# **R-MINI PROJECT**

**PROJECT TOPIC:** Prediction and Analysis on Diabetes Dataset

# **Project Description:**

The system will allow us to predict if the patient has diabetes on the basis of certain diagnostic measures available in the dataset. The different steps involved in EDA include: 1.Data Collection, 2.Data Cleaning and 3.Data Visualization. This project first conducts Exploratory Data Analysis (EDA) and data visualization on the diabetes dataset and then predicts the diabetes.

### **Exploratory Data Analysis (EDA)**

## 1. Descriptive statistics

Attribute type, Class distribution, Mean, Standard Deviation, Median, Quartile, Skewness, and Correlation.

### 2. Data Visualization

Histogram plot

Density plot

Box and Whisker plot

Bar plot

Missing data map

Pairwise correlation plot

### **Prediction on Diabetes**

We compare the performance for the following classifiers:

1. Logistic Regression

Logistic regression is basically a supervised classification algorithm. In a classification problem, the target variable (or output), y, can take only discrete values for given set of features (or inputs), X.

#### 2. Support Vector Machine (SVM)

"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well

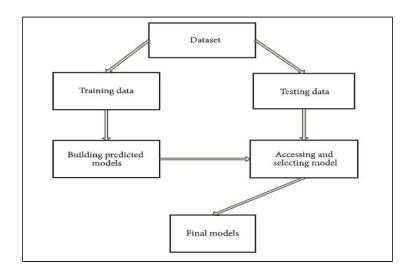
#### 3. Random Forest

The random forest algorithm works by aggregating the predictions made by multiple decision trees of varying depth. Every decision tree in the forest is trained on a subset of the dataset called the bootstrapped dataset.

#### **Dataset:**

$\mathbf{Z}$	Α	В	C	D	E	F	G	H	1	J	K	L	M	N	0	P	Q	R	S
1 i	d	chol	stab.glu	hdl	ratio	glyhb	location	age	gender	height	weight	frame	bp.1s	bp.1d	bp.2s	bp.2d	waist	hip	time.ppn
2	1000	203	82	56	3.6	4.31	Buckingha	46	female	62	121	medium	118	59			29	38	720
3	100	165	97	24	6.9	4.44	Buckingha	29	female	64	218	large	112	68			46	48	360
4	1002	228	92	37	6.2	4.64	Buckingha	58	female	61	256	large	190	92	185	92	49	57	7 180
5	1003	78	93	12	6.5	4.63	Buckingha	67	male	67	119	large	110	50			33	38	480
6	1005	249	90	28	8.9	7.72	Buckingha	64	male	68	183	medium	138	80			44	41	300
7	1008	248	94	69	3.6	4.81	Buckingha	34	male	71	190	large	132	86			36	42	195
8	1013	195	92	41	4.8	4.84	Buckingha	30	male	69	191	medium	161	112	161	112	46	49	720
9	1015	227	75	44	5.2	3.94	Buckingha	37	male	59	170	medium					34	39	1020
10	1016	177	87	49	3.6	4.84	Buckingha	45	male	69	166	large	160	80	128	86	34	40	300
11	1022	263	89	40	6.6	5.78	Buckingha	55	female	63	202	small	108	72			45	50	240
12	1024	242	82	54	4.5	4.77	Louisa	60	female	65	156	medium	130	90	130	90	39	45	300
13	1029	215	128	34	6.3	4.97	Louisa	38	female	58	195	medium	102	68			42	2 50	90
14	1030	238	75	36	6.6	4.47	Louisa	27	female	60	170	medium	130	80			35	41	720
15	1033	183	79	46	5 4	4.59	Louisa	40	female	59	165	medium					37	7 43	60
16	1035	191	76	30	6.4	4.67	Louisa	36	male	69	183	medium	100	66			36	40	225
17	1036	213	83	47	4.5	3.41	Louisa	33	female	65	157	medium	130	90	120	96	37	7 41	1 240
18	1037	255	78	38	6.7	4.33	Louisa	50	female	65	183	medium	130	100			37	43	180
19	104:	230	112	64	3.6	4.53	Louisa	20	male	67	159	medium	100	90			31	39	1440
20	1045	194	81	36	5.4	5.28	Louisa	36	male	64	126	medium	110	76			30	34	1 120
21	1250	196	206	41	4.8	11.24	Buckingha	62	female	65	196	large	178	90			46	5 51	L 540
22	1252	186	97	50	3.7	6.49	Buckingha	70	male	67	178	large	148	88	148	84	42	2 41	1020

Our research dataset is divided into two parts; two-thirds of the data is used as a training set, and one-third of the dataset is defined as a testing set to evaluate the performance of several classifiers. All classifiers were fitted to the same training and testing data. The specific process is: .



