AI19542 - DATA SCIENCE USING R - LAB MANUAL

RAJALAKSHMI ENGINEERING COLLEGE

An AUTONOMOUS Institution

Affiliated to ANNA UNIVERSITY, Chennai

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

AI19542 – DATA SCIENCE USING R

LAB MANUAL

THIRD YEAR

FIFTH SEMESTER

2024 - 2025

ODD SEMESTER

Ex No:1 Date:	Basics of R – data types, vectors, factors, list and data frames

AIM:

To implement and understand the basics of R programming with its data types, vectors, factors, list and data frames.

ALGORITHM:

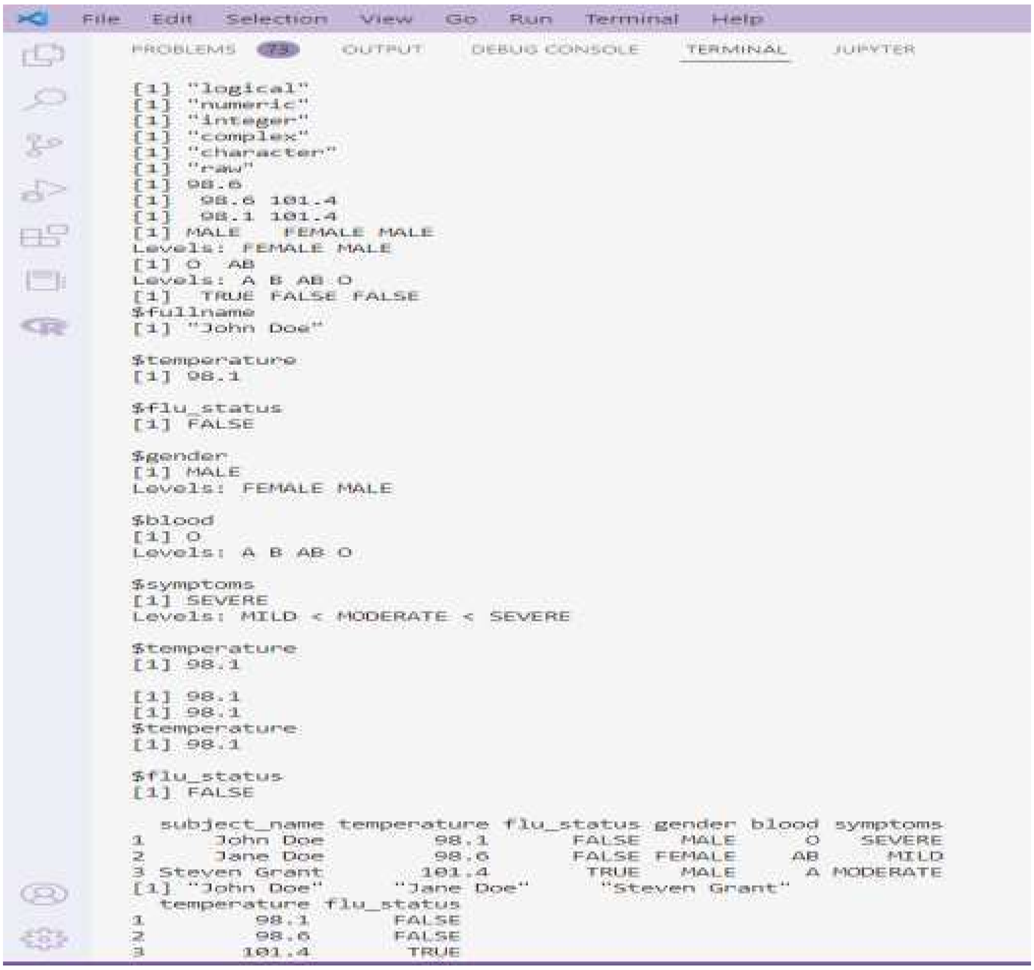
1. Start
2. Assign values in logical, numerical, character, complex and character in raw form to a variable v.
3. Print the class of v.
4. Assign a vector for subject Names, temperature and flu_status for three patients using c() function and access the elements.
5. Create a factor using factor() with duplicate values and assign level with distinct values.
6. Display the specific element and check for certain values in factor.
7. Create a list using list() from the patient details and access the multiple elements.
8. Create a data frame using data.frame() with multiple vectors as features. Access the elements.
9. Create a matrix using matrix() with different allocations and access the elements.
10. Stop.

PROGRAM:

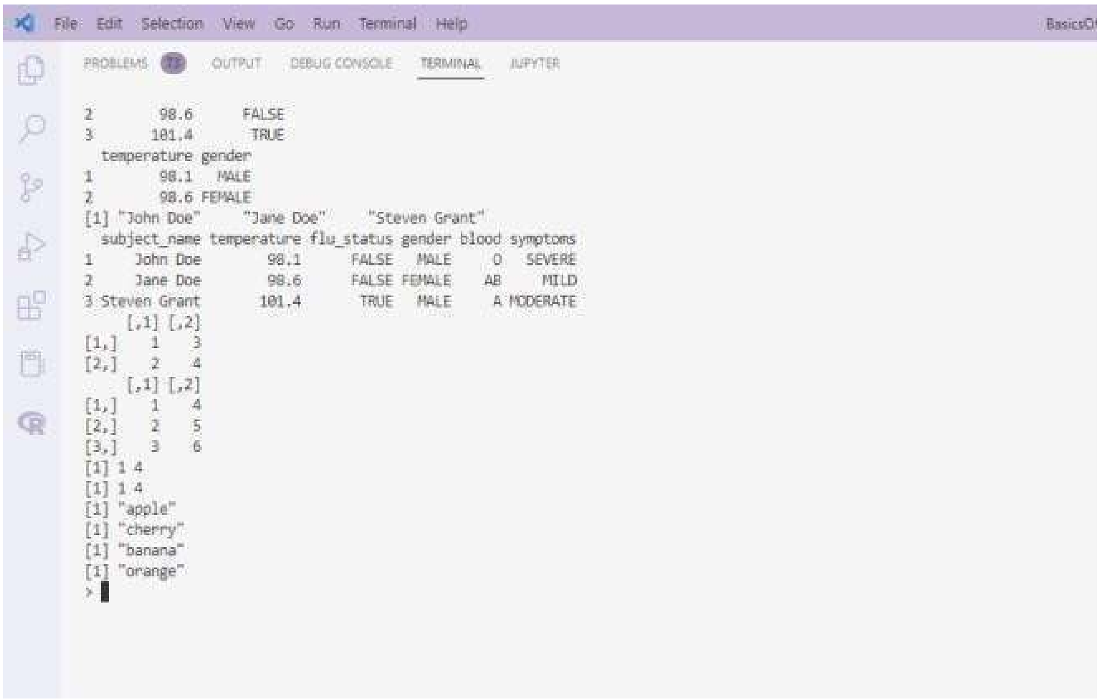
```
#Data Types
v<-TRUE
print(class(v))
v<-23.5
print(class(v))
v<-2L
print(class(v))
v<-2+5i
print(class(v))
v<-"TRUE"
print(class(v))
v<-charToRaw("Hello")
print(class(v))

#Vectors
subject_name<-c("John Doe","Jane Doe","Steven Grant")
temperature<-c(98.1,98.6,101.4)
flu_status<-c(FALSE,FALSE,TRUE)
temperature[2]
temperature[2:3]
temperature[-2]

#Factors
gender<-factor(c("MALE","FEMALE","MALE"))
gender
blood<-factor(c("O","AB","A"),levels=c("A","B","AB","O"))
```

```
blood[1:2]
symptoms<-factor(c("SEVERE","MILD","MODERATE"),
             levels=c("MILD","MODERATE","SEVERE"),
             ordered=TRUE)
symptoms>"MODERATE"

#Lists
subject1<-list(fullname=subject_name[1],
           temperature=temperature[1],
           flu_status=flu_status[1],
           gender=gender[1],
           blood=blood[1],
           symptoms=symptoms[1])
subject1
subject1[2]
subject1[[2]]
subject1$temperature
subject1[c("temperature","flu_status")]

#Data Frames
pt_data<-data.frame(subject_name, temperature, flu_status,
               gender,blood,symptoms)
pt_data
pt_data$subject_name
pt_data[c("temperature","flu_status")]
pt_data[c(1,2),c(2,4)]
pt_data[,1]
pt_data[,]

#Matrices
m<-matrix(c(1,2,3,4),ncol=2)
print(m)
m<-matrix(c(1,2,3,4,5,6),nrow=3)
print(m)
print(m[1,])
print(m[1,])
thismatrix <- matrix(c("apple", "banana", "cherry","orange"), nrow = 2, ncol = 2)
for (rows in 1:nrow(thismatrix)) {
  for (columns in 1:ncol(thismatrix)) {
    print(thismatrix[rows, columns])
  }
}
```

OUTPUT:



```
[1] "logical"
[1] "numeric"
[1] "integer"
[1] "complex"
[1] "character"
[1] "raw"
[1] 98.6
[1]  98.6 101.4
[1]  98.1 101.4
[1] MALE   FEMALE MALE
Levels: FEMALE MALE
[1] O  AB
Levels: A B AB O
[1]  TRUE FALSE FALSE
$fullname
[1] "John Doe"

$temperature
[1] 98.1

$flu_status
[1] FALSE

$gender
[1] MALE
Levels: FEMALE MALE

$blood
[1] O
Levels: A B AB O

$symptoms
[1] SEVERE
Levels: MILD < MODERATE < SEVERE

$temperature
[1] 98.1

[1] 98.1
[1] 98.1
$temperature
[1] 98.1

$flu_status
[1] FALSE

  subject_name temperature flu_status gender blood symptoms
1     John Doe        98.1      FALSE   MALE     O   SEVERE
2     Jane Doe        98.6      FALSE FEMALE    AB     MILD
3 Steven Grant       101.4       TRUE   MALE     A MODERATE
[1] "John Doe"     "Jane Doe"     "Steven Grant"
  temperature flu_status
1        98.1      FALSE
2        98.6      FALSE
3       101.4       TRUE
```



```
2        98.6      FALSE
3       101.4       TRUE
  temperature gender
1        98.1   MALE
2        98.6 FEMALE
[1] "John Doe"     "Jane Doe"     "Steven Grant"
  subject_name temperature flu_status gender blood symptoms
1     John Doe        98.1      FALSE   MALE     O   SEVERE
2     Jane Doe        98.6      FALSE FEMALE    AB     MILD
3 Steven Grant       101.4       TRUE   MALE     A MODERATE
     [,1] [,2]
[1,]    1    3
[2,]    2    4
     [,1] [,2]
[1,]    1    4
[2,]    2    5
[3,]    3    6
[1] 1 4
[1] 1 4
[1] "apple"
[1] "cherry"
[1] "banana"
[1] "orange"
> 
```

Result:

Thus the R Script program to implement various data types, vectors, factors, lists and data frames is executed successfully and the output is verified.

