#------------------------Assignment 9.2 -----------------------------

# Decision Tree - Weight Lifting Excercise

data\_set <- read.csv("E:/Data Analytics with RET/Assignment/Example\_WearableComputing\_weight\_lifting\_exercises\_biceps\_curl\_variations.csv")

View(data\_set)

# remove irrelevant collumns viz. name, cvtd\_timestamp, new\_window

data <- data\_set[,-c(1,4,5)]

View(data)

str(data)

sum(is.na(data)) # there are no missing values

# spliting the data set for train and test

library(caTools)

set.seed(123)

split = sample.split(data$classe, SplitRatio = 0.7)

train = subset(data, split == TRUE) # train data

test = subset(data, split == FALSE) # test data

# a. Create classification model using different decision trees.

library(tree); library(rpart); library(caret); library(C50); library(randomForest)

# Decision Tree

model\_tree <- tree(classe ~., data = train)

summary(model\_tree)

plot(model\_tree); text(model\_tree)

pred\_tree <- predict(model\_tree, test, type = 'class') # make prediction

conf\_tree <- confusionMatrix(test$classe, pred\_tree) # confusion matrix

conf\_tree

# CART

model\_cart <- rpart(classe ~ ., data = train)

summary(model\_cart)

rpart.plot::rpart.plot(model\_cart)

plotcp(model\_cart)

pred\_cart <- predict(model\_cart, test, type = 'class') # make prediction

conf\_cart <- confusionMatrix(test$classe, pred\_cart) # confusion matrix

conf\_cart

# CV

train\_control <- trainControl(method = "cv", number = 10)

model\_cv <- train(classe ~ ., data = train, trControl = train\_control, method = "rpart")

model\_cv

pred\_cv <- predict(model\_cv, test) # make prediction

conf\_cv <- confusionMatrix(test$classe, pred\_cv) # confusion matrix

conf\_cv

# Ross Quinlan C5.0

train\_control <- trainControl(method = "cv", number = 10)

model\_c5.0 <- train(classe ~ ., data = train, trControl = train\_control, method = "C5.0")

model\_c5.0

pred\_c5.0 <- predict(model\_c5.0, test) # make prediction

conf\_c5.0 <- confusionMatrix(test$classe, pred\_c5.0) # confusion matrix

conf\_c5.0

# Boosted Tree

train\_control <- trainControl(method = "cv", number = 10)

model\_bst <- train(classe ~ ., data = train, trControl = train\_control, method = "bstTree")

model\_bst

pred\_bst <- predict(model\_bst, test) # make prediction

conf\_bst <- confusionMatrix(test$classe, pred\_bst) # confusion matrix

conf\_bst

# C5.0 Rules

train\_control <- trainControl(method = "cv", number = 10)

model\_c5.0rules <- train(classe ~ ., data = train, trControl = train\_control, method = "C5.0Rules")

model\_c5.0rules

pred\_c5.0rules <- predict(model\_c5.0rules, test) # make prediction

conf\_c5.0rules <- confusionMatrix(test$classe, pred\_c5.0rules) # confusion matrix

conf\_c5.0rules

# C5.0 Tree

train\_control <- trainControl(method = "cv", number = 10)

model\_c5.0tree <- train(classe ~ ., data = train, trControl = train\_control, method = "C5.0Tree")

model\_c5.0tree

pred\_c5.0tree <- predict(model\_c5.0tree, test) # make prediction

conf\_c5.0tree <- confusionMatrix(test$classe, pred\_c5.0tree) # confusion matrix

conf\_c5.0tree

# conditional inference trees

# Ctree

train\_control <- trainControl(method = "cv", number = 10)

model\_ctree <- train(classe ~ ., data = train, trControl = train\_control, method = "ctree")

model\_ctree

pred\_ctree <- predict(model\_ctree, test) # make prediction

conf\_ctree <- confusionMatrix(test$classe, pred\_ctree) # confusion matrix

conf\_ctree

# Ctree2

train\_control <- trainControl(method = "cv", number = 10)

model\_ctree2 <- train(classe ~ ., data = train, trControl = train\_control, method = "ctree2")

model\_ctree2

pred\_ctree2 <- predict(model\_ctree2, test) # make prediction

conf\_ctree2 <- confusionMatrix(test$classe, pred\_ctree2) # confusion matrix

conf\_ctree2

# Random forest

model\_rf <- randomForest(classe ~., train, ntree = 500)

model\_rf

pred\_rf <- predict(model\_rf, test) # make prediction

conf\_rf <- confusionMatrix(test$classe, pred\_rf) # confusion matrix

conf\_rf

model <