## **Libraries:**

#### Randomforest

Random Forest implements Breiman's random forest algorithm (based on Breiman's and Cutler's original FORTRAN code) for classification and regression. It can also be used in unsupervised mode for assessing proximities among data points.

#### Caret

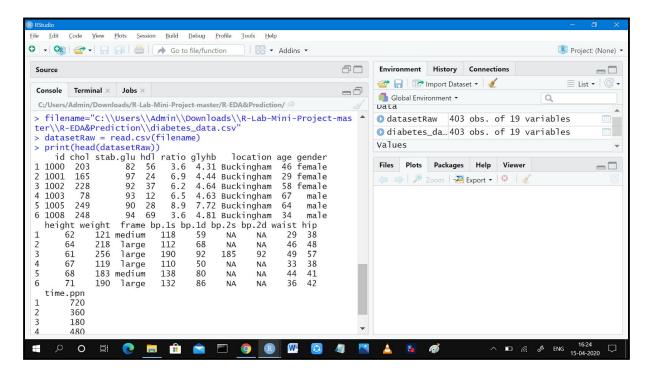
The caret package (short for Classification And REgression Training) is a set of functions that attempt to streamline the process for creating predictive models. The package contains tools for:

- data splitting
- pre-processing
- feature selection
- model tuning using resampling
- variable importance estimation
- as well as other functionality.

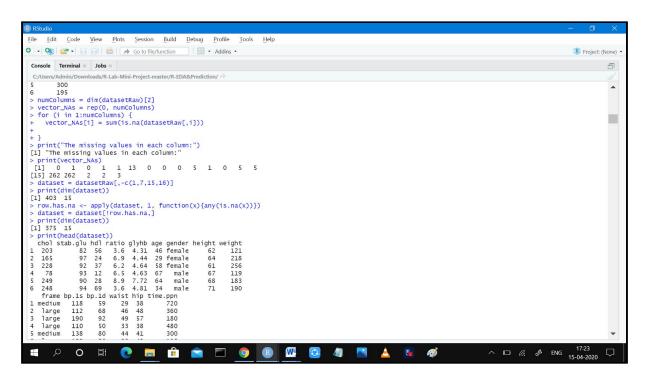
# Output:

## Step1: Load the data

- > filename="C:\\Users\\Admin\\Desktop\\\\ R-Lab-Mini-Project \\diabetes data.csv"
- > datasetRaw = read.csv(filename)
- > print(head(datasetRaw))



### Step 2: Clean the data

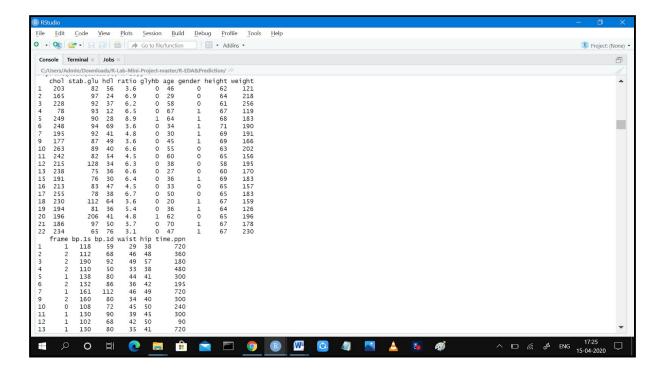


```
# encodes the class label (column 5): Glycosylated haemoglobin > 7.0 is taken as a positive
diagnosis of diabetes.
> dataset [,5] = if else(dataset[,5] >= 7.0, 1, 0)
> dataset [,5] = factor(dataset[,5])

# encode the categorical data (column-7 gender)
> dataset[,7] = if else(dataset[,7] == "female", 0, 1)
> dataset[,7] = factor(dataset[,7])

# encode the categorical data (column-10 frame)
```

```
> dataset[,10] = if else(dataset[,10] == "small", 0, if else(dataset[,10] == "medium", 1,2) )
> dataset[,10] = factor(dataset[,10])
# Descriptive statistics %%%%%%%
# display the first 20 rows
> print(head(dataset, n=20))
```

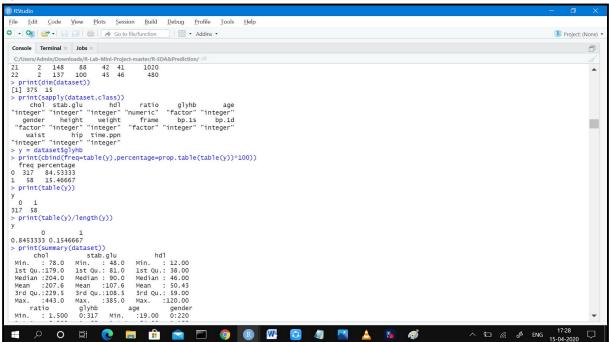


#### # display the dimensions of the dataset

> print(dim(dataset))

