

Logistic Regression Analysis on Heart Health Data

The Issue:

The given dataset related to heart health, which includes 18 factors including the "delay days" variable, measured in days until a person seeks medical treatment. Our objective is to create a logistic regression model to predict whether a person seeks medical treatment in three ways. The first method involves categorizing those who seek treatment in 2 days or less as "1" and those who seek treatment after 2 days as "0". The second method involves calculating the average delay time for a group of people and labeling those who seek treatment in less than the average time as "1" and those who seek treatment after the average time as "0". The third method involves labeling those who seek treatment in less than 1 day as "1" and those who seek treatment after 1 day as "0".

Findings:

We are developing a logistic regression model using 18 variables, including "delay days," to determine the significance of these variables in predicting delay days. We can evaluate the statistical significance of each variable using their corresponding p-values and z-values. Our results show that only "cough" has a statistically significant association with delay days, with a p-value of 0.000505 and edema 0.007666. Variables with p-values less than 0.05 are considered statistically significant and indicate a non-chance association with the dependent variable. Therefore, we can conclude that there is a significant association between cough, edema and delay days, while the remaining variables (ID, age, gender, ethnicity, marital status, living situation, education, palpitations, orthopnea, chest pain, nausea, fatigue, dyspnea, PND, tight shoes, weight gain, and DOE) are not significant predictors of delay days. We also generated a ROC curve to evaluate the performance of our model, which resulted in an ROC-AUC value of 0.581, suggesting that our model's performance is satisfactory.

Discussions:

When interpreting the results of the logistic model with 18 variables, it is important to consider the corresponding p-values. A p-value greater than 0.05 suggests that the variable has no significant impact, while a p-value less than 0.05 suggests that the variable is significant to some extent. The coefficient values provide insights into the direction and magnitude of the relationship between the predictor and dependent variables. A positive coefficient indicates that an increase in the predictor variable is associated with an increase in the dependent variable, and a negative coefficient suggests the opposite. The ROC curve and AUC value are useful in evaluating the model's performance. Based on these metrics, we can determine if the model's performance is satisfactory or poor.

Appendix A Method:

To build our logistic model, we used the R programming language and installed relevant packages such as pROC and caTools. We imported the dataset and separated the dependent variable, delay days, from the other variables. We created a new dataset with the remaining variables and split it into training and testing data sets. Using the training data, we constructed the generalized logistic model and applied it to generate predictions with the testing data. We analyzed the model predictions to determine the significant variables. We evaluated the effectiveness of our model by creating a ROC curve using the generalized logistic model and calculating the AUC. We also obtained the confusion matrix to calculate the accuracy.

Appendix B: Result

Results of generalized logistic model for case 1

```
> library(readxl)
> library(pROC)
> file <- "C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
> data <- read_excel(file, sheet = 1)
> data$delay <- ifelse(data$delaydays < 2, 1, 0)
> summary(data)
```

	ID	Age	Gender	Ethnicity	Marital	Mi
Livewith						
Min.	: 1.0	Min. :41.00	Min. :1.000	Min. :1.000	Min. :1.000	Mi
n.	:1.000					

1st Qu.: 52.0	1st Qu.:67.00	1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000	1st
Median :103.5	Median :77.00	Median :1.000	Median :1.000	Median :2.000	Me
Mean :127.9	Mean :74.25	Mean :1.448	Mean :1.126	Mean :1.665	Me
3rd Qu.:189.8	3rd Qu.:84.00	3rd Qu.:2.000	3rd Qu.:1.000	3rd Qu.:2.000	3r
Max. :512.0	Max. :96.00	Max. :2.000	Max. :5.000	Max. :3.000	Ma

's :2

Education	palpitations	orthopnea	chestpain	nausea
Min. :1.000	Min. :0.0000	Min. :0.000	Min. :0.000	Min. :0.0000
1st Qu.:1.000	1st Qu.:0.0000	1st Qu.:0.000	1st Qu.:0.000	1st Qu.:0.0000
Median :2.000	Median :0.0000	Median :2.000	Median :0.000	Median :0.0000
Mean :2.118	Mean :0.6478	Mean :1.638	Mean :0.564	Mean :0.5025
3rd Qu.:3.000	3rd Qu.:1.0000	3rd Qu.:3.000	3rd Qu.:1.000	3rd Qu.:1.0000
Max. :6.000	Max. :3.0000	Max. :3.000	Max. :3.000	Max. :3.0000