Ex no: 2 **Date:**	**Diagnosis of Breast Cancer using KNN.**

Aim:

To implement a R program to predict and diagnose Breast Cancer using KNN algorithm.

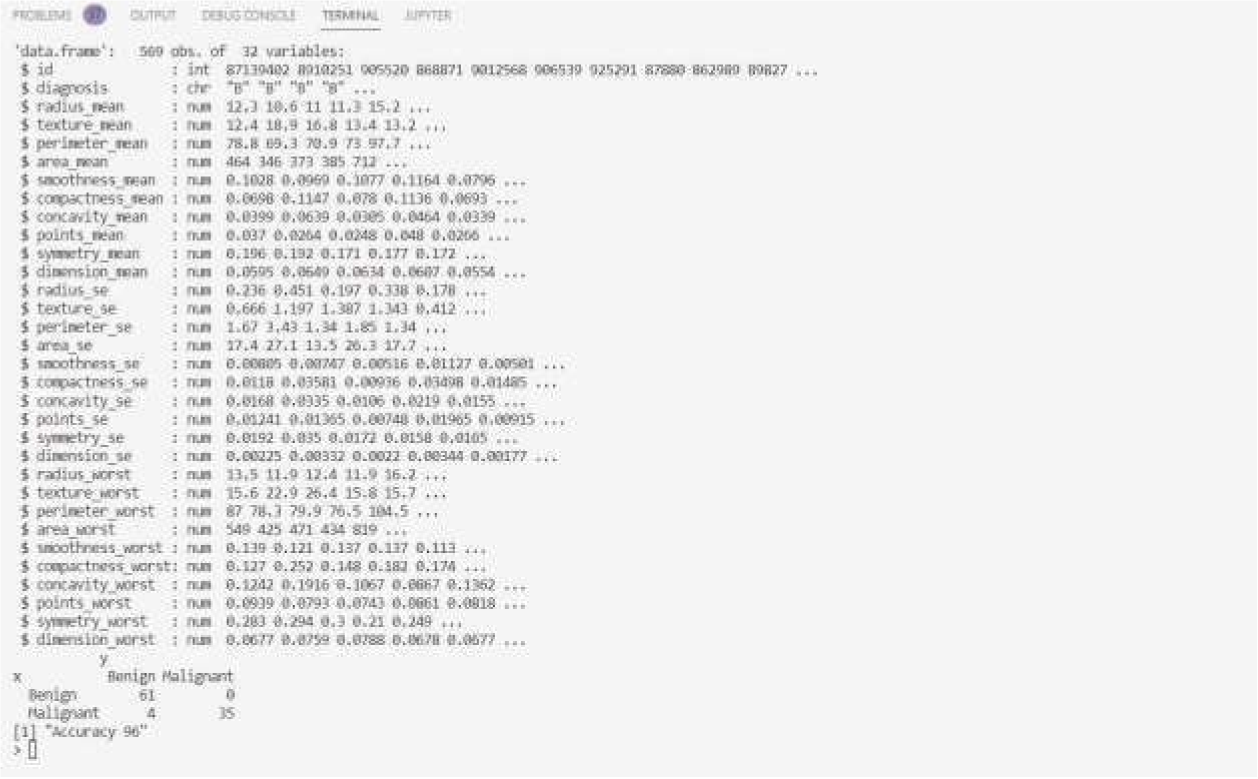
Algorithm:

1. Start
2. Read the csv file from the directory and store it in bcd variable.
3. Drop the first column id.
4. Change the diagnosis feature with categorical values B and M in a factor
5. Normalize the dataset.
6. Split the dataset for training and testing, with diagnosis as the response variable and the rest as the predictor variables.
7. Import the library “class” for knn classification.
8. Predict the knn model using knn() with 5 clusters with the corresponding training and testing data.
9. Display the confusion matrix and accuracy of the knn model.
10. Stop

PROGRAM:

```
bcd<-read.csv("../input/breast-cancer-dataset/Breast_Cancer.csv", stringsAsFactors=FALSE)

bcd<-bcd[-1]

bcd$diagnosis<-factor(bcd$diagnosis, levels=c("B","M"), labels=c("Benign","Malignant"))

normalize<-function(x){

   return (x-min(x)) / (max(x)- min(x))

}
bcd_n <- as.data.frame(lapply(bcd[2:31], normalize))

x_train <- bcd_n[1:469,]

x_test <- bcd_n[470:569,]

y_train <- bcd[1:469,1]

y_test <- bcd[470:569,1]

library(class)

y_pred<-knn(train=x_train,test=x_test,cl=y_train,k=5)

tbl=table(x=y_test,y=y_pred)

tbl

accuracy = sum(diag(tbl))
```

OUTPUT:



```
'data.frame':   569 obs. of  32 variables:
 $ id               : int  87139402 8910251 905520 868871 9012568 906539 925291 87880 862980 89827 ...
 $ diagnosis        : chr  "B" "B" "B" "B" ...
 $ radius_mean      : num  12.3 10.6 11 11.3 15.2 ...
 $ texture_mean     : num  12.4 18.9 16.8 13.4 13.2 ...
 $ perimeter_mean   : num  78.8 69.3 70.9 73 97.7 ...
 $ area_mean        : num  464 346 373 385 712 ...
 $ smoothness_mean  : num  0.1028 0.0969 0.1077 0.1164 0.0796 ...
 $ compactness_mean : num  0.0698 0.1147 0.078 0.1136 0.0693 ...
 $ concavity_mean   : num  0.0399 0.0639 0.0305 0.0464 0.0339 ...
 $ points_mean      : num  0.037 0.0264 0.0248 0.048 0.0266 ...
 $ symmetry_mean    : num  0.196 0.192 0.171 0.177 0.172 ...
 $ dimension_mean   : num  0.0595 0.0649 0.0634 0.0607 0.0554 ...
 $ radius_se        : num  0.236 0.451 0.197 0.338 0.178 ...
 $ texture_se       : num  0.666 1.197 1.387 1.343 0.412 ...
 $ perimeter_se     : num  1.67 3.43 1.34 1.85 1.34 ...
 $ area_se          : num  17.4 27.1 13.5 26.3 17.7 ...
 $ smoothness_se    : num  0.00805 0.00747 0.00516 0.01127 0.00501 ...
 $ compactness_se   : num  0.0118 0.03581 0.00936 0.03498 0.01485 ...
 $ concavity_se     : num  0.0168 0.0335 0.0106 0.0219 0.0155 ...
 $ points_se        : num  0.01241 0.01365 0.00748 0.01965 0.00915 ...
 $ symmetry_se      : num  0.0192 0.035 0.0172 0.0158 0.0165 ...
 $ dimension_se     : num  0.00225 0.00332 0.0022 0.00344 0.00177 ...
 $ radius_worst     : num  13.5 11.9 12.4 11.9 16.2 ...
 $ texture_worst    : num  15.6 22.9 26.4 15.8 15.7 ...
 $ perimeter_worst  : num  87 78.3 79.9 76.5 104.5 ...
 $ area_worst       : num  549 425 471 434 819 ...
 $ smoothness_worst : num  0.139 0.121 0.137 0.137 0.113 ...
 $ compactness_worst: num  0.127 0.252 0.148 0.182 0.174 ...
 $ concavity_worst  : num  0.1242 0.1916 0.1067 0.0867 0.1362 ...
 $ points_worst     : num  0.0939 0.0793 0.0743 0.0861 0.0818 ...
 $ symmetry_worst   : num  0.283 0.294 0.3 0.21 0.249 ...
 $ dimension_worst  : num  0.0677 0.0759 0.0788 0.0678 0.0677 ...
           y
x           Benign Malignant
  Benign        61         0
  Malignant      4        35
[1] "Accuracy 96"
> 
```

Result:

Thus the R Script program to implement diagnosis of Breast Cancer using K-Nearest Neighbour algorithm is executed successfully and the output is verified.

Ex No: 3 **Date:**	**Filtering Mobile phone spam using Naïve Bayes**

AIM:

To implement a R program to Filter Mobile phone spam using Naïve Bayes.