[1] 375 15

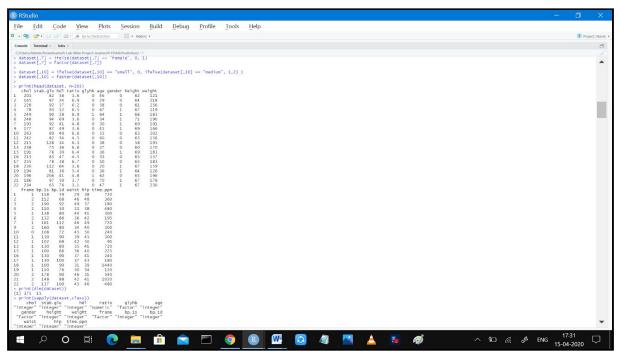
> print(head(dataset))



```
> # encode the class label (column 5): Glycosylated hemoglobin > 7.0 is taken as a positive diagnosis of diabetes.
```

```
> dataset[,5] = ifelse(dataset[,5] >= 7.0, 1, 0)
```

- > dataset[,5] = factor(dataset[,5])
- > # encode the categorical data (column-7 gender)
- > dataset[,7] = ifelse(dataset[,7] == "female", 0, 1)
- > dataset[,7] = factor(dataset[,7])
- > # encode the categorical data (column-10 frame)
- > dataset[,10] = ifelse(dataset[,10] == "small", 0, ifelse(dataset[,10] == "medium", 1,2))
- > dataset[,10] = factor(dataset[,10])
- > # Descriptive statistics %%%%%%%
- > # display the first 20 rows
- > print(head(dataset, n=20))



- > # display the dimensions of the dataset
- > print(dim(dataset))
- [1] 375 15
- > # list types for each attribute
- > print(sapply(dataset, class))

```
chol stab.glu hdl ratio glyhb age gender height weight frame bp.1s
"integer" "integer" "integer" "factor" "integer" "factor"
"integer"
bp.1d waist hip time.ppn
"integer" "integer" "integer" "integer"
```

- > # distribution of the class labels
- > y = dataset\$glyhb
- > print(cbind(freq=table(y),percentage=prop.table(table(y))\*100))

```
freq percentage
0 317 84.53333
1 58 15.46667
```

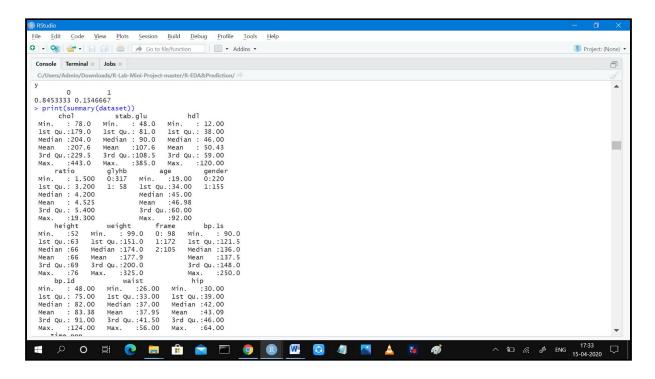
#### > print(table(y))

```
y
0 1
317 58
```

#### > print(table(y)/length(y))

```
y
0 1
0.8453333 0.1546667
```

- > # summarize the dataset
- > print(summary(dataset))



## Step 3: To Do EDA (Analysis of the dataset)

- # Standard Deviations for the non-categorical columns
- > std=sapply(dataset[,-c(5,7,10)],sd)
- > print('The standard deviations are:')
- [1] "The standard deviations are:"

#### > print(std)

```
chol stab.glu hdl ratio age height weight bp.1s
44.700780 54.082496 17.444346 1.755499 16.661203 3.915210 40.568940 23.178154
bp.1d waist hip time.ppn
13.544167 5.777105 5.642679 309.056806
```

#### # Skewness

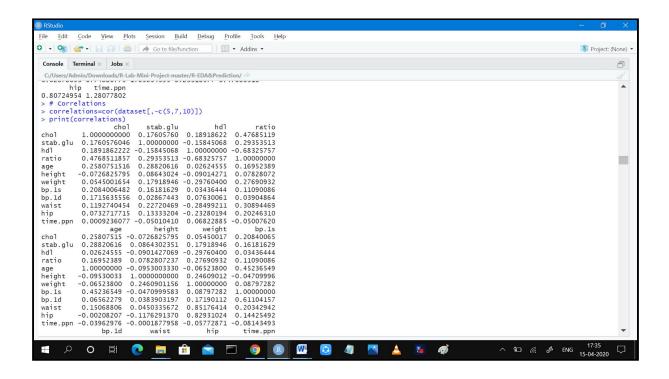
#The further the distribution of the skew value from zero,
# the larger the skew to the left (negative skew value) or right (positive skew value).