cough	fatigue	dyspnea	edema	PND
Min. :0.000	Min. :0.000	Min. :0.000	Min. :0.000	Min. :0.000
1st Qu.:0.000	1st Qu.:2.000	1st Qu.:2.000	1st Qu.:0.000	1st Qu.:0.000
Median :1.000	Median :2.000	Median :2.000	Median :1.000	Median :1.000
Mean :1.081	Mean :1.951	Mean :1.995	Mean :1.227	Mean :1.286
3rd Qu.:2.000	3rd Qu.:3.000	3rd Qu.:3.000	3rd Qu.:2.000	3rd Qu.:2.000
Max. :3.000	Max. :3.000	Max. :3.000	Max. :3.000	Max. :3.000

tightshoes	weightgain	DOE	delaydays	delay
Min. :0.0000	Min. :0.0000	Min. :0.000	Min. : 0.000	Min. :0.0000
1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:1.000	1st Qu.: 0.500	1st Qu.:0.0000
Median :0.0000	Median :0.0000	Median :2.000	Median : 2.000	Median :0.0000
Mean :0.8399	Mean :0.8892	Mean :1.739	Mean : 5.726	Mean :0.4367
3rd Qu.:2.0000	3rd Qu.:2.0000	3rd Qu.:2.750	3rd Qu.: 7.000	3rd Qu.:1.0000
Max. :3.0000	Max. :3.0000	Max. :3.000	Max. :225.000	Max. :1.0000
			NA's :3	NA's :3

```

>
> data1 <- subset(data,select = -delaydays)
>
> #Splitting the data
>
> div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
> training<-data1[div==1,]
> testing<-data1[div==2,]
>
>
>
> lm<-glm(delay~.,data=training,family='binomial')
> summary(lm)

```

Call:
glm(formula = delay ~ ., family = "binomial", data = training)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.4254	-0.9968	-0.6028	1.0498	1.9553

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.9134731	1.5437641	-0.592	0.554039
ID	-0.0009859	0.0014254	-0.692	0.489161
Age	0.0157609	0.0122649	1.285	0.198779
Gender	0.2951178	0.2776102	1.063	0.287752
Ethnicity	-0.1772361	0.2467537	-0.718	0.472590
Marital	0.4340413	0.2316556	1.874	0.060979 .
Livewith	0.0925823	0.3369537	0.275	0.783499
Education	-0.0361904	0.0987332	-0.367	0.713957
palpitations	0.1373554	0.1558103	0.882	0.378017
orthopnea	-0.1218716	0.1520376	-0.802	0.422791
chestpain	0.3399483	0.1651191	2.059	0.039513 *
nausea	-0.0181303	0.1686904	-0.107	0.914411
cough	-0.5183568	0.1490328	-3.478	0.000505 ***
fatigue	-0.2322050	0.1743744	-1.332	0.182977
dyspnea	0.1130933	0.1665321	0.679	0.497069
edema	-0.4238133	0.1589450	-2.666	0.007666 **
PND	-0.0558181	0.1471694	-0.379	0.704482
tightshoes	0.2206363	0.1677055	1.316	0.188302

```
weightgain 0.1914854 0.1473069 1.300 0.193633
DOE        -0.2504334 0.1566355 -1.599 0.109859
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 377.73 on 274 degrees of freedom
Residual deviance: 333.15 on 255 degrees of freedom
(2 observations deleted due to missingness)
AIC: 373.15
```

Number of Fisher Scoring iterations: 3

```
>
> pre<-predict(lm, testing, type='response')
>
> #ROC curve
> ROC <- roc(testing$delay,pre)
Setting levels: control = 0, case = 1
Setting direction: controls < cases
> plot(ROC , print.auc= TRUE)
>
> #Confusion Matrix
> pre1<-ifelse(pre>0.5,1,0)
>
> table(pre1)
pre1
 0  1
75 53
> tab<-table(Prediction=pre1,Actual=testing$delay)
>
> #Accuracy,Misclassification error
> Accuracy<-sum(diag(tab))/sum(tab)
> error<-1-Accuracy
> error
[1] 0.4047619
```

