

Coursera – Assignment Project Writeup

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Project execution

According to the goal of the project (practical machine learning assignment), I am requested to develop a model through a machine learning approach to predict the target variable "classe", using other variables which can have a statistical relevance with respect to the target variable.

I performed a data analysis to prepare the data set properly for the training phase and the validation phase to assess the performance of the models. I used different R methods to evaluate which of the models has better performance for the prediction of the target variable, by comparing the outcomes obtained. Using the validation data set provided, I predicted the target variable of 20 different cases with the final model.

DATA INGESTION

Setting up of R libraries and packages necessary to run the code.

```
# Set libraries
library(knitr)
library(caret)
library(rpart)
library(rpart.plot)
library(rattle)
library(randomForest)
library(corrplot)
library(RColorBrewer)
```

Setting up of URL to download training data and test data.

```
# Set the URL for the download from external link
UrlTrain <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"
UrlTest  <- "http://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"

# Download the datasets
training_data <- read.csv(url(UrlTrain))
testing_data  <- read.csv(url(UrlTest))
```

Creation of two partition of data by splitting the training data set into two different parts, with a proportion of 70% for the training data set and 30% for the test data set.

I obtained a training data set with 13737 rows and 160 columns, 5885 are the remaining rows to be used as test data.

```
# Create a partition with the training dataset
```

```
set.seed(14042020)
```

```
inTrain <- createDataPartition(training_data$classe, p=0.7, list=FALSE)
```

```
TrainDataSet <- training_data[inTrain, ]
```

```
TestDataSet <- training_data[-inTrain, ]
```

```
dim(TrainDataSet)
```

```
dim(TestDataSet)
```

```
> # Create a partition with the training dataset
> inTrain <- createDataPartition(training_data$classe, p=0.7, list=FALSE)
> TrainDataSet <- training_data[inTrain, ]
> TestDataSet <- training_data[-inTrain, ]
> dim(TrainDataSet)
[1] 13737 160
> dim(TestDataSet)
[1] 5885 160
```

DATA CLEANING

Data cleaning phases necessary to remove variables with near zero variance, not relevant for the statistical analysis. After removing variables with near zero variance, I obtained 105 columns, hence, 55 variables have been removed due to the variance near to zero.

```
# Remove variables with Nearly Zero Variance
```

```
NZV <- nearZeroVar(TrainDataSet)
```

```
TrainDataSet <- TrainDataSet[, -NZV]
```

```
TestDataSet <- TestDataSet[, -NZV]
```

```
dim(TrainDataSet)
```

```
dim(TestDataSet)
```

```
> # Remove variables with Nearly Zero Variance
> NZV <- nearZeroVar(TrainDataSet)
> TrainDataSet <- TrainDataSet[, -NZV]
> TestDataSet <- TestDataSet[, -NZV]
> dim(TrainDataSet)
[1] 13737 105
> dim(TestDataSet)
[1] 5885 105
```

I removed also columns which contains mostly "not available/missing" value (columns with a number of rows with "not available/missing" higher or equal than 95% of total are excluded). After removing variables with non-relevant information, I obtained 59 columns.

```
# Remove variables which contain mostly missing values
```

```

ColIndex <- colSums(is.na(TrainDataSet))/nrow(TrainDataSet) < 0.95
TrainDataSet <- TrainDataSet[,ColIndex]
TestDataSet <- TestDataSet[,ColIndex]
dim(TrainDataSet)
dim(TestDataSet)

> # Remove variables which contain mostly missing value
>
> ColIndex <- colSums(is.na(TrainDataSet))/nrow(TrainDataSet) < 0.95
> TrainDataSet <- TrainDataSet[,ColIndex]
> TestDataSet <- TestDataSet[,ColIndex]
> dim(TrainDataSet)
[1] 13737    59
> dim(TestDataSet)
[1] 5885    59