- > library(e1071) # the library for skewness
- > skew=apply(dataset[,-c(5,7,10)], 2, skewness)
- > print(skew)

chol stab.glu hdl ratio age height weight bp.1s
0.97739823 2.69790949 1.21275829 2.24132546 0.30061280 0.02678693 0.74880775 1.05634395
bp.1d waist hip time.ppn
0.23310577 0.47060516 0.80724954 1.28077802

### **CORRELATION:**

- # Correlations
- > correlations=cor(dataset[,-c(5,7,10)])
- > print(correlations)

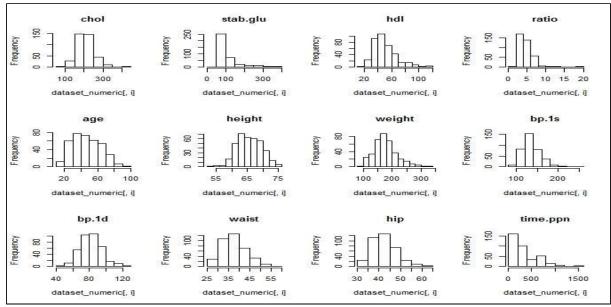


## **PART 2: Data visualizations:**

# 1:Histogram

- > dataset numeric = dataset[,-c(5,7,10)]
- > #Histograms
- > par(mfrow=c(3,4)) # put four figures in a row (2\*4)
- > for (i in 1:12) {
- + hist(dataset\_numeric[,i],main=names(dataset\_numeric)[i])

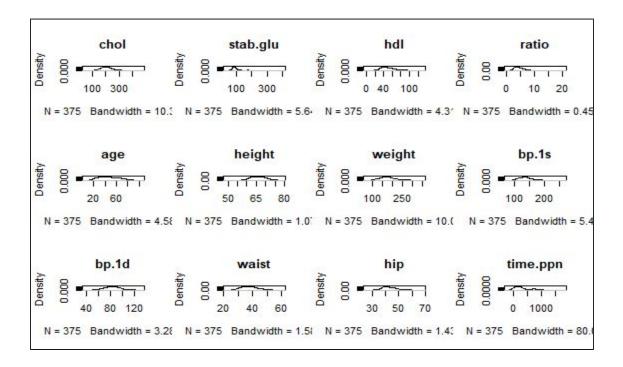
+ }



# 2:Density Plots

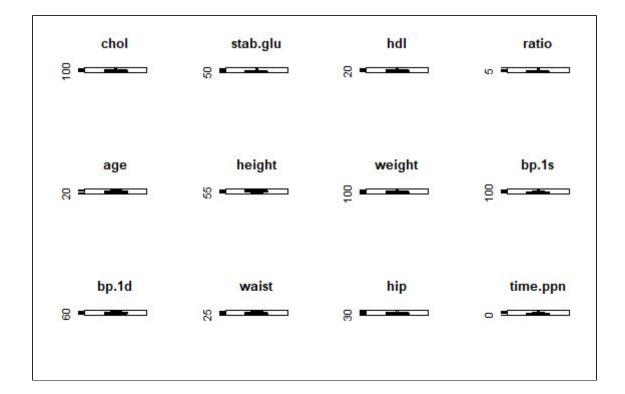
- > par(mfrow=c(3,4))
- > for(i in 1:12) {
- + plot(density(dataset\_numeric[,i]), main=names(dataset\_numeric)[i])

+ }



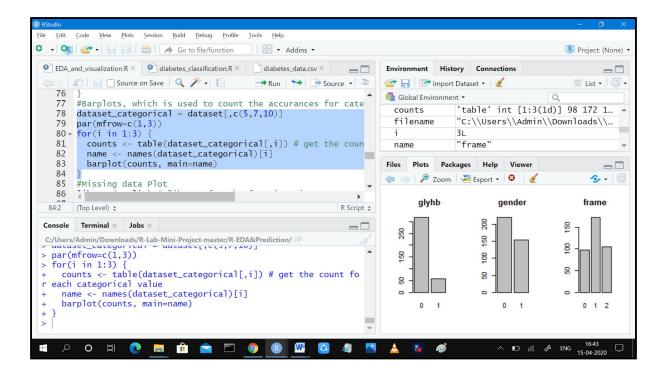
### **3:Box And Whisker Plots**

```
> par(mfrow=c(3,4))
> for(i in 1:12) {
+ boxplot(dataset_numeric[,i], main=names(dataset_numeric)[i])
+ }
```