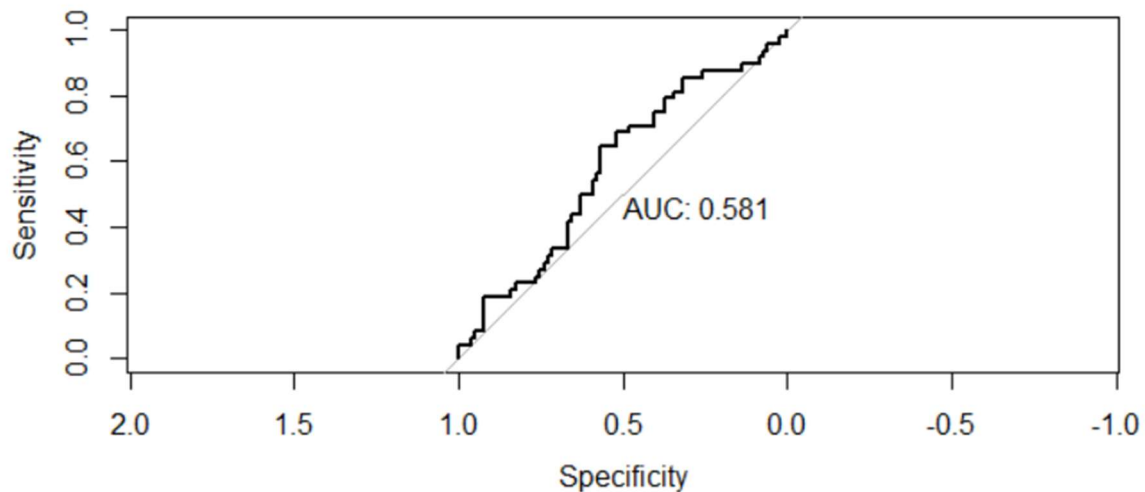


Fig1 : ROC curve and AUC for case 1.

Results of generalized logistic model for case 2

```
> file <-"C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
```

```

> data <- read_excel(file, sheet = 1)
> mean_d
[1] 5.725779
> data$delay<-ifelse(data$delaydays<mean_d,1,0)
>
> data1<-subset(data,select = -delaydays)
>
> #splitting the data
> div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
> training<-data1[div==1,]
> testing<-data1[div==2,]
>
> #logistic model
> lm<-glm(delay~.,data=training,family='binomial')
> summary(lm)

```

```

Call:
glm(formula = delay ~ ., family = "binomial", data = training)

```

```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9902  -1.1513   0.6622   0.8230   1.4104

```

```

Coefficients:
(Intercept)      Estimate Std. Error z value Pr(>|z|)
ID              -0.002366  0.001423  -1.662  0.0965 .
Age              -0.002292  0.011759  -0.195  0.8455
Gender            0.059303  0.284840   0.208  0.8351
Ethnicity        -0.163910  0.217080  -0.755  0.4502
Marital          0.030560  0.241537   0.127  0.8993
Livewith         -0.047014  0.352192  -0.133  0.8938
Education        0.006434  0.107460   0.060  0.9523
palpitations    -0.149900  0.156099  -0.960  0.3369
orthopnea       -0.005254  0.150863  -0.035  0.9722
chestpain        0.084100  0.156627   0.537  0.5913
nausea          -0.388581  0.172856  -2.248  0.0246 *
cough           -0.033916  0.142562  -0.238  0.8120
fatigue         -0.013613  0.176807  -0.077  0.9386
dyspnea         -0.032985  0.174692  -0.189  0.8502
edema           -0.376465  0.151807  -2.480  0.0131 *
PND             -0.168877  0.137572  -1.228  0.2196
tightshoes      0.237411  0.164488   1.443  0.1489
weightgain      0.089100  0.142861   0.624  0.5328
DOE            -0.053832  0.162044  -0.332  0.7397
---

```

```

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

(Dispersion parameter for binomial family taken to be 1)

```

```

Null deviance: 346.58 on 288 degrees of freedom
Residual deviance: 326.88 on 269 degrees of freedom
(3 observations deleted due to missingness)
AIC: 366.88