```

I completed the data cleaning phase by removing also columns related to information not relevant for this analysis (time stamp, name). After removing these latter variables, I obtained 52 columns.

```

# Remove identification only variables (columns 1 to 7)
TrainDataSet <- TrainDataSet[, -(1:7)]
TestDataSet <- TestDataSet[, -(1:7)]
dim(TrainDataSet)
dim(TestDataSet)

> # Remove first seven variables (columns 1 to 7)
> TrainDataSet <- TrainDataSet[, -(1:7)]
> TestDataSet <- TestDataSet[, -(1:7)]
> dim(TrainDataSet)
[1] 13737    52
> dim(TestDataSet)
[1] 5885    52

```

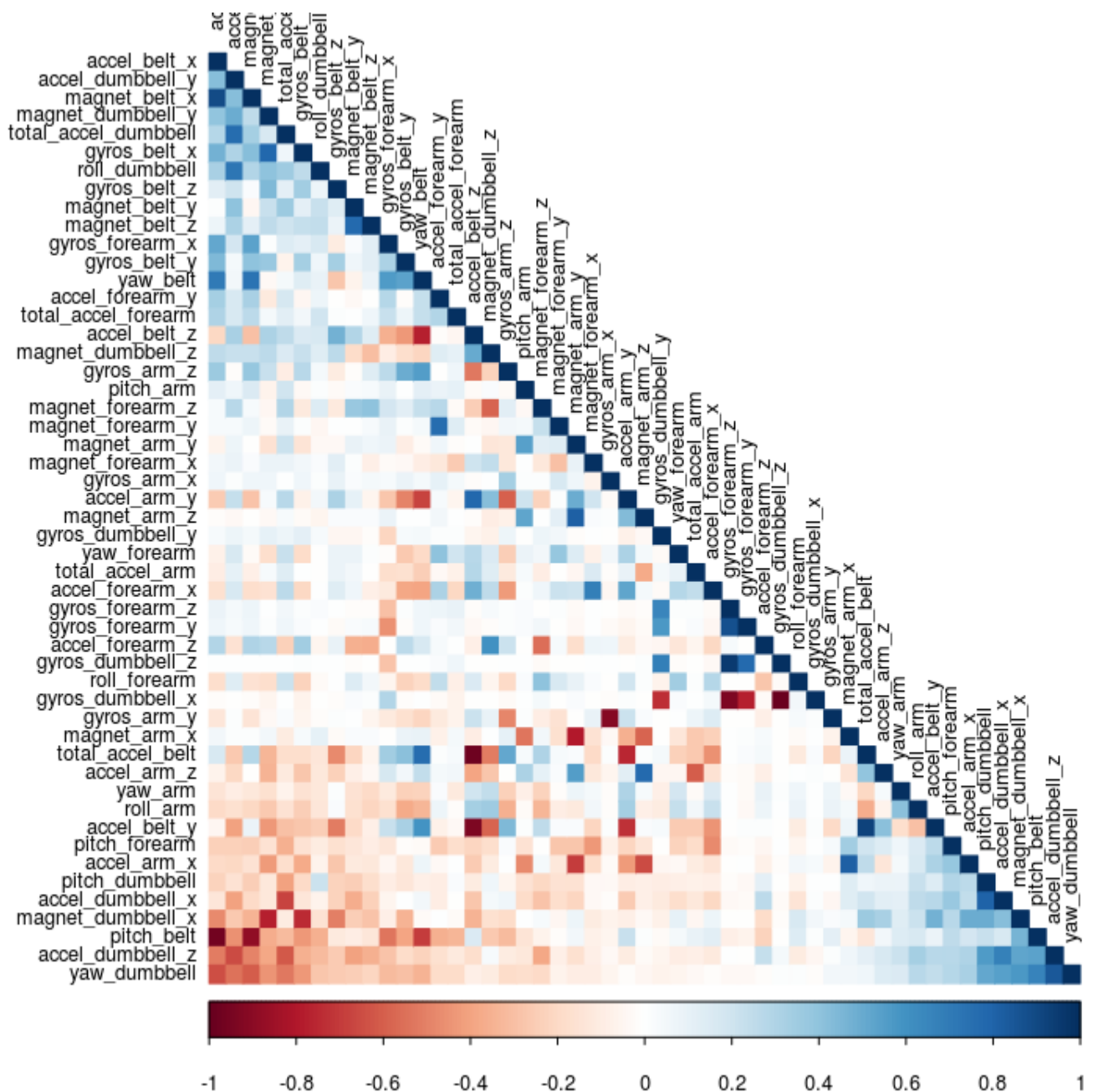
CORRELATION ANALYSIS

I performed a correlation analysis to find the highly correlated variables and plotting the overall correlation analysis. Darker colours in the graph below represents the highly correlated variables.

```

# Correlation analysis
corMat <- cor(TrainDataSet[, -52])
corrplot(corMat, order = "FPC", method = "color", type = "lower",
         tl.cex = 0.8, tl.col = rgb(0, 0, 0))