ALGORITHM:

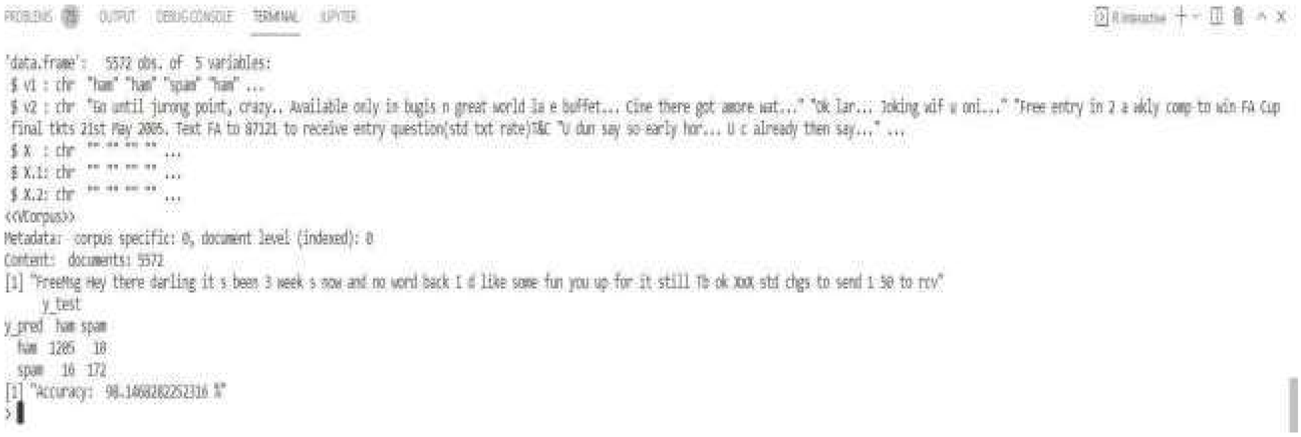
1. Start
2. Import the csv file and store the dataframe in “Sms”. Have a glimpse at the structure of the data frame.
3. Remove the unneccesary columns which is from column 3 to 5.
4. Convert the labels as factors.
5. Remove special characters from the dataset and retain only alpha numeric characters using alnum in str_replace_all() from “stringr” package.
6. Create a volatile corpus VCorpus() for text mining from the source object of “v2” which is extracted using VectorSource() .
7. Create a DocumentTermMatrix() to split the SMS message into individual Components.
8. Create training and testing dataset with the split ratio 0.75.
9. Find the frequent terms which appear for atleast 5 times in DocumentTermMatrix in training and testing dataset respectively.
10. Train the model using naiveBayes() from e1071 library.
11. Evaluate the model Performance.
12. Print the confusion matrix and Accuracy of the model.
13. Stop.

PROGRAM:

```
sms <- read.csv("../input/spam-ham-dataset/spam.csv", stringsAsFactors=FALSE)
str(sms)
sms <-sms[-3:-5]
sms$v1 <- factor(sms$v1)
library(stringr)
sms$v2 = str_replace_all(sms$v2, "[^[:alnum:]]", " ") %>% str_replace_all(.,"[
]+", " ")
library(tm)
sms_corpus <- VCorpus(VectorSource(sms$v2))
```

```
print(sms_corpus)
print(as.character(sms_corpus[[6]]))
sms_dtm <- DocumentTermMatrix(sms_corpus, control = list
(tolower=TRUE,removeNumbers=TRUE,stopwords=TRUE,removePunctuations=TRUE,stemmi
ng=TRUE))
x_train <- sms_dtm[1:4169, ]
x_test <- sms_dtm[4170:5572, ]
y_train <- sms[1:4169, ]$v1
y_test <- sms[4170:5572, ]$v1
sms_freq_word_train <- findFreqTerms(x_train, 5)
sms_freq_word_test <- findFreqTerms(x_test, 5)
x_train<- x_train[ , sms_freq_word_train]
x_test <- x_test[ , sms_freq_word_test]
convert_counts <- function(x) {x <- ifelse(x > 0, "Yes", "No")}
x_train <- apply(x_train, MARGIN = 2,convert_counts)
x_test <- apply(x_test, MARGIN = 2,convert_counts)
library(e1071)
model <- naiveBayes(x_train, y_train,laplace=1)
y_pred <- predict(model, x_test)
cm = table(y_pred, y_test)
print(cm)
acc = sum(diag(cm))/sum(cm)
print(paste("Accuracy: ",acc*100,"%"))
```

OUTPUT:



```
'data.frame':   5572 obs. of  5 variables:
 $ v1 : chr  "ham" "ham" "spam" "ham" ...
 $ v2 : chr  "Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat..." "Ok lar... Joking wif u oni..." "Free entry in 2 a wkly comp to win FA Cup
 final tkts 21st May 2005. Text FA to 87121 to receive entry question(std txt rate)T&C "U dun say so early hor... U c already then say..." ...
 $ X  : chr  "" "" "" "" ...
 $ X.1: chr  "" "" "" "" ...
 $ X.2: chr  "" "" "" "" ...
<<VCorpus>>
Metadata:  corpus specific: 0, document level (indexed): 0
Content:  documents: 5572
[1] "FreeMsg Hey there darling it s been 3 week s now and no word back I d like some fun you up for it still Tb ok XXX std chgs to send 1 50 to rcv"
      y_test
y_pred  ham spam
  ham  1205   18
  spam   16  172
[1] "Accuracy:  98.1468282252316 %"
> 
```

RESULT:

Thus the R program to implement filtering of Mobile phone spam using Naïve Bayes is executed successfully and the output is verified.

Ex No:4 **Date:**	**Risky Bank Loans using Decision Trees**

AIM:

To implement a R program to find Risky Bank loans using Decision Tree.

ALGORITHM:

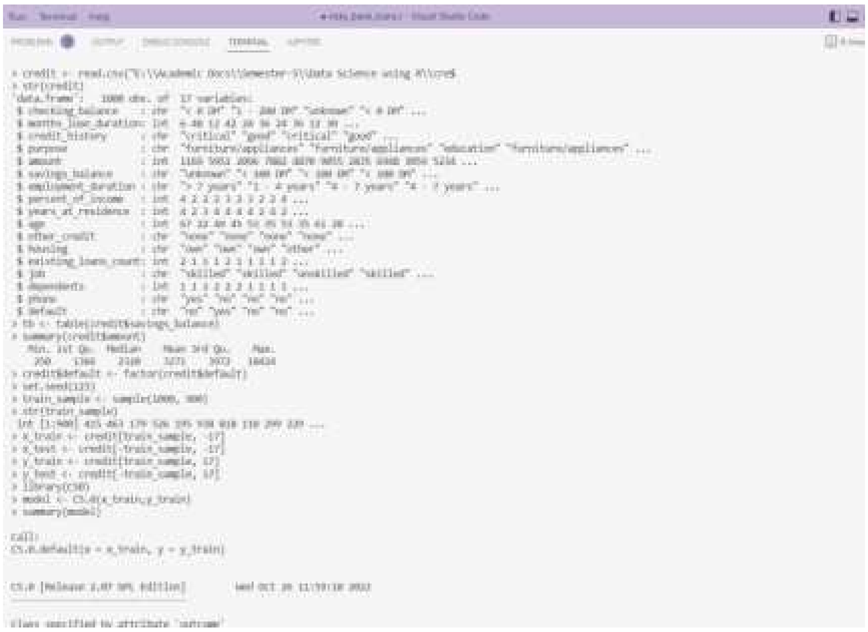
1. Start
2. Import the dataset credit.csv and display the structure of the dataset.
3. Display the table to find the range of values and find the missing values.
4. Factorise the default column and set seed of 123.
5. Split the dataset for training and testing in the ratio of 0.8, with “default” as the response variable, and the rest as predictor variables.
6. Import the library C5.0 for implementing decision tree.
7. Train the decision tree model using C5.0 function for the training dataset.
8. Test the model to predict using predict(). Print the confusion matrix.
9. Print the accuracy of the decision tree model.
10. Stop

PROGRAM:

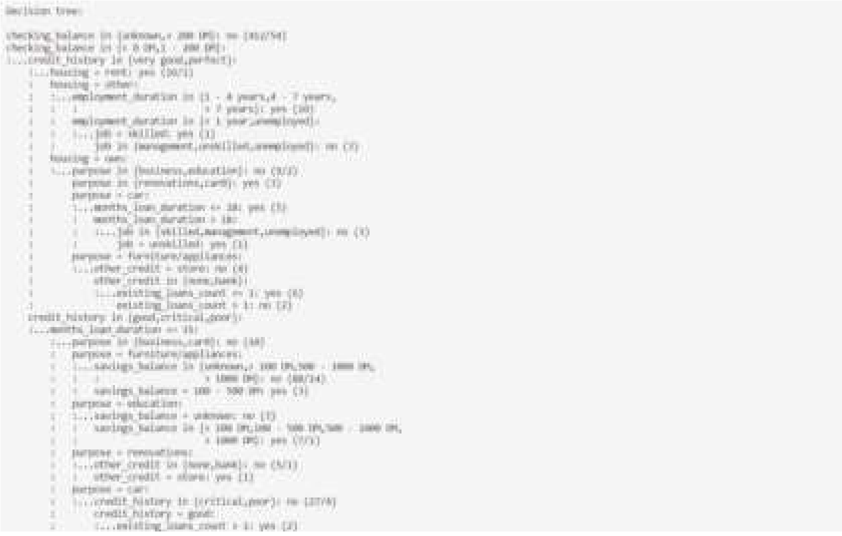
```
credit <- read.csv("credit.csv")

str(credit)

table(credit$savings_balance)

summary(credit$amount)

credit$default <- factor(credit$default)

set.seed(123)

train_sample <- sample(1000, 800)

str(train_sample)

x_train <- credit[train_sample, -17]

x_test <- credit[-train_sample, -17]

y_train <- credit[train_sample, 17]

y_test <- credit[-train_sample, 17]

library(C50)

model <- C5.0(x_train,y_train)
```

```
summary(model)

y_pred <- predict(model,x_test)

cm = table(y_pred,y_test)

print(cm)

acc=sum(diag(cm))/sum(cm)

print(paste("Accuaracy: ",acc*100,"%"))
```

