Practical-ML-Project

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Loading of required libraries

```
library(caret)
```

```
## Loading required package: lattice

## Loading required package: ggplot2
```

```
library(rpart)
library(rpart.plot)
library(RColorBrewer)
library(rattle)
```

```
## Loading required package: tibble

## Loading required package: bitops

## Rattle: A free graphical interface for data science with R.
## Version 5.4.0 Copyright (c) 2006-2020 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(randomForest)
```

```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:rattle':
##
##     importance

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```r
library(gbm)
```

```
## Loaded gbm 2.1.8
```

Dowanloading Reading Data files

Downloading Script

```r
if(!file.exists("pml-training.csv"))
{
  download.file("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv", "pml-training.cs
}
dataset <- read.csv("pml-training.csv", na.strings = c("NA", ""))
if(!file.exists("pml-testing.csv"))
{
  download.file("https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv", "pml-testing.csv
}
validation <- read.csv("pml-testing.csv")
```

Data Loading Script

```r
train_in <- read.csv('./pml-training.csv', header=T)
valid_in <- read.csv('./pml-testing.csv', header=T)
```

Basic Data Exploration, Cleaning, Preprocessing

```r
dim(train_in)
```

```
## [1] 19622   160
```

```r
dim(valid_in)
```

```
## [1]  20 160
```

NA removal

```r
trainData<- train_in[, colSums(is.na(train_in)) == 0]
validData <- valid_in[, colSums(is.na(valid_in)) == 0]
dim(trainData)
```

```
## [1] 19622    93
```

```r
dim(validData)
```

```
## [1] 20 60
```

removal of 1st 7 variables that are less usefull on classe

```r
trainData <- trainData[, -c(1:7)]
validData <- validData[, -c(1:7)]
dim(trainData)
```

```
## [1] 19622    86
```

```r
dim(validData)
```

```
## [1] 20 53
```

Preparation of dataset for prediction by dividiong into 70% as traindata and 30% test dataset

```r
set.seed(1234)
inTrain <- createDataPartition(trainData$classe, p = 0.7, list = FALSE)
trainData <- trainData[inTrain, ]
testData <- trainData[-inTrain, ]
dim(trainData)
```

```
## [1] 13737    86
```

```r
dim(testData)
```

```
## [1] 4123   86
```

Nero-Zero-Variance removal

```r
NZV <- nearZeroVar(trainData)
trainData <- trainData[, -NZV]
testData  <- testData[, -NZV]
dim(trainData)
```

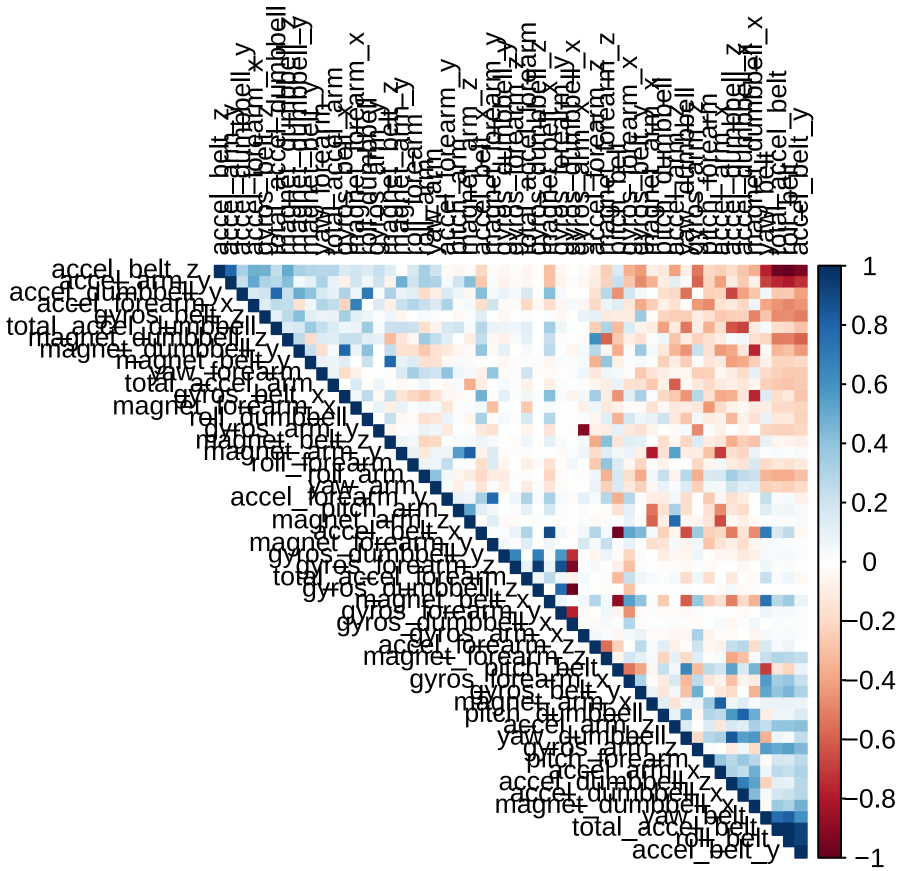
```
## [1] 13737    53
```

```r
dim(testData)
```

```
## [1] 4123   53
```