```



Below the highly correlated variables using a cutoff of 90%.

```
highlyCorr = findCorrelation(corMat, cutoff=0.9)
```

```
names(TrainDataSet)[highlyCorr]
```

```
> names(TrainDataSet)[highlyCorr]
[1] "accel_belt_z"      "accel_belt_y"      "accel_belt_x"      "gyros_dumbbell_x"
[5] "gyros_dumbbell_z" "gyros_arm_x"
```

MODELS DESIGN

I performed two different analysis using different model methods to evaluate which model has best performance on this data.

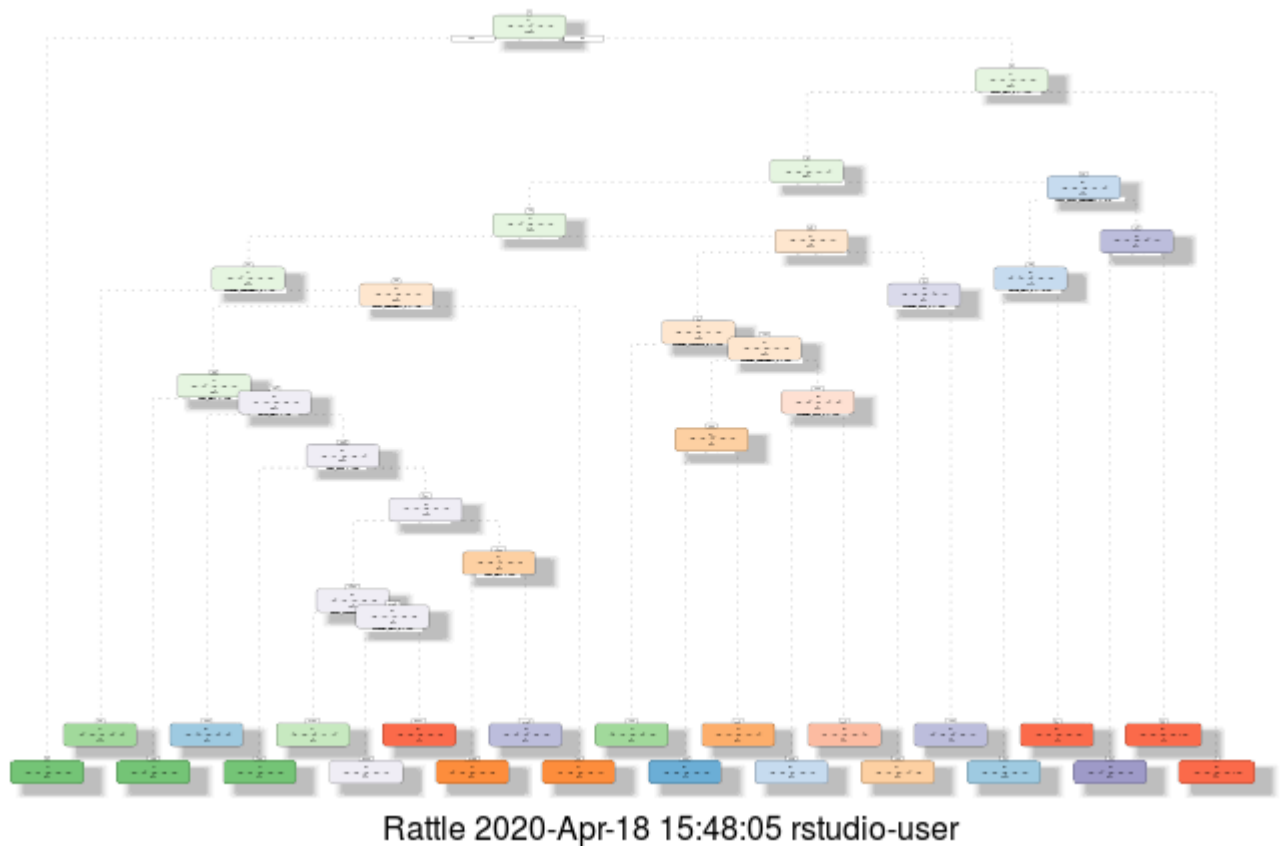
As first model, I performed a decision tree model by applying the training dataset created previously.

```
#Decision Tree Model
```

```
set.seed(14042020)
```

```
decisionTreeModel <- rpart(classe ~ ., data=TrainDataSet, method="class")
```

```
fancyRpartPlot(decisionTreeModel)
```