```

```

Number of Fisher Scoring iterations: 4

```

```

>
> #Prediction
> pre<-predict(lm, testing, type='response')
> pre
   1         2         3         4         5         6         7         8
9  0.8408764 0.5141380 0.8736205 0.8467192 0.8467192 0.9064892 0.8384055 0.7238536 0.7
706020
10         11         12         13         14         15         16         17
18  0.8287406 0.8231606 0.8407530 0.8819686 0.8766920 0.9037667 0.3767912 0.8737457 0.7
975919
19         20         21         22         23         24         25         26
27  0.7494097 0.8130017 0.7799863 0.7884709 0.8061686 0.7780027 0.7491107 0.8080437 0.6
425924
28         29         30         31         32         33         34         35
36  0.8111050 0.5743026 0.6826423 0.7325440 0.7581208 0.7661918 0.8142332 0.8466834 0.3
866615

```

```

45      37      38      39      40      41      42      43      44
0.7919466 0.8249310 0.7887095 0.6876546 0.7454760 0.7310816 0.6122362 0.5918874 0.6
055657
54      46      47      48      49      50      51      52      53
NA 0.8810881 0.6295598 0.8636308 0.8311080 0.8308963 0.8799356 0.8286788 0.4
692084
63      55      56      57      58      59      60      61      62
0.5956719 0.6843973 0.7545373 0.6128855 0.5470719 0.6885544 0.6783366 0.7872351 0.7
555715
72      64      65      66      67      68      69      70      71
0.6917214 0.6504256 0.6085514 0.5931528 0.6647217 0.8646614 0.6013581 0.5971433 0.7
933604
81      73      74      75      76      77      78      79      80
0.7454263 0.6463831 0.6737098 0.7637558 0.6941591 0.7071066 0.7675496 0.5278110 0.7
684027
90      82      83      84      85      86      87      88      89
0.7372016 0.7065059 0.4858055 0.8645326 0.7047265 0.6772332 0.6327062 0.6124889 0.6
002613
99      91      92      93      94      95      96      97      98
0.5338180 0.7743471 0.7006888 0.6805711 0.8117873 0.5025104 0.4695909 0.7833172 0.6
396541
108     100     101     102     103     104     105     106     107
0.7797908 0.7878563 0.6109720 0.7614416 0.5384182 0.6458852 0.6021039 0.5676860 0.8
208245
109     110     111     112     113     114
0.5530519 0.4739046 0.6348737 0.5519041 0.4773750 0.6312300
>
> #ROC curve
> ROC <- roc(testing$delay,pre)
Setting levels: control = 0, case = 1
Setting direction: controls < cases
> plot(ROC , print.auc= TRUE)
>
> #Confusion Matrix
> pre1<-ifelse(pre>0.5,1,0)
>
> table(pre1)
pre1
  0   1
  7 106
> tab<-table(Prediction=pre1,Actual=testing$delay)
>
>
> #Accuracy,Misclassification error
> Accuracy<-sum(diag(tab))/sum(tab)
> M_error<-1-Accuracy
> M_error
[1] 0.3125