correlation plot uses the following parameters for abstract visualization

```r
cor_mat <- cor(trainData[, -53])
corrplot(cor_mat, order = "FPC", method = "color", type = "upper", tl.cex = 0.8, tl.col = rgb(0, 0, 0))
```



Identification of names of the variables

```
highlyCorrelated = findCorrelation(cor_mat, cutoff=0.75)
names(trainData)[highlyCorrelated]
```

```
##  [1] "accel_belt_z"      "roll_belt"          "accel_belt_y"
##  [4] "total_accel_belt"  "accel_dumbbell_z"   "accel_belt_x"
##  [7] "pitch_belt"        "magnet_dumbbell_x"  "accel_dumbbell_y"
## [10] "magnet_dumbbell_y" "accel_dumbbell_x"   "accel_arm_x"
## [13] "accel_arm_z"       "magnet_arm_y"       "magnet_belt_z"
## [16] "accel_forearm_y"   "gyros_forearm_y"    "gyros_dumbbell_x"
## [19] "gyros_dumbbell_z"  "gyros_arm_x"
```

ML Model build

the dataset will be trained andpredicted using following algorithms

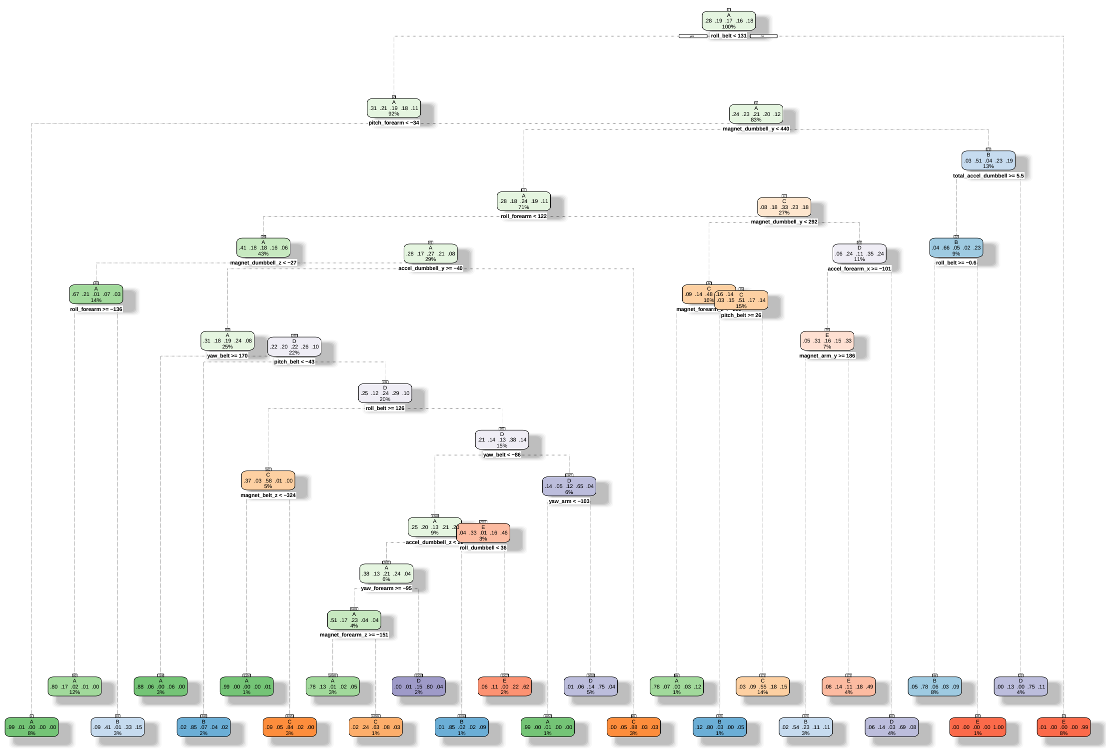
1. Classification trees (CT)
2. Random forests (RF)
3. Generalized Boosted Model (GBM)