I evaluated the performance of the model obtained using the test data set created previously and checking the accuracy through a confusion matrix applied to the prediction.

```
predictTreeModel <- predict(decisionTreeModel, TestDataSet, type = "class")
```

```
ConfMatrixTree <- confusionMatrix(predictTreeModel, TestDataSet$classe)
```

```
ConfMatrixTree
```

```
> predictTreeModel <- predict(decisionTreeModel, TestDataSet, type = "class")
> ConfMatrixTree <- confusionMatrix(predictTreeModel, TestDataSet$classe)
> ConfMatrixTree
```

Confusion Matrix and Statistics

		Reference				
Prediction		A	B	C	D	E
A	1520	240	25	103	94	
B	46	603	117	36	130	
C	30	76	703	90	117	

D	69	172	142	678	107
E	9	48	39	57	634

Overall Statistics

Accuracy : 0.7031
 95% CI : (0.6913, 0.7148)
 No Information Rate : 0.2845
 P-Value [Acc > NIR] : < 2.2e-16

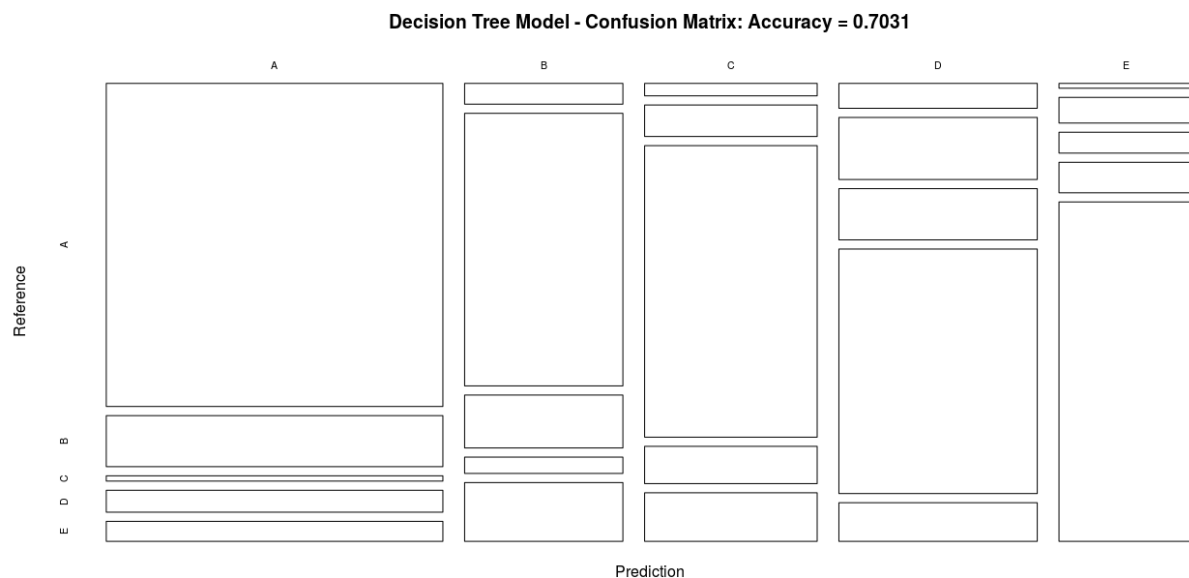
Kappa : 0.6225

McNemar's Test P-Value : < 2.2e-16

Statistics by Class:

	Class: A	Class: B	Class: C	Class: D	Class: E
Sensitivity	0.9080	0.5294	0.6852	0.7033	0.5860
Specificity	0.8903	0.9307	0.9356	0.9004	0.9681
Pos Pred Value	0.7669	0.6470	0.6919	0.5805	0.8056
Neg Pred Value	0.9605	0.8918	0.9337	0.9394	0.9121
Prevalence	0.2845	0.1935	0.1743	0.1638	0.1839
Detection Rate	0.2583	0.1025	0.1195	0.1152	0.1077
Detection Prevalence	0.3368	0.1584	0.1726	0.1985	0.1337
Balanced Accuracy	0.8991	0.7300	0.8104	0.8019	0.7770

```
plot(ConfMatrixTree$table, col = ConfMatrixTree$byClass, main = paste("Decision Tree
Model - Confusion Matrix: Accuracy =", round(ConfMatrixTree$overall['Accuracy'], 4)))
```



According to the outcomes obtained above, the decision tree model has an **accuracy of 70.31%**.

I performed a random forest model using the same data set to get a better accuracy.

```
#random forest model
```

```
set.seed(14042020)
```

```

TrainControlRF <- trainControl(method = "cv",
                                number = 3,
                                allowParallel = TRUE,
                                verboseIter = TRUE)

ModelFitRandomForest <- train(classe ~ ., data=TrainDataSet, method="rf",
                               trControl=TrainControlRF, ntree=100, importance=TRUE)

ModelFitRandomForest$finalModel

varImp(ModelFitRandomForest)

```

```
> ModelFitRandomForest$finalModel
```

Call:

```

randomForest(x = x, y = y, ntree = 100, mtry = param$mtry, importance = TRUE)
      Type of random forest: classification
      Number of trees: 100

```

No. of variables tried at each split: 26

OOB estimate of error rate: 0.77%

Confusion matrix:

	A	B	C	D	E	class.error
A	3898	6	1	0	1	0.002048131
B	24	2625	7	0	2	0.012415350
C	0	17	2375	4	0	0.008764608
D	1	1	25	2223	2	0.012877442
E	0	1	4	10	2510	0.005940594

```
>
```

```
> varImp(ModelFitRandomForest)
```

rf variable importance

variables are sorted by maximum importance across the classes
only 20 most important variables shown (out of 51)

	A	B	C	D	E
yaw_belt	100.00	81.37	64.96	95.70	78.80
pitch_belt	24.94	90.82	57.60	50.22	46.71
pitch_forearm	63.10	76.91	88.80	48.58	71.56
magnet_dumbbell_z	82.70	63.58	79.38	66.22	73.04
magnet_dumbbell_y	69.02	59.21	77.45	52.65	52.58
gyros_belt_z	28.72	47.78	33.10	26.28	42.89
accel_belt_z	34.68	41.41	41.90	45.62	27.63
accel_forearm_x	21.98	36.35	32.10	37.61	32.49
roll_forearm	37.03	35.35	35.71	23.38	32.04
magnet_belt_x	15.94	33.83	24.40	18.30	35.46
gyros_arm_y	24.35	33.33	20.37	28.17	24.30
yaw_arm	33.30	29.16	24.11	26.61	24.06
accel_dumbbell_z	22.71	32.51	18.00	25.04	26.45
gyros_dumbbell_y	31.83	15.14	27.81	18.72	13.52
accel_dumbbell_y	23.25	24.44	31.79	23.31	30.54
roll_dumbbell	18.16	31.51	23.25	27.19	24.45
magnet_arm_z	14.38	29.72	22.10	16.70	15.54
total_accel_dumbbell	17.33	24.47	17.55	21.83	28.94
gyros_forearm_y	11.26	19.32	28.77	11.66	14.83
magnet_belt_z	21.10	28.07	23.92	28.57	27.21

I evaluated the performance of the model obtained using the test data set created previously and checking the accuracy through a confusion matrix applied to the prediction.

```
PredictRF <- predict(ModelFitRandomForest, newdata=TestSet)
```

```
ConfMatrixRF <- confusionMatrix(PredictRF, TestSet$classe)
```

```
ConfMatrixRF
```

```
> PredictRF <- predict(ModelFitRandomForest, newdata=TestDataSet)
> ConfMatrixRF <- confusionMatrix(PredictRF, TestDataSet$classe)
> ConfMatrixRF
```