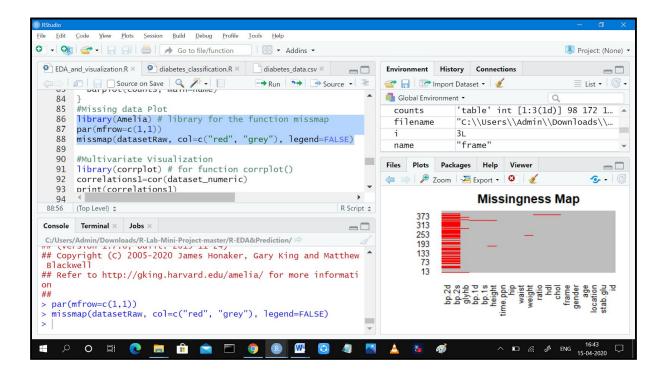
### 4:Barplots:

```
> dataset_categorical = dataset[,c(5,7,10)]
> par(mfrow=c(1,3))
> for(i in 1:3) {
+ counts <- table(dataset_categorical[,i]) # get the count for each categorical value
+ name <- names(dataset_categorical)[i]
+ barplot(counts, main=name)
+}</pre>
```



### 5:Missing data Plot

- > library (Amelia) # library for the function missmap
- > par(mfrow=c(1,1))
- > missmap (datasetRaw, col=c("red", "grey"), legend=FALSE)

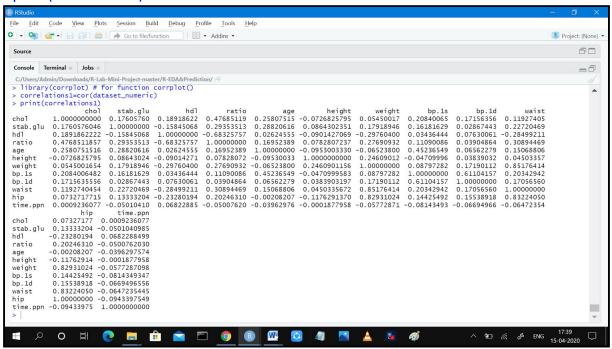


#### **6:Multivariate Visualization**

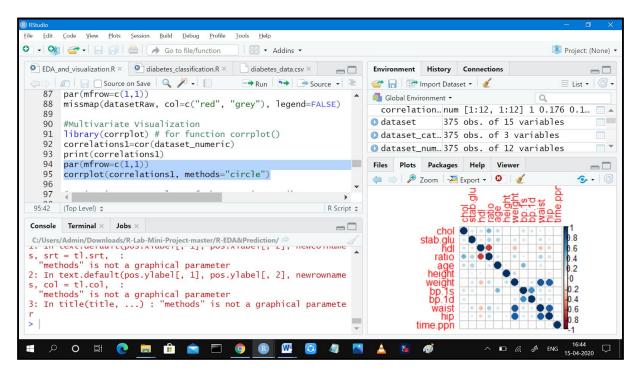
> library(corrplot) # for function corrplot()

Corrplot 0.84 loaded

- > correlations1=cor (dataset numeric)
- > print (correlations1)

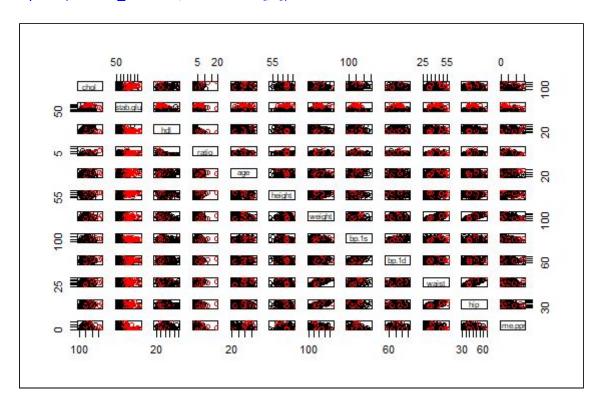


- > par(mfrow=c(1,1))
- > corrplot(correlations1, methods="circle")



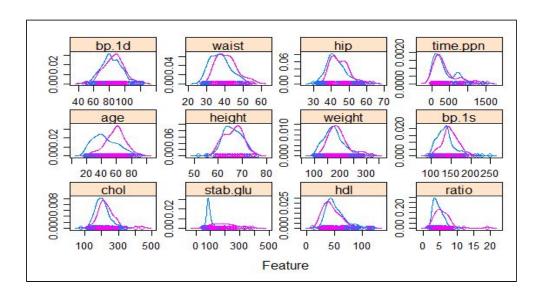
#### 7:Pairwise scatterplots of the numeric attributes