```

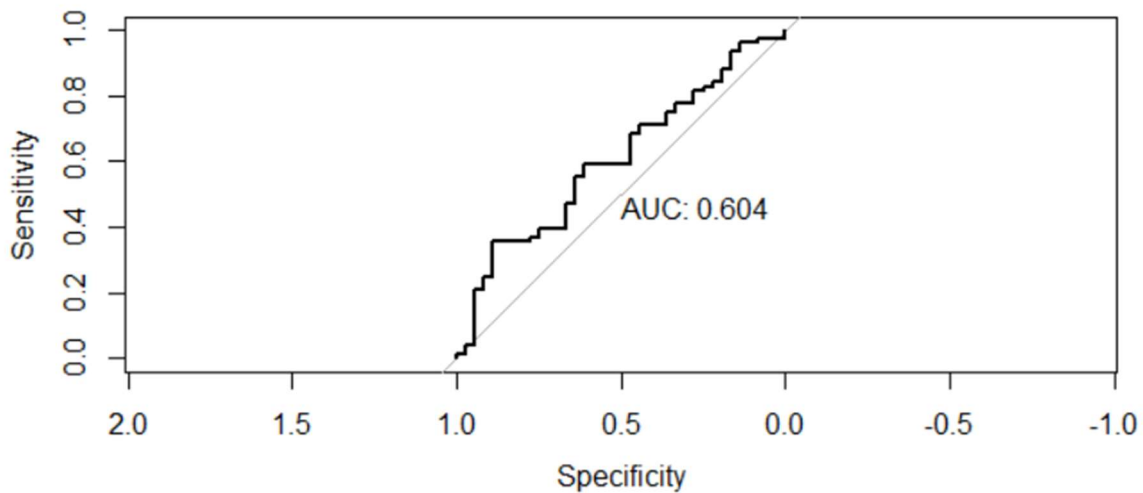


Fig2: ROC curve and AUC for case 2

Results of generalized logistic model for case 3

```
> file <-"C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
> data <- read_excel(file, sheet = 1)
>
> data$delay<-ifelse(data$delaydays<1,1,0)
>
> #subset of original dataset by removing delaydays column
> data1 <- subset(data,select = -delaydays)
>
> #Splitting the data
> div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
> training<-data1[div==1,]
> testing<-data1[div==2,]
>
> #logistic model
> lm<-glm(delay~.,data=training,family='binomial')
> summary(lm)
```

Call:
glm(formula = delay ~ ., family = "binomial", data = training)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.4299	-0.8535	-0.6787	1.2178	2.0456

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.2255233	1.6063376	0.763	0.4455
ID	0.0001782	0.0014432	0.123	0.9017
Age	0.0088701	0.0122514	0.724	0.4691
Gender	-0.0830137	0.2862066	-0.290	0.7718
Ethnicity	-0.2676876	0.2815853	-0.951	0.3418
Marital	-0.0146799	0.2447695	-0.060	0.9522
Livewith	-0.7626177	0.3503349	-2.177	0.0295 *
Education	-0.0265897	0.1018326	-0.261	0.7940
palpitations	-0.0498858	0.1634236	-0.305	0.7602
orthopnea	-0.1417594	0.1531118	-0.926	0.3545
chestpain	-0.0338475	0.1709948	-0.198	0.8431


```

118      119      120      121      122      123      124      125
126
0.2387496 0.2178770 0.1509393 0.1820763 0.3864026 0.3014749 0.3396654 0.4117844 0.3
508576
      127      128      129      130      131
0.3247837 0.5261205 0.3367690 0.5041361 0.4548994
>
> #ROC curve
> ROC <- roc(testing$delay,pre)
Setting levels: control = 0, case = 1
Setting direction: controls < cases
> plot(ROC , print.auc= TRUE)
>
> #Confusion Matrix
> pre1<-ifelse(pre>0.5,1,0)
> pre1
  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21
22 0  0  0  1  1  1  1  0  0  0  0  0  0  0  0  1  1  0  0  0
0  0  0
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45
46 0  0  1  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0
0  0  0
49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69
70 0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0
0  0  0
73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93
94 0  0  0  0  0  0  1  0  0  0  0  1  0  0  0  0  0  1  0  1
0  0  0
97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117
118 0  0  0  0  0  0  1  0  0  0  0  1  0  0  0  1  0  0  0  0
0  0  0
121 122 123 124 125 126 127 128 129 130 131
0  0  0  0  0  0  1  0  1  0
> table(pre1)
pre1
  0  1
113 18
> tab<-table(Prediction=pre1,Actual=testing$delay)
> tab
      Actual
Prediction 0  1
          0 82 31
          1 11  6
>
> #Accuracy,Misclassification error
> Accuracy<-sum(diag(tab))/sum(tab)
> M_error<-1-Accuracy
> M_error
[1] 0.3230769