Confusion Matrix and Statistics

	Reference				
Prediction	A	B	C	D	E
A	1673	14	0	0	0
B	0	1121	3	0	1
C	0	3	1017	21	0
D	0	0	4	943	8
E	1	1	2	0	1073

Overall Statistics

Accuracy : 0.9901
95% CI : (0.9873, 0.9925)
No Information Rate : 0.2845
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9875

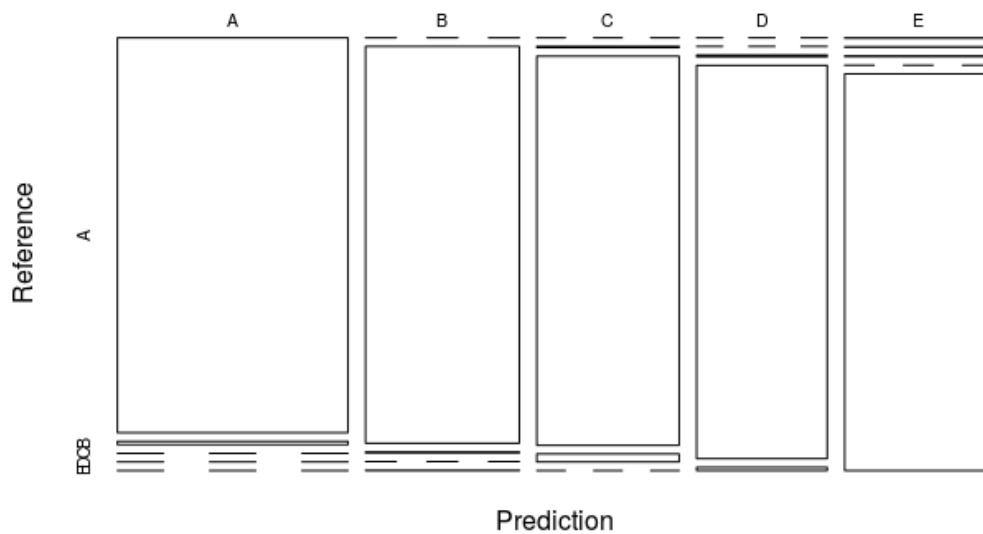
Mcnemar's Test P-Value : NA

Statistics by Class:

	Class: A	Class: B	Class: C	Class: D	Class: E
Sensitivity	0.9994	0.9842	0.9912	0.9782	0.9917
Specificity	0.9967	0.9992	0.9951	0.9976	0.9992
Pos Pred Value	0.9917	0.9964	0.9769	0.9874	0.9963
Neg Pred Value	0.9998	0.9962	0.9981	0.9957	0.9981
Prevalence	0.2845	0.1935	0.1743	0.1638	0.1839
Detection Rate	0.2843	0.1905	0.1728	0.1602	0.1823
Detection Prevalence	0.2867	0.1912	0.1769	0.1623	0.1830
Balanced Accuracy	0.9980	0.9917	0.9931	0.9879	0.9954

```
plot(ConfMatrixRF$table, col = ConfMatrixRF$byClass, main = paste("Random Forest Model  
- Confusion Matrix: Accuracy =", round(ConfMatrixRF$overall['Accuracy'], 4)))
```


Random Forest Model - Confusion Matrix: Accuracy = 0.9901



According to the outcomes obtained above, the random forest model has an **accuracy of 99.01%**; The accuracy ratio of random forest model is significantly higher than the one of the decision tree model (70.31%).

I can assume that the random forest approach is the best method to predict the target variable of the dataset provided for this project.

Finally, I submitted the final prediction applying the random forest model to the new data provided (test data). Below is showed the outcome of the prediction performed.

#Final prediction on Test data

```
predict(ModelFitRandomForest, newdata = testing_data)
```

```
> #Final prediction on Test data
> predict(ModelFitRandomForest, newdata = testing_data)
[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
```