1. Classification trees (CT)

classification tree dendogram is plotted using fancyRpartPlot() function

```r
set.seed(12345)
decisionTreeMod1 <- rpart(classe ~ ., data=trainData, method="class")
fancyRpartPlot(decisionTreeMod1)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



Rattle 2020−Oct−03 11:25:30 chamikasenanayake

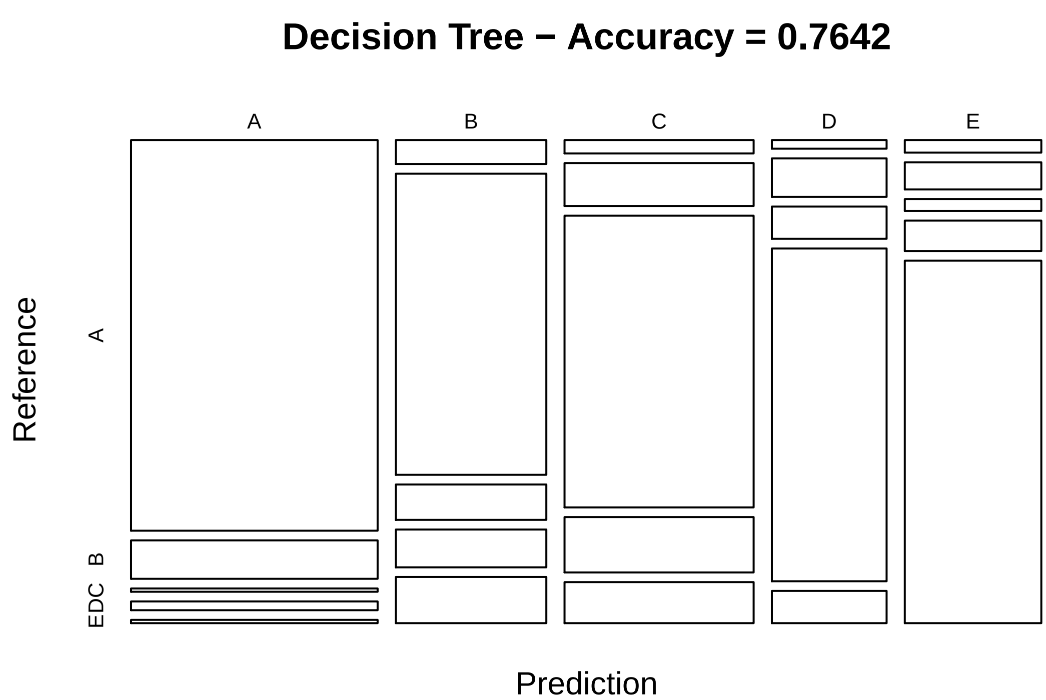
validation of the model “decisionTreeModel” on the testData to visualize and generate pro matrix results as below

