tenth of the data set is considered, it only achieves a precision of 28%. When the complete dataset is given into the system, however, the accuracy increases to 33%. Because of the significant disparity between the number of legitimate and authentic transactions, this high percentage of accuracy is to be expected.

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