- > par(mfrow=c(1,1))
- pairs (dataset numeric)
- > #Scatterplot Matrix By Class (use different color to distinguish different class)
- > par(mfrow=c(1,1))
- > pairs (dataset numeric, col=dataset[,5])



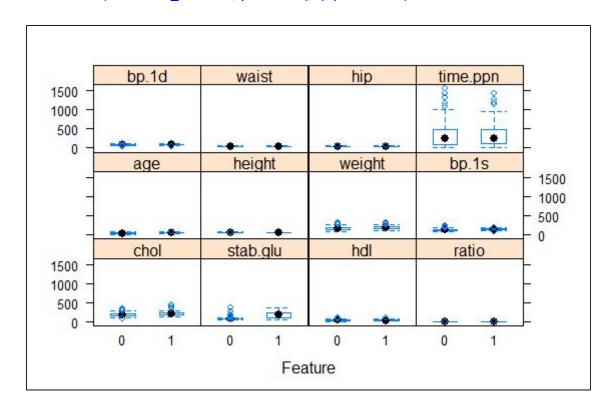
### **8:Density By Class**

- > library(caret)
- > # load the data
- > data(iris)
- > # density plots for each attribute by class value
- > x <- dataset numeric
- > y <- dataset[,5]
- > scales <- list(x=list(relation="free"), y=list(relation="free"))
- > par(mfrow=c(1,1))
- > feature Plot(x=dataset\_numeric, y=dataset[,5], plot="density", scales=scales)

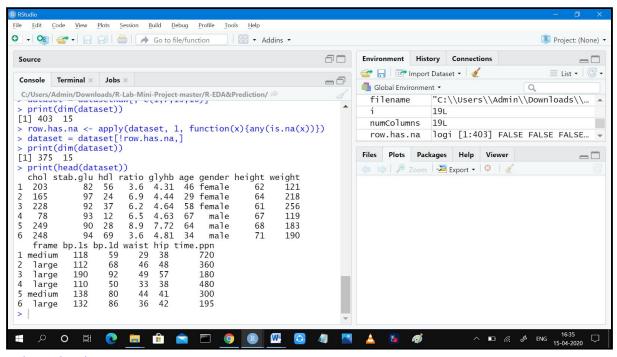


# 9:Box And Whisker Plots By Class

> featurePlot(x=dataset\_numeric, y=dataset[,5], plot="box")



- # Load libraries
- > library(randomForest)
- > library(caret)
- > # load the data
- > filename="C:\Users\Admin \Desktop\\\ R-Lab-Mini-Project \diabetes data.csv"
- > datasetRaw = read.csv(filename)
- > print(head(datasetRaw))



# clean the data

- > numColumns = dim(datasetRaw)[2]
- > vector\_NAs = rep (0, numColumns)
- > for (i in 1:numColumns) {
- + vector\_NAs[i] = sum (is.na (datasetRaw [,i]))

. 1

+ }

> print ("The missing values in each column :")

[1] "The missing values in each column:"

> print (vector\_NAs)

[1] 0 1 0 1 1 13 0 0 0 5 1 0 5 5 262 262 2 2 3

# delete columns 15 and 16 due to many missing values

- > # delete column 1 (id), column 7 (location) because they contain no useful information
- > dataset = datasetRaw[,-c(1,7,15,16)]
- > print(dim(dataset))

[1] 403 15

# remove the row with missing values

> row.has.na <- apply(dataset, 1, function(x){any(is.na(x))})

```
> dataset = dataset[!row.has.na,]
```