```r
testData$classe<-as.factor(testData$classe)
predictTreeMod1 <- predict(decisionTreeMod1, testData, type = "class")
cmtree <- confusionMatrix(predictTreeMod1, testData$classe)
cmtree
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1067  105    9   24    9
##          B   40  502   59   63   77
##          C   28   90  611  116   86
##          D   11   49   41  423   41
##          E   19   41   18   46  548
##
## Overall Statistics
```

```
##
##                Accuracy : 0.7642
##                  95% CI : (0.751, 0.7771)
##     No Information Rate : 0.2826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7015
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9159   0.6379   0.8279   0.6295   0.7201
## Specificity            0.9503   0.9284   0.9055   0.9589   0.9631
## Pos Pred Value         0.8789   0.6775   0.6563   0.7487   0.8155
## Neg Pred Value         0.9663   0.9157   0.9602   0.9300   0.9383
## Prevalence             0.2826   0.1909   0.1790   0.1630   0.1846
## Detection Rate         0.2588   0.1218   0.1482   0.1026   0.1329
## Detection Prevalence   0.2944   0.1797   0.2258   0.1370   0.1630
## Balanced Accuracy      0.9331   0.7831   0.8667   0.7942   0.8416
```

```r
# plot matrix results
plot(cmtree$table, col = cmtree$byClass,
     main = paste("Decision Tree - Accuracy =", round(cmtree$overall['Accuracy'], 4)))
```



thus illustrates accuracy rate of ***0.7642**

2. Random forests (RF)

as done in CT model we validate the RF1 model and generate a confusionMatrix as following

```
controlRF <- trainControl(method="cv", number=3, verboseIter=FALSE)
modRF1 <- train(classe ~ ., data=trainData, method="rf", trControl=controlRF)
modRF1$finalModel
```