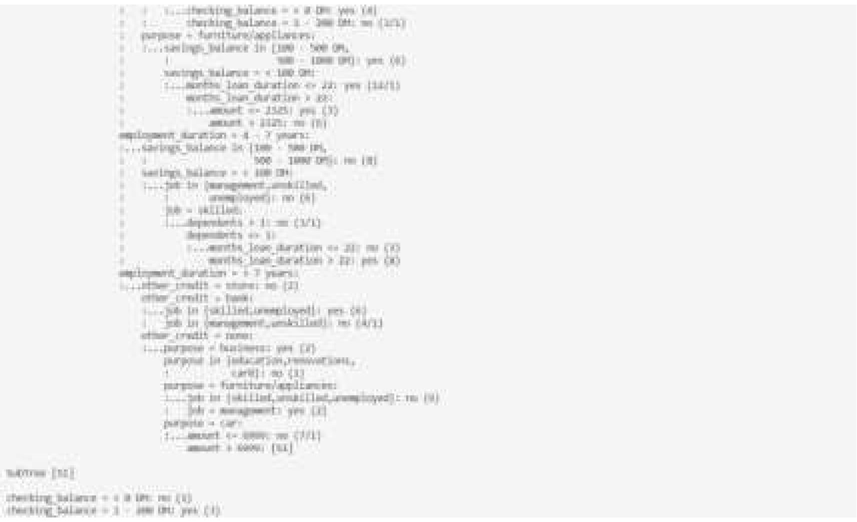
OUTPUT:



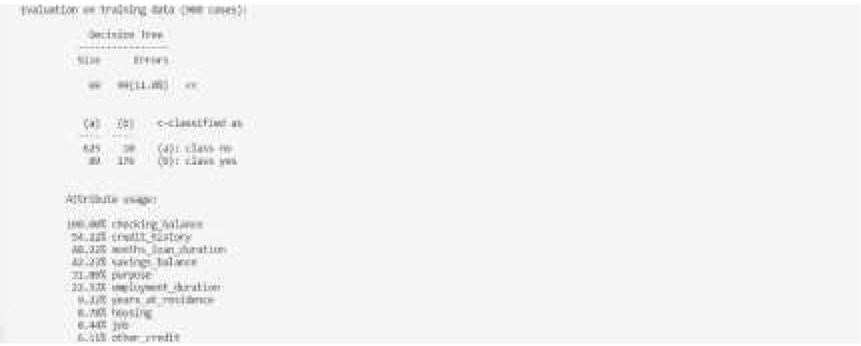
```
> credit <- read.csv("E:\\Academic Docs\\Semester-5\\Data Science using R\\cre$
> str(credit)
'data.frame':   1000 obs. of  17 variables:
 $ checking_balance    : chr  "< 0 DM" "1 - 200 DM" "unknown" "< 0 DM" ...
 $ months_loan_duration: int  6 48 12 42 24 36 24 36 12 30 ...
 $ credit_history      : chr  "critical" "good" "critical" "good" ...
 $ purpose             : chr  "furniture/appliances" "furniture/appliances" "education" "furniture/appliances" ...
 $ amount              : int  1169 5951 2096 7882 4870 9055 2835 6948 3059 5234 ...
 $ savings_balance     : chr  "unknown" "< 100 DM" "< 100 DM" "< 100 DM" ...
 $ employment_duration : chr  "> 7 years" "1 - 4 years" "4 - 7 years" "4 - 7 years" ...
 $ percent_of_income   : int  4 2 2 2 3 2 3 2 2 4 ...
 $ years_at_residence  : int  4 2 3 4 4 4 4 2 4 2 ...
 $ age                 : int  67 22 49 45 53 35 53 35 61 28 ...
 $ other_credit        : chr  "none" "none" "none" "none" ...
 $ housing             : chr  "own" "own" "own" "other" ...
 $ existing_loans_count: int  2 1 1 1 2 1 1 1 1 2 ...
 $ job                 : chr  "skilled" "skilled" "unskilled" "skilled" ...
 $ dependents          : int  1 1 2 2 2 2 1 1 1 1 ...
 $ phone               : chr  "yes" "no" "no" "no" ...
 $ default             : chr  "no" "yes" "no" "no" ...
> tb <- table(credit$savings_balance)
> summary(credit$amount)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    250    1366    2320    3271    3972   18424
> credit$default <- factor(credit$default)
> set.seed(123)
> train_sample <- sample(1000, 900)
> str(train_sample)
 int [1:900] 415 463 179 526 195 938 818 118 299 229 ...
> x_train <- credit[train_sample, -17]
> x_test <- credit[-train_sample, -17]
> y_train <- credit[train_sample, 17]
> y_test <- credit[-train_sample, 17]
> library(C50)
> model <- C5.0(x_train,y_train)
> summary(model)

Call:
C5.0.default(x = x_train, y = y_train)


C5.0 [Release 2.07 GPL Edition]         Wed Oct 26 11:59:18 2022
-------------------------------

Class specified by attribute `outcome'
```



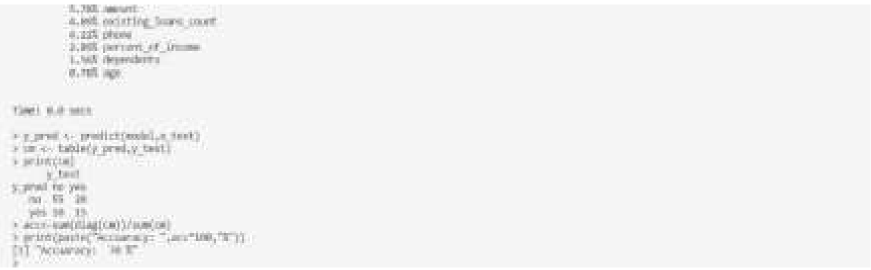
```
Decision tree:

checking_balance in {unknown,> 200 DM}: no (412/54)
checking_balance in {< 0 DM,1 - 200 DM}:
:...credit_history in {very good,perfect}:
:   :...housing = rent: yes (20/1)
:   :   housing = other:
:   :   :...employment_duration in {1 - 4 years,4 - 7 years,
:   :   :   :                       > 7 years}: yes (10)
:   :   :   employment_duration in {< 1 year,unemployed}:
:   :   :   :...job = skilled: yes (3)
:   :   :       job in {management,unskilled,unemployed}: no (7)
:   :   housing = own:
:   :   :...purpose in {business,education}: no (3/1)
:   :       purpose in {renovations,car0}: yes (3)
:   :       purpose = car:
:   :       :...months_loan_duration <= 18: yes (3)
:   :       :   months_loan_duration > 18:
:   :       :   :...job in {skilled,management,unemployed}: no (3)
:   :       :       job = unskilled: yes (1)
:   :       purpose = furniture/appliances:
:   :       :...other_credit = store: no (4)
:   :           other_credit in {none,bank}:
:   :           :...existing_loans_count <= 1: yes (6)
:   :               existing_loans_count > 1: no (2)
:   credit_history in {good,critical,poor}:
:   :...months_loan_duration <= 15:
:       :...purpose in {business,car0}: no (18)
:       :   purpose = furniture/appliances:
:       :   :...savings_balance in {unknown,< 100 DM,500 - 1000 DM,
:       :   :   :                   > 1000 DM}: no (60/14)
:       :   :   savings_balance = 100 - 500 DM: yes (3)
:       :   purpose = education:
:       :   :...savings_balance = unknown: no (7)
:       :   :   savings_balance in {< 100 DM,100 - 500 DM,500 - 1000 DM,
:       :   :                       > 1000 DM}: yes (7/1)
:       :   purpose = renovations:
:       :   :...other_credit in {none,bank}: no (5/1)
:       :   :   other_credit = store: yes (1)
:       :   purpose = car:
:       :   :...credit_history in {critical,poor}: no (27/4)
:       :       credit_history = good:
:       :       :...existing_loans_count > 1: yes (2)
```



```
:   :   :...checking_balance = < 0 DM: yes (4)
:   :       checking_balance = 1 - 200 DM: no (2/1)
:   purpose = furniture/appliances:
:   :...savings_balance in {100 - 500 DM,
:       :                   500 - 1000 DM}: yes (4)
:       savings_balance = < 100 DM:
:       :...months_loan_duration <= 22: yes (14/3)
:           months_loan_duration > 22:
:           :...amount <= 2325: yes (3)
:               amount > 2325: no (5)
employment_duration = 4 - 7 years:
:...savings_balance in {100 - 500 DM,
:   :                   500 - 1000 DM}: no (8)
:   savings_balance = < 100 DM:
:   :...job in {management,unskilled,
:       :       unemployed}: no (6)
:       job = skilled:
:       :...dependents > 1: no (3/1)
:           dependents <= 1:
:           :...months_loan_duration <= 22: no (3)
:               months_loan_duration > 22: yes (8)
employment_duration = > 7 years:
:...other_credit = store: no (2)
    other_credit = bank:
    :...job in {skilled,unemployed}: yes (4)
    :   job in {management,unskilled}: no (4/1)
    other_credit = none:
    :...purpose = business: yes (2)
        purpose in {education,renovations,
        :           car0}: no (3)
        purpose = furniture/appliances:
        :...job in {skilled,unskilled,unemployed}: no (9)
        :   job = management: yes (2)
        purpose = car:
        :...amount <= 6995: no (7/1)
            amount > 6995: [S1]

SubTree [S1]

checking_balance = < 0 DM: no (1)
checking_balance = 1 - 200 DM: yes (3)
```



```
Evaluation on training data (900 cases):

	    Decision Tree
	  ----------------
	  Size      Errors

	    66   99(11.0%)   <<


	   (a)   (b)    <-classified as
	  ----  ----
	   625    38    (a): class no
	    61   176    (b): class yes


	Attribute usage:

	100.00% checking_balance
	 54.22% credit_history
	 48.22% months_loan_duration
	 42.22% savings_balance
	 31.89% purpose
	 22.33% employment_duration
	  9.33% years_at_residence
	  8.78% housing
	  8.44% job
	  6.11% other_credit
```



```
	  5.78% amount
	  4.89% existing_loans_count
	  4.22% phone
	  2.89% percent_of_income
	  1.56% dependents
	  0.78% age


Time: 0.0 secs

> y_pred <- predict(model,x_test)
> cm <- table(y_pred,y_test)
> print(cm)
      y_test
y_pred no yes
   no  55  20
   yes 10  15
> acc<-sum(diag(cm))/sum(cm)
> print(paste("Accuracy: ",acc*100,"%"))
[1] "Accuracy:  70 %"
>
```