> print(dim(dataset))

```
[1] 375 15
```

### > print(head(dataset))

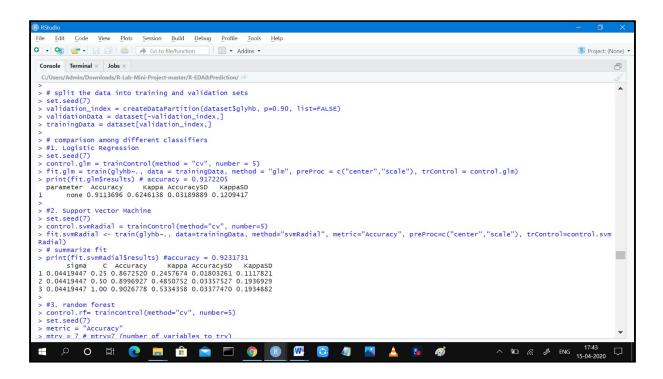
```
Id chol stab.glu hdl ratio glyhb age gender height weight frame bp.1s bp.1d waist hip
1 203 82 56 3.6 4.31 46 female 62 121 medium 118 59 29 38
2 165 97 24 6.9 4.44 29 female 64 218 large 112 68 46 48
3 228 92 37 6.2 4.64 58 female 61 256 large 190 92 49 57
4 78 93 12 6.5 4.63 67 male 67 119 large 110 50 33 38
5 249 90 28 8.9 7.72 64 male 68 183 medium 138 80 44 41
6 248 94 69 3.6 4.81 34 male 71 190 large 132 86 36 42
```

```
# encode the class label (column 5): Glycosylated hemoglobin > 7.0 is taken as
a positive diagnosis of diabetes.
> dataset[,5] = ifelse(dataset[,5] >= 7.0, 1, 0)
> dataset[,5] = factor(dataset[,5])
> # encode the categorical data (column-7 gender)
> dataset[,7] = ifelse(dataset[,7] == "female", 0, 1)
> dataset[,7] = factor(dataset[,7])
> # encode the categorical data (column-10 frame)
> dataset[,10] = ifelse(dataset[,10] == "small", 0, ifelse(dataset[,10] ==
"medium", 1,2))
> dataset[,10] = factor(dataset[,10])
> # split the data into training and validation sets
> set.seed(7)
> validation_index = createDataPartition(dataset$glyhb, p=0.90, list=FALSE)
> validationData = dataset[-validation index,]
> trainingData = dataset[validation_index,]
```

### **PART 3:DATA CLASSIFICATION**

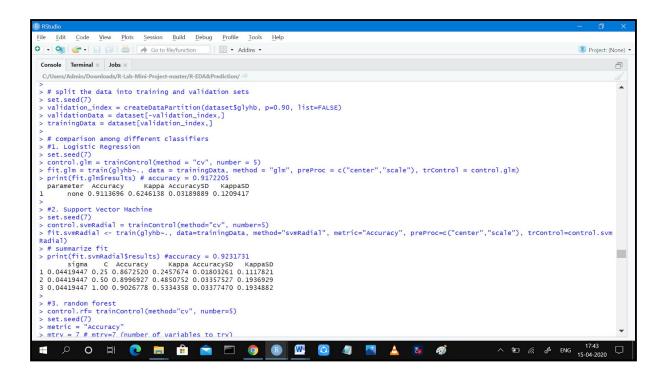
### **#1. Logistic Regression**

- > set.seed(7)
- > control.glm = trainControl(method = "cv", number = 5)
- > fit.glm = train(glyhb~., data = trainingData, method = "glm", preProc = c("center", "scale"), trControl = control.glm)
- > print(fit.glm\$results)



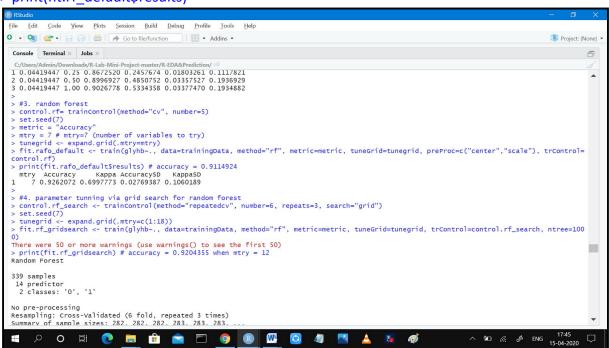
# 2. <u>Support Vector Machine</u>

- > set.seed(7)
- > control.svmRadial = trainControl(method="cv", number=5)
- > fit.svmRadial <- train(glyhb~., data=trainingData, method="svmRadial", metric="Accuracy", preProc=c("center","scale"), trControl=control.svmRadial)
- > # summarize fit
- > print(fit.svmRadial\$results)



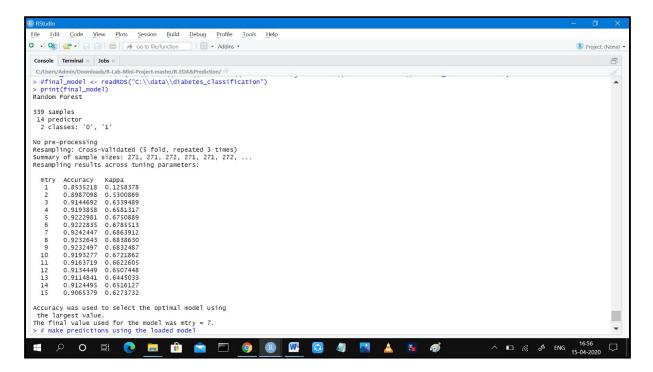
#### 3. Random forest

- > control.rf = trainControl(method="cv", number=5)
- > set.seed(7)
- > metric = "Accuracy"
- > mtry = 7 # mtry=7 (number of variables to try)
- > tunegrid <- expand.grid(.mtry=mtry)
- > fit.rf\_default <- train(glyhb~., data=trainingData, method="rf", metric=metric, tuneGrid=tunegrid, preProc=c("center", "scale"), trControl=control)
- > print(fit.rf\_default\$results)