```
##
## Call:
##  randomForest(x = x, y = y, mtry = param$mtry)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 27
##
##         OOB estimate of  error rate: 0.7%
## Confusion matrix:
##      A    B    C    D    E class.error
## A 3902    3    0    0    1 0.001024066
## B   19 2634    5    0    0 0.009029345
## C    0   17 2369   10    0 0.011268781
## D    0    1   26 2224    1 0.012433393
## E    0    2    5    6 2512 0.005148515
```

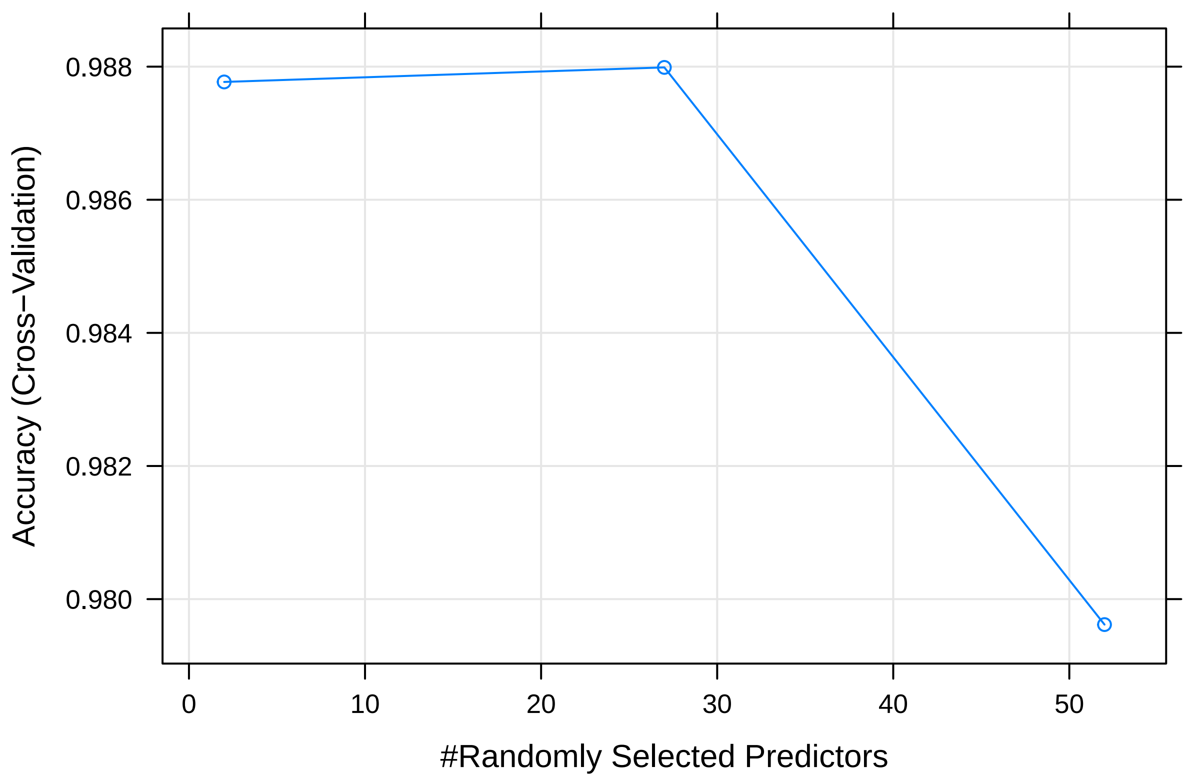
```
predictRF1 <- predict(modRF1, newdata=testData)
cmrf <- confusionMatrix(predictRF1, testData$classe)
cmrf
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1165    0    0    0    0
##          B    0  787    0    0    0
##          C    0    0  738    0    0
##          D    0    0    0  672    0
##          E    0    0    0    0  761
##
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9991, 1)
##     No Information Rate : 0.2826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
```

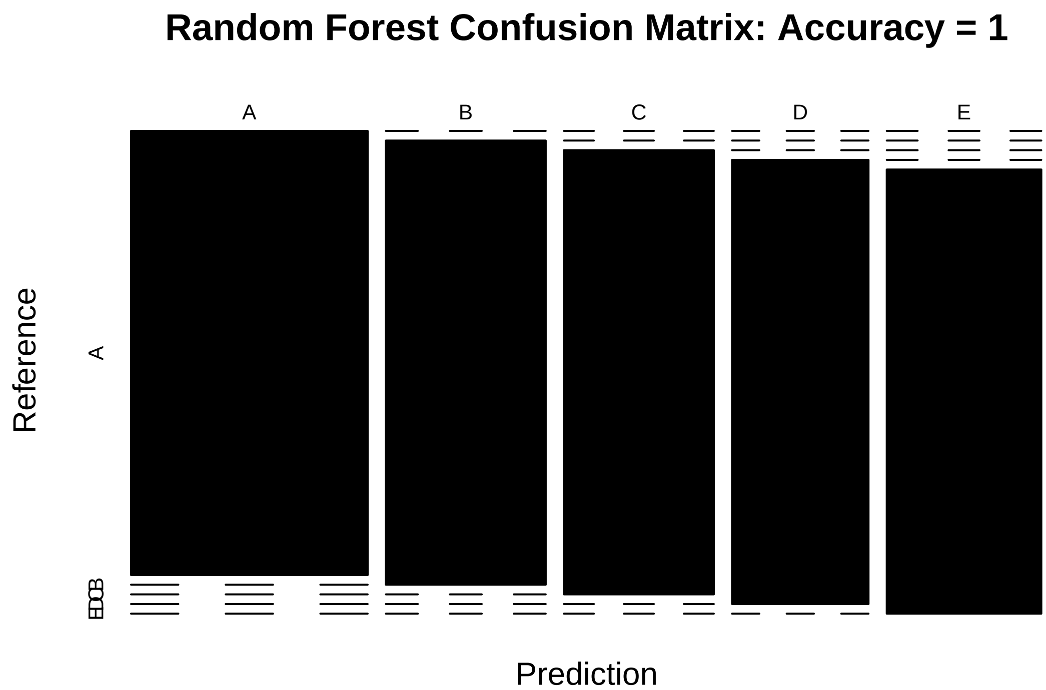
```
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            1.0000   1.0000    1.000    1.000   1.0000
## Specificity            1.0000   1.0000    1.000    1.000   1.0000
## Pos Pred Value         1.0000   1.0000    1.000    1.000   1.0000
## Neg Pred Value         1.0000   1.0000    1.000    1.000   1.0000
## Prevalence             0.2826   0.1909    0.179    0.163   0.1846
## Detection Rate         0.2826   0.1909    0.179    0.163   0.1846
## Detection Prevalence   0.2826   0.1909    0.179    0.163   0.1846
## Balanced Accuracy      1.0000   1.0000    1.000    1.000   1.0000
```

the model is plotted as following