```

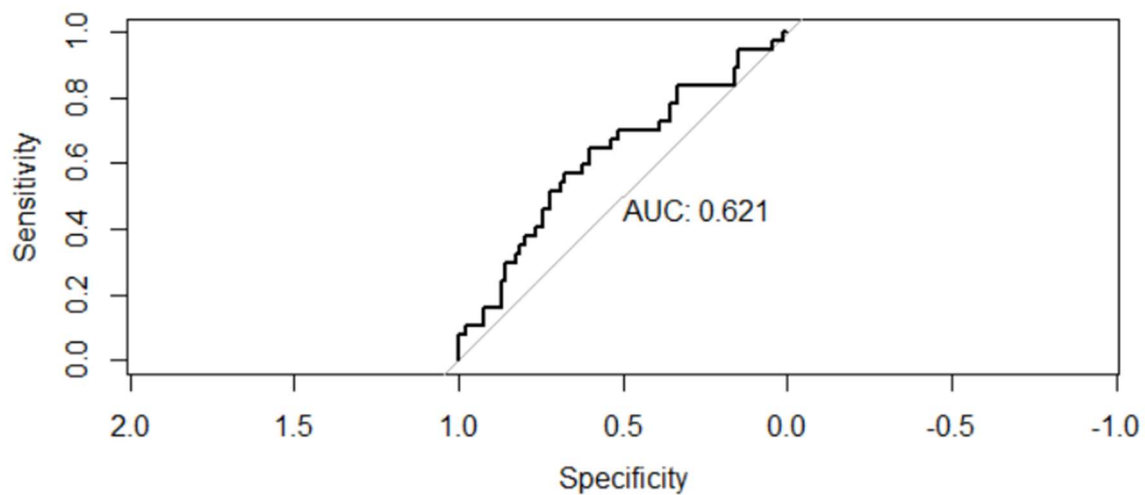


Fig3 : ROC curve and AUC for case 3

Appendix C Code:

Case1 :

```
library(readxl)
library(pROC)
file <- "C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
data <- read_excel(file, sheet = 1)
data$delay<-ifelse(data$delaydays<2,1,0)
summary(data)

data1 <- subset(data,select = -delaydays)

#Splitting the data
div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
training<-data1[div==1,]
testing<-data1[div==2,]

lm<-glm(delay~.,data=training,family='binomial')
summary(lm)
```

```
pre<-predict(lm, testing, type='response')
```

```
#ROC curve
```

```
ROC <- roc(testing$delay,pre)
```

```
plot(ROC , print.auc= TRUE)
```

```
#Confusion Matrix
```

```
pre1<-ifelse(pre>0.5,1,0)
```

```
table(pre1)
```

```
tab<-table(Prediction=pre1,Actual=testing$delay)
```

```
#Accuracy,Misclassification error
```

```
Accuracy<-sum(diag(tab))/sum(tab)
```

```
error<-1-Accuracy
```

```
error
```

```
Case2 :
```

```
file <-"C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
```

```
data <- read_excel(file, sheet = 1)
```

```
data
```

```
str(data)
```

```
#mean for delaydays
```

```
mean_d<-mean(data$delaydays,na.rm=TRUE)
```

```
mean_d
```

```
data$delay<-ifelse(data$delaydays<mean_d,1,0)
```

```
data1<-subset(data,select = -delaydays)

#Splitting the data
div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
training<-data1[div==1,]
testing<-data1[div==2,]

#logistic model
lm<-glm(delay~.,data=training,family='binomial')
summary(lm)

#Prediction
pre<-predict(lm, testing, type='response')
pre

#ROC curve
ROC <- roc(testing$delay,pre)
plot(ROC , print.auc= TRUE)

#Confusion Matrix
pre1<-ifelse(pre>0.5,1,0)

table(pre1)
tab<-table(Prediction=pre1,Actual=testing$delay)

#Accuracy,Misclassification error
Accuracy<-sum(diag(tab))/sum(tab)
M_error<-1-Accuracy
M_error
```

Case3 :

```
file <-"C:\\Users\\sasik\\OneDrive\\Desktop\\heart-health-data.xls"
```

```
data <- read_excel(file, sheet = 1)
```

```
data$delay<-ifelse(data$delaydays<1,1,0)
```

```
#subset of original dataset by removing delaydays column
```

```
data1 <- subset(data,select = -delaydays)
```

```
#Splitting the data
```

```
div<-sample(2,nrow(data1),replace=T,prob=c(0.7,0.3))
```

```
training<-data1[div==1,]
```

```
testing<-data1[div==2,]
```

```
#logistic model
```

```
lm<-glm(delay~.,data=training,family='binomial')
```

```
summary(lm)
```

```
#Prediction
```

```
pre<-predict(lm, testing, type='response')
```

```
pre
```

```
#ROC curve
```

```
ROC <- roc(testing$delay,pre)
```

```
plot(ROC , print.auc= TRUE)
```

```
#Confusion Matrix
```

```
pre1<-ifelse(pre>0.5,1,0)
```

```
pre1
```

```
table(pre1)
```

```
tab<-table(Prediction=pre1,Actual=testing$delay)
```

```
tab
```

```
#Accuracy,Misclassification error
```

```
Accuracy<-sum(diag(tab))/sum(tab)
```

```
M_error<-1-Accuracy
```

```
M_error
```