RESULT:

Thus the R program to find Risky Bank loans using Decision Tree is executed successfully and the output is verified.

Ex No: 5 Date:	**Medical Expense with Linear Regression.**

AIM:

To implement a R program to predict Medical Expense using Linear Regression

ALGORITHM:

1. Start
2. Load the Insurance dataset and analyse the structure of the dataset.
3. Get the summary statistics.Check whether the distribution is right-skewed or left skewed by comapring the mean and median. Verify the same using histogram.
4. Check the distribution of "region" using table.
5. Create a correlation matrix of "age", "bmi", "children", "expenses".
6. To determine the pattern of the dataset, use scatterplot using pairs() for "age", "bmi", "children", "expenses".
7. To display a more informative scatterplot use pairs.panel() from "psych" library.
8. Fit the linear regression model using lm() with expenses as the dependent variable.
9. Evaluate the model performance using summary().
10. To improve the model performance, square the age variable as age2 and bmi30 is 1 if bmi>=30 else 0.
11. Train the model with age + age2+bmi30 as also as the independent variables.
12. Evaluate the model performance for model2 using summary().
13. Stop.

PROGRAM:

```
insurance<-read.csv("insurance.csv",stringsAsFactors = TRUE)

str(insurance)

summary(insurance$expenses)

hist(insurance$expenses)

table(insurance$region)

cor(insurance[c("age","bmi","children","expenses")])

pairs(insurance[c("age","bmi","children","expenses")])

library(psych)

pairs.panels(insurance[c("age","bmi","children","expenses")])8

ins_model <- lm(expenses ~ age + children + bmi + sex + smoker + region, data =
insurance)

ins_model
```

summary(ins_model)

insurance$age2 <- insurance$age^2

insurance$bmi30 <- ifelse(insurance$bmi >= 30,1,0)

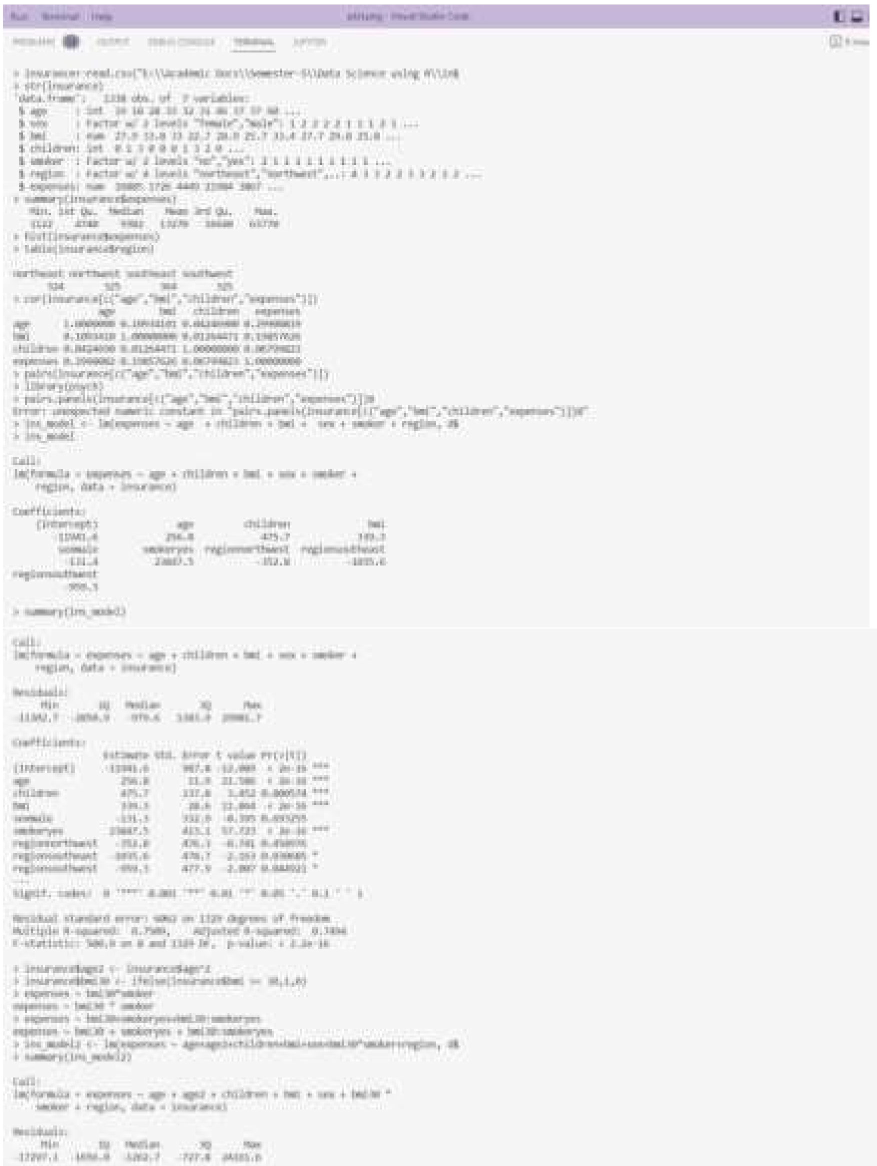
expenses ~ bmi30*smoker

expenses ~ bmi30+smokeryes+bmi30:smokeryes

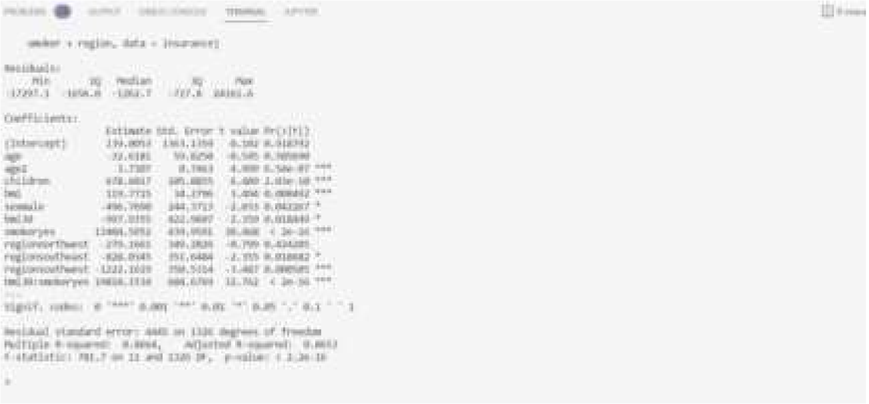
ins_model2 <- lm(expenses ~ age+age2+children+bmi+sex+bmi30*smoker+region, data=insurance)

summary(ins_model2)

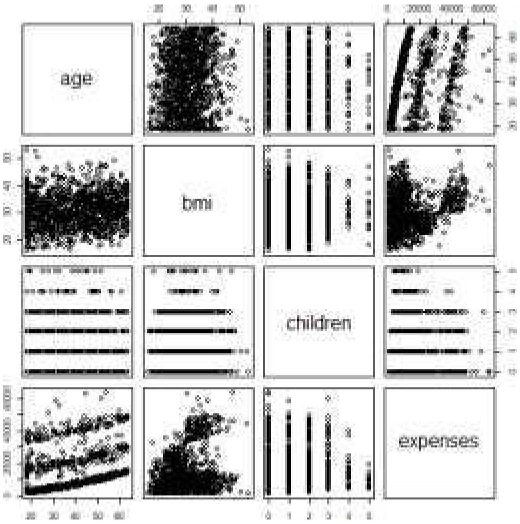
OUTPUT:

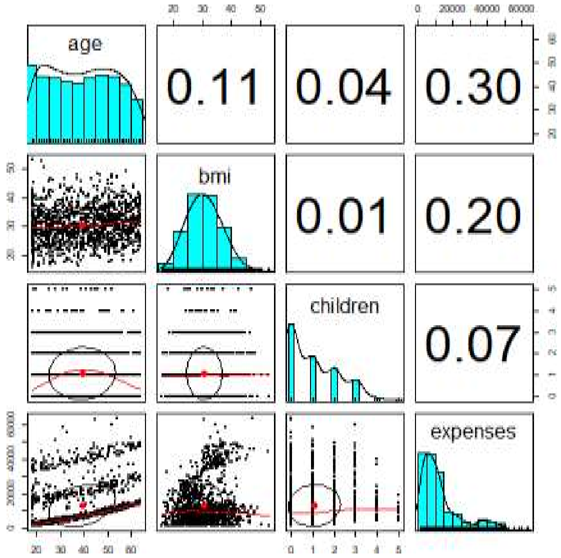


```
> insurance<-read.csv("E:\\Academic Docs\\Semester-5\\Data Science using R\\Ins
> str(insurance)
'data.frame':   1338 obs. of  7 variables:
 $ age     : int  19 18 28 33 32 31 46 37 37 60 ...
 $ sex     : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 1 1 2 1 ...
 $ bmi     : num  27.9 33.8 33 22.7 28.9 25.7 33.4 27.7 29.8 25.8 ...
 $ children: int  0 1 3 0 0 0 1 3 2 0 ...
 $ smoker  : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 1 ...
 $ region  : Factor w/ 4 levels "northeast","northwest",..: 4 3 3 2 2 3 3 2 1 2 ...
 $ expenses: num  16885 1726 4449 21984 3867 ...
> summary(insurance$expenses)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1122    4740    9382   13270   16640   63770
> hist(insurance$expenses)
> table(insurance$region)

northeast northwest southeast southwest
      324       325       364       325
> cor(insurance[c("age","bmi","children","expenses")])
               age        bmi   children   expenses
age      1.0000000 0.10934101 0.04246900 0.29900819
bmi      0.1093410 1.00000000 0.01264471 0.19857626
children 0.0424690 0.01264471 1.00000000 0.06799823
expenses 0.2990082 0.19857626 0.06799823 1.00000000
> pairs(insurance[c("age","bmi","children","expenses")])
> library(psych)
> pairs.panels(insurance[c("age","bmi","children","expenses")])8
Error: unexpected numeric constant in "pairs.panels(insurance[c("age","bmi","children","expenses")])8"
> ins_model <- lm(expenses ~ age  + children + bmi +  sex + smoker + region, da
> ins_model

Call:
lm(formula = expenses ~ age + children + bmi + sex + smoker +
    region, data = insurance)

Coefficients:
    (Intercept)              age         children              bmi
       -11941.6            256.8            475.7            339.3
        sexmale        smokeryes  regionnorthwest  regionsoutheast
         -131.4          23847.5           -352.8          -1035.6
regionsouthwest
         -959.3

> summary(ins_model)

Call:
lm(formula = expenses ~ age + children + bmi + sex + smoker +
    region, data = insurance)

Residuals:
     Min       1Q   Median       3Q      Max
-11302.7  -2850.9   -979.6   1383.9  29981.7

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     -11941.6      987.8 -12.089  < 2e-16 ***
age                256.8       11.9  21.586  < 2e-16 ***
children           475.7      137.8   3.452 0.000574 ***
bmi                339.3       28.6  11.864  < 2e-16 ***
sexmale           -131.3      332.9  -0.395 0.693255
smokeryes        23847.5      413.1  57.723  < 2e-16 ***
regionnorthwest   -352.8      476.3  -0.741 0.458976
regionsoutheast  -1035.6      478.7  -2.163 0.030685 *
regionsouthwest   -959.3      477.9  -2.007 0.044921 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6062 on 1329 degrees of freedom
Multiple R-squared:  0.7509,    Adjusted R-squared:  0.7494
F-statistic: 500.9 on 8 and 1329 DF,  p-value: < 2.2e-16

> insurance$age2 <- insurance$age^2
> insurance$bmi30 <- ifelse(insurance$bmi >= 30,1,0)
> expenses ~ bmi30*smoker
expenses ~ bmi30 * smoker
> expenses ~ bmi30+smokeryes+bmi30:smokeryes
expenses ~ bmi30 + smokeryes + bmi30:smokeryes
> ins_model2 <- lm(expenses ~ age+age2+children+bmi+sex+bmi30*smoker+region, da
> summary(ins_model2)

Call:
lm(formula = expenses ~ age + age2 + children + bmi + sex + bmi30 *
    smoker + region, data = insurance)

Residuals:
     Min       1Q   Median       3Q      Max
-17297.1  -1656.0  -1262.7   -727.8  24161.6
```



```
    smoker + region, data = insurance)

Residuals:
     Min       1Q   Median       3Q      Max
-17297.1  -1656.0  -1262.7   -727.8  24161.6

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        139.0053  1363.1359   0.102 0.918792
age                -32.6181    59.8250  -0.545 0.585690
age2                 3.7307     0.7463   4.999 6.54e-07 ***
children           678.6017   105.8855   6.409 2.03e-10 ***
bmi                119.7715    34.2796   3.494 0.000492 ***
sexmale           -496.7690   244.3713  -2.033 0.042267 *
bmi30             -997.9355   422.9607  -2.359 0.018449 *
smokeryes        13404.5952   439.9591  30.468  < 2e-16 ***
regionnorthwest   -279.1661   349.2826  -0.799 0.424285
regionsoutheast   -828.0345   351.6484  -2.355 0.018682 *
regionsouthwest  -1222.1619   350.5314  -3.487 0.000505 ***
bmi30:smokeryes  19810.1534   604.6769  32.762  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4445 on 1326 degrees of freedom
Multiple R-squared:  0.8664,	Adjusted R-squared:  0.8653
F-statistic: 781.7 on 11 and 1326 DF,  p-value: < 2.2e-16

>
```





RESULT:

Thus the R program to predict medical expenses using linear regression is executed successfully and the output is verified.

Ex No: 6 Date:	Modeling strength of concrete.

AIM:

To build a predictive model for the compressive strength of concrete based on its composition and age using linear regression in R.

ALGORITHM:

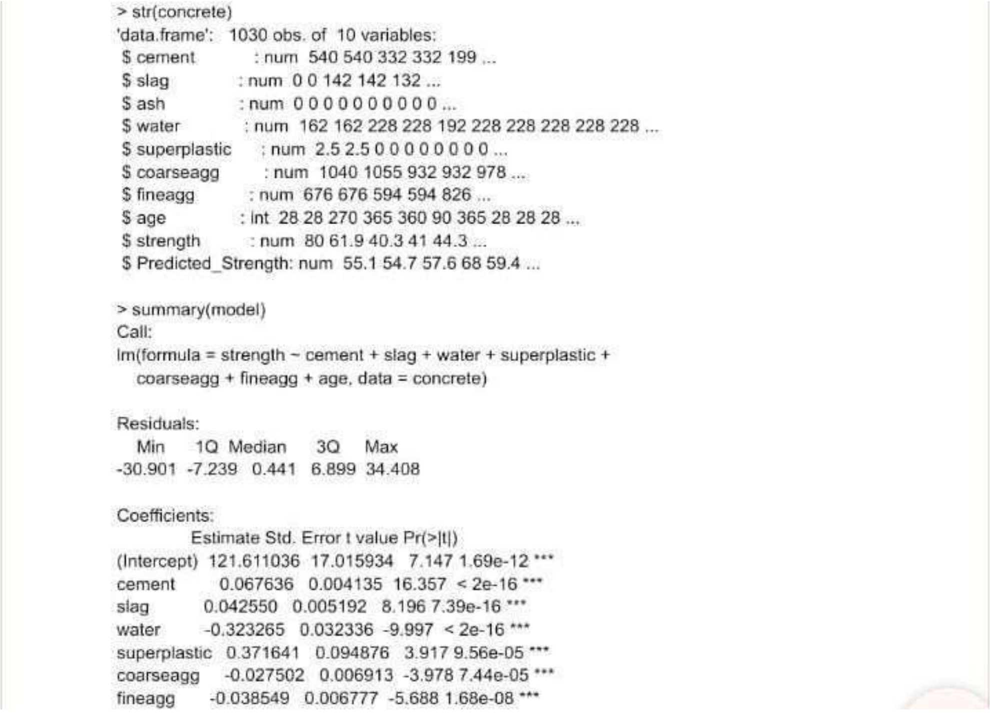
1. Start
2. Load the Insurance dataset and check its structure.
3. Get summary statistics and check skewness using mean, median, and histogram.
4. Check the distribution of “region” using a table.
5. Create a correlation matrix for “age,” “bmi,” “children,” and “expenses.”
6. Use scatterplots to examine relationships among “age,” “bmi,” “children,” and “expenses.”
7. Fit an initial linear model with “expenses” as the target, then improve by adding `age2` (age squared) and `bmi30` (1 if bmi >= 30) and re-evaluate.
8. Stop

PROGRAM:

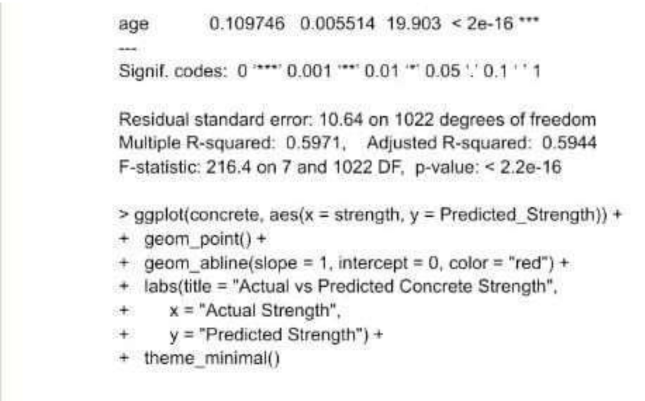
```
library(caret)

library(ggplot2)

data <- read.csv("concrete.csv")

head(data)

sum(is.na(data))

set.seed(123)

trainIndex <- createDataPartition(data$CompressiveStrength, p =

0.8 , list = FALSE)

trainData <- data[trainIndex,]

testData <- data[-trainIndex,]
```

```
model <- lm(CompressiveStrength ~ ., data = trainData)


summary(model)


predictions <- predict(model, newdata = testData)


mae <- mean(abs(predictions - testData$CompressiveStrength))
print(paste("Mean Absolute Error:", round(mae, 2)))


ggplot() +
  geom_point(aes(x = testData$CompressiveStrength, y = predictions), color = 'blue') +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed", color = "red") +
  labs(title = "Predicted vs Actual Compressive Strength",
       x = "Actual Strength",
       y = "Predicted Strength") +
  theme_minimal()
```