```r
plot(modRF1)
```




```r
plot(cmrf$table, col = cmrf$byClass, main = paste("Random Forest Confusion Matrix: Accuracy =", round(cr
```



3. Generalized Boosted Model (GBM)

formulation of the model is done by

```
set.seed(12345)
controlGBM <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
modGBM  <- train(classe ~ ., data=trainData, method = "gbm", trControl = controlGBM, verbose = FALSE)
modGBM$finalModel
```

```
## A gradient boosted model with multinomial loss function.
## 150 iterations were performed.
## There were 52 predictors of which 52 had non-zero influence.
```

```
print(modGBM)
```

```
## Stochastic Gradient Boosting
##
## 13737 samples
##    52 predictor
##     5 classes: 'A', 'B', 'C', 'D', 'E'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 1 times)
## Summary of sample sizes: 10990, 10990, 10989, 10991, 10988
```

```
## Resampling results across tuning parameters:
##
##   interaction.depth  n.trees  Accuracy   Kappa
##   1                   50      0.7521285  0.6858434
##   1                  100      0.8227397  0.7756753
##   1                  150      0.8521496  0.8129547
##   2                   50      0.8563724  0.8180344
##   2                  100      0.9059465  0.8809760
##   2                  150      0.9302623  0.9117412
##   3                   50      0.8969931  0.8695557
##   3                  100      0.9398712  0.9238994
##   3                  150      0.9593802  0.9486037
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 150, interaction.depth =
##  3, shrinkage = 0.1 and n.minobsinnode = 10.
```

Validation

```
predictGBM <- predict(modGBM, newdata=testData)
cmGBM <- confusionMatrix(predictGBM, testData$classe)
cmGBM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    A    B    C    D    E
##          A 1155   20    0    0    1
##          B    9  754   17    5    6
##          C    1   12  713   16    3
##          D    0    1    6  647    8
##          E    0    0    2    4  743
##
## Overall Statistics
##
##                Accuracy : 0.9731
##                  95% CI : (0.9677, 0.9778)
##     No Information Rate : 0.2826
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.966
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: A Class: B Class: C Class: D Class: E
## Sensitivity            0.9914   0.9581   0.9661   0.9628   0.9763
## Specificity            0.9929   0.9889   0.9905   0.9957   0.9982
## Pos Pred Value         0.9821   0.9532   0.9570   0.9773   0.9920
## Neg Pred Value         0.9966   0.9901   0.9926   0.9928   0.9947
```

```
## Prevalence             0.2826   0.1909   0.1790   0.1630   0.1846
## Detection Rate         0.2801   0.1829   0.1729   0.1569   0.1802
## Detection Prevalence   0.2852   0.1919   0.1807   0.1606   0.1817
## Balanced Accuracy      0.9922   0.9735   0.9783   0.9792   0.9873
```

Using RF method the accuracy is high

best model application for data validation

```r
Results <- predict(modRF1, newdata=validData)
Results
```

```
##  [1] B A B A A E D B A A B C B A E E A B B B
## Levels: A B C D E
```