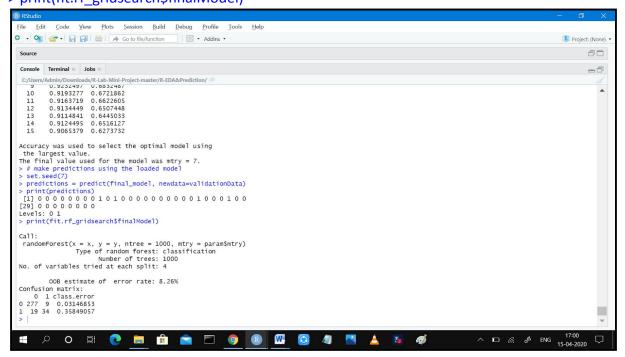


### > #4. Parameter tuning via grid search for random forest

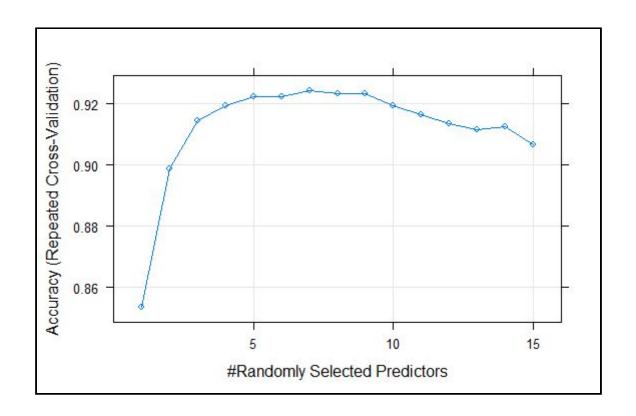
- > control.rf\_search <- trainControl(method="repeatedcv", number=5, repeats=3, search="grid")
- > set.seed(7)
- > tunegrid <- expand.grid(.mtry=c(1:15))
- > fit.rf\_gridsearch <- train(glyhb~., data=trainingData, method="rf", metric=metric, tuneGrid=tunegrid, trControl=control.rf\_search, ntree=1000)
- > print(fit.rf\_gridsearch) # accuracy = 0.9204355 when mtry = 12



### > print(fit.rf\_gridsearch\$finalModel)



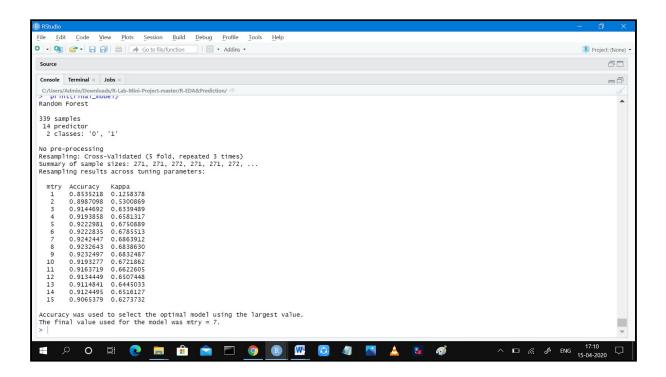
- > plot(fit.rf\_gridsearch)
- > # make predictions on the validation set
- > set.seed(7)
- > predictions = predict(fit.rf\_gridsearch, newdata=validationData)
- > confusionMatrix = confusionMatrix(predictions, validationData\$glyhb)
- > # confusion matrix
- > print(confusionMatrix\$table)



## **PART 4:Prediction of Accuracy**

#save the final classifier model into disk
> saveRDS(fit.rf\_gridsearch, "C:\\Users\\Admin\\Desktop\\
R-Lab-Mini-Project\\diabetes classification1")

- > # load the model from the disk
- > final\_model <- readRDS("C:\\Users\\Admin\\Desktop\\\\ R-Lab-Mini-Project \\diabetes\_classification")
- > #final\_model <- readRDS("C:\\data\\diabetes\_classification")
- > print(final\_model)



# # make predictions using the loaded model

- > set.seed(7)
- > predictions = predict(final\_model, newdata=validationData)
- > print(predictions)