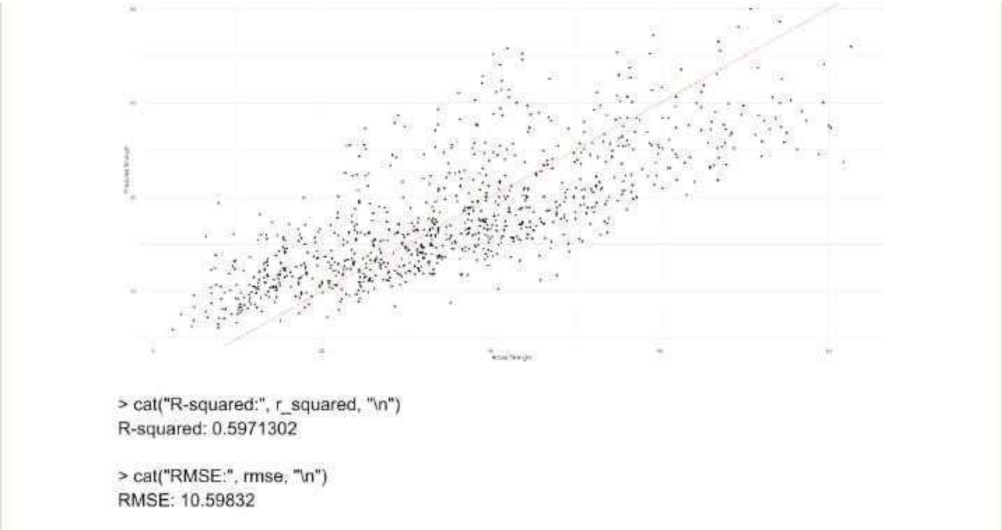
OUTPUT:



```
> str(concrete)
'data.frame':   1030 obs. of  10 variables:
 $ cement           : num  540 540 332 332 199 ...
 $ slag             : num  0 0 142 142 132 ...
 $ ash              : num  0 0 0 0 0 0 0 0 0 0 ...
 $ water            : num  162 162 228 228 192 228 228 228 228 228 ...
 $ superplastic     : num  2.5 2.5 0 0 0 0 0 0 0 0 ...
 $ coarseagg        : num  1040 1055 932 932 978 ...
 $ fineagg          : num  676 676 594 594 826 ...
 $ age              : int  28 28 270 365 360 90 365 28 28 28 ...
 $ strength         : num  80 61.9 40.3 41 44.3 ...
 $ Predicted_Strength: num  55.1 54.7 57.6 68 59.4 ...

> summary(model)
Call:
lm(formula = strength ~ cement + slag + water + superplastic +
    coarseagg + fineagg + age, data = concrete)

Residuals:
    Min      1Q  Median      3Q     Max
-30.901  -7.239   0.441   6.899  34.408

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  121.611036  17.015934   7.147 1.69e-12 ***
cement         0.067636   0.004135  16.357  < 2e-16 ***
slag           0.042550   0.005192   8.196 7.39e-16 ***
water         -0.323265   0.032336  -9.997  < 2e-16 ***
superplastic   0.371641   0.094876   3.917 9.56e-05 ***
coarseagg     -0.027502   0.006913  -3.978 7.44e-05 ***
fineagg       -0.038549   0.006777  -5.688 1.68e-08 ***
```



```
age          0.109746   0.005514  19.903  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 10.64 on 1022 degrees of freedom
Multiple R-squared:  0.5971,    Adjusted R-squared:  0.5944
F-statistic: 216.4 on 7 and 1022 DF,  p-value: < 2.2e-16

> ggplot(concrete, aes(x = strength, y = Predicted_Strength)) +
+   geom_point() +
+   geom_abline(slope = 1, intercept = 0, color = "red") +
+   labs(title = "Actual vs Predicted Concrete Strength",
+        x = "Actual Strength",
+        y = "Predicted Strength") +
+   theme_minimal()
```



```
> cat("R-squared:", r_squared, "\n")
R-squared: 0.5971302

> cat("RMSE:", rmse, "\n")
RMSE: 10.59832
```

RESULT:

Thus the R Script program to implement Modeling strength of concrete is executed successfully and the output is verified.

Ex No: 7 **Date:**	**Identification of frequently Purchased groceries with Apriori algorithm.**

AIM:

To identify frequent itemsets of grocery items that are commonly purchased together using the Apriori algorithm. This will help in understanding customer buying patterns and optimizing store layout or inventory.

ALGORITHM:

1. Start
2. Load Data: Load the transaction dataset (assume each transaction is a list of items purchased).
3. Data Preprocessing: Convert the data into a transactional format suitable for association rule mining.
4. Set Parameters: Define minimum support and confidence levels for the Apriori algorithm.
5. Apply Apriori Algorithm: Use the Apriori algorithm to find frequent itemsets.
6. Generate Association Rules: Extract association rules from the frequent itemsets based on support and confidence thresholds.
7. Analyze Results: Sort and filter rules to identify the most frequently purchased item combinations.
8. Stop

PROGRAM:

```
if(!require(arules)) install.packages("arules", dependencies=TRUE)
library(arules)
data("Groceries")
summary(Groceries)
min_support <- 0.01  # Example: at least 1% of transactions
min_confidence <- 0.5  # Example: at least 50% confidence
frequent_itemsets <- apriori(Groceries, parameter = list(supp = min_support, conf =
min_confidence))
summary(frequent_itemsets)
inspect(frequent_itemsets[1:10])
rules <- apriori(Groceries, parameter = list(supp = min_support, conf = min_confidence,
target = "rules"))
summary(rules)
inspect(sort(rules, by = "confidence")[1:10]) # Display top 10 rules by confidence
if(!require(arulesViz)) install.packages("arulesViz", dependencies=TRUE)
library(arulesViz)
plot(rules, method = "graph", control = list(type = "items"))
```

OUTPUT:

Summary of the Groceries Dataset

```
transactions as itemMatrix in sparse format with 9835 rows (elements/itemsets/transactions) and
169 columns (items) and a density of 0.02609146

most frequent items:
 whole milk other vegetables     rolls/buns       soda       yogurt       (Other)
      2513            1903           1809           1715          1372              34055
```

Frequent Itemsets:

```
set of 50 itemsets

example of first 10 itemsets (sorted by support):
  items                         support
[1] {whole milk}                0.25551601
[2] {other vegetables}            0.19349263
[3] {rolls/buns}               0.18393493
[4] {soda}                    0.17437722
[5] {yogurt}                   0.13950178
[6] {whole milk, other vegetables}  0.0751
[7] {whole milk, yogurt}            0.0561
```

Association Rules (Top 10 by Confidence):

```
set of 10 rules

example of first 10 rules (sorted by confidence):
  lhs              rhs              support confidence lift
[1] {yogurt}      => {whole milk}    0.0561   0.4032      1.57
[2] {rolls/buns}  => {whole milk}    0.0567   0.3084      1.21
[3] {soda}        => {whole milk}    0.0569   0.3058      1.20
[4] {tropical fruit} => {whole milk} 0.0519   0.2674      1.03
[5] {other vegetables} => {whole milk} 0.0751 0.3926      1.53
```

RESULT:

Thus the R program to Identification of frequently Purchased groceries with Apriori algorithm is executed successfully and the output is verified.

Ex No: 8 Date:	**Finding Teen Segments of Market.**

AIM:

The aim of this process is to identify and segment the teen demographic in a market based on behavior, preferences, or other relevant characteristics for targeted marketing or product development.

ALGORITHM:

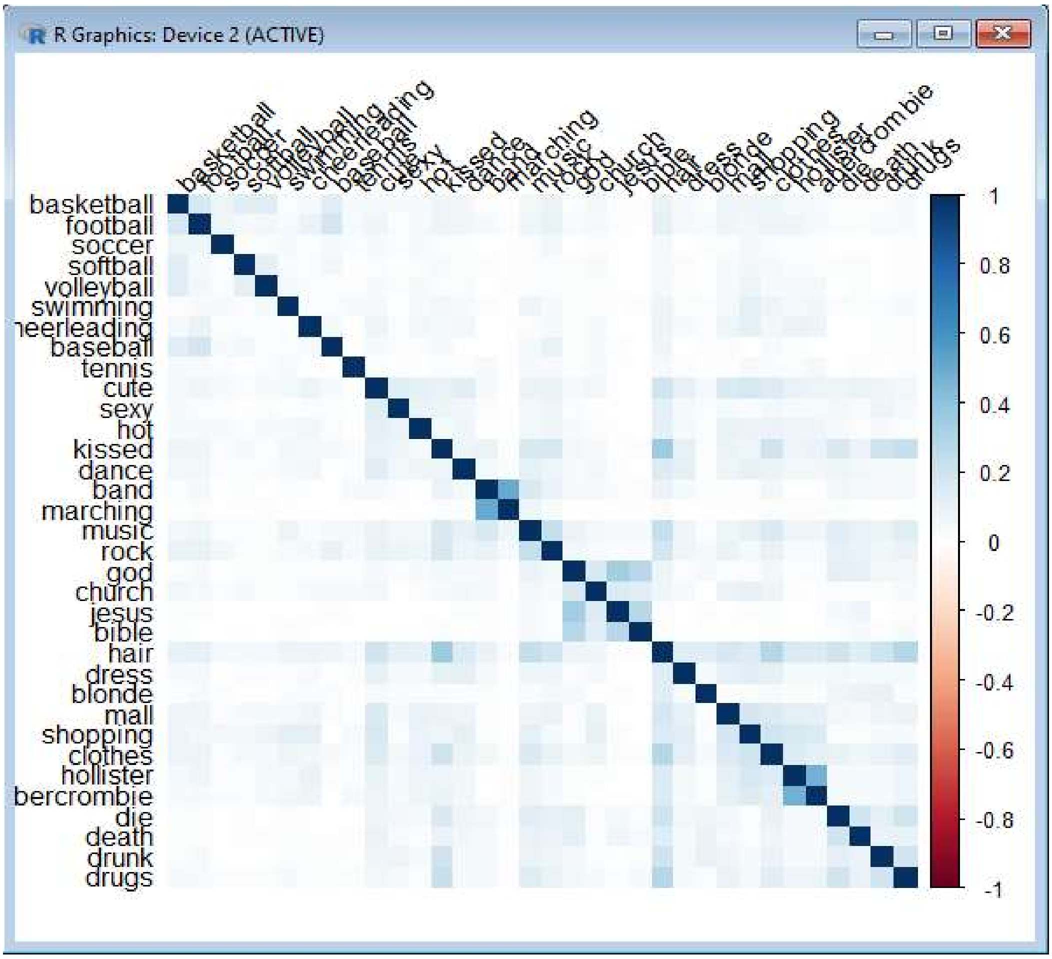
1. START: Collect raw data from sources relevant to the teen market (e.g., social media data, survey responses).
2. PREPROCESSING: Clean the data (e.g., remove missing values, correct errors).
3. SELECT FEATURES: Choose features that help in segmentation (e.g., age, purchase patterns, interests).
4. APPLY CLUSTERING ALGORITHM: Run clustering algorithms (e.g., K-Means or DBSCAN) to create market segments.
5. EVALUATE MODEL: Evaluate the clustering performance using a scoring metric (e.g., silhouette score).
6. VISUALIZE DATA: Visualize the segmented data to understand different groups.
7. EXTRACT INSIGHTS: Identify unique patterns and preferences within each segment.
8. STOP: Develop targeted marketing strategies based on the insights from the segmentation.
9. This approach allows businesses to better understand the teen market and tailor their products or marketing campaigns accordingly.

PROGRAM:

```
library(dplyr)
library(ggplot2)
library(corrplot)
load_data <- function(file_path) {
  df <- read.csv(file_path)
  return(df)
}
preprocess_data <- function(df) {
  # Check for missing values
  print(colSums(is.na(df)))
  df[is.na(df)] <- 0 # Fill missing values with 0
  return(df)
}
```

```
analyze_segments <- function(df) {
  # Example: Segment by gender
  gender_counts <- table(df$gender)
  print("Gender Distribution:")
  print(gender_counts)
  interest_features <- c('basketball', 'football', 'soccer', 'softball', 'volleyball',
                        'swimming', 'cheerleading', 'baseball', 'tennis',
                        'cute', 'sexy', 'hot', 'kissed', 'dance',
                        'band', 'marching', 'music', 'rock', 'god',
                        'church', 'jesus', 'bible', 'hair', 'dress',
                        'blonde', 'mall', 'shopping', 'clothes',
                        'hollister', 'abercrombie', 'die', 'death',
                        'drunk', 'drugs')
  corr_matrix <- cor(df[interest_features])
  corrplot(corr_matrix, method = "color", tl.col = "black", tl.srt = 45)
}

main <- function(file_path) {
  df <- load_data(file_path)
  df <- preprocess_data(df)
  analyze_segments(df)
}
main('path_to_your_file.csv')
```

OUTPUT:



RESULT:

Thus the R program to Finding Teen Segments of Market is executed successfully and the output is verified.

Ex No: 9 **Date:**	**Tuning stock models for better performance.**

AIM:

The aim is to enhance the predictive performance of stock market models by optimizing hyperparameters, improving data features, and using techniques like cross-validation and model selection to better forecast stock prices or trends.

ALGORITHM:

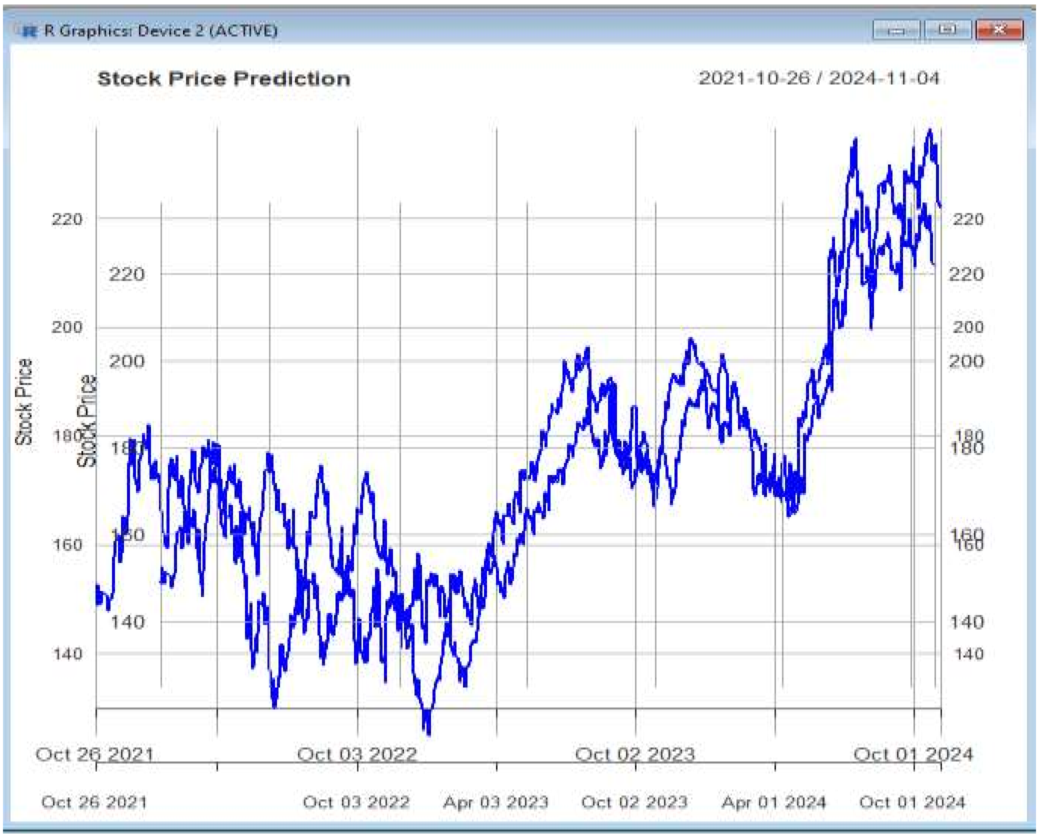
1. Start
2. Data Collection: Gather historical stock data (e.g., price, volume, market sentiment, technical indicators).
3. Data Preprocessing: Clean the data by handling missing values, normalizing features, and creating relevant indicators (e.g., moving averages, RSI).
4. Feature Engineering: Create new features based on existing data to improve model predictions (e.g., lagged values, percentage changes, or volatility).
5. Model Selection: Choose an appropriate model (e.g., Linear Regression, Decision Trees, Random Forest, LSTM for time series).
6. Hyperparameter Tuning: Tune the hyperparameters of the model using techniques like Grid Search or Random Search to optimize performance.
7. Cross-Validation: Implement cross-validation (e.g., k-fold) to ensure that the model generalizes well on unseen data.
8. Model Evaluation: Evaluate the model's performance using metrics like RMSE, MAE, or accuracy, and compare the results with different models.
9. Model Refinement: Refine the model by adjusting hyperparameters further, adding/removing features, or testing different algorithms to achieve better results
10. End.

PROGRAM:

```
library(randomForest)
library(Metrics)
data <- read.csv("C:/Users/AI_LAB/Desktop/77/stock.csv")
if (is.null(data)) {
  stop("Data not loaded. Please check the file path.")
}
str(data)
data$Closing.Volume <- as.numeric(as.character(data$Closing.Volume))  # Update based on
your target variable
data <- na.omit(data)
```

```
set.seed(123)
train_index <- sample(1:nrow(data), 0.8 * nrow(data))
train_data <- data[train_index, ]
test_data <- data[-train_index, ]
rf_model <- randomForest(Closing.Volume ~ ., data = train_data, ntree = 100)
predictions <- predict(rf_model, newdata = test_data)
actuals <- test_data$Closing.Volume
mae <- mean(abs(predictions - actuals))
rmse <- sqrt(mean((predictions - actuals)^2))
cat("Mean Absolute Error:", mae, "\n")
cat("Root Mean Squared Error:", rmse, "\n")
plot(test_data$Date, actuals, type = 'l', col = 'blue', ylim = range(c(actuals, predictions)),
     xlab = 'Date', ylab = 'Closing Price', main = 'Actual vs Predicted Closing Prices')
lines(test_data$Date, predictions, col = 'red')
legend("topright", legend = c("Actual", "Predicted"), col = c("blue", "red"), lty = 1)
```

OUTPUT:



RESULT:

Thus the R program to Tuning stock models for better performance is executed successfully and the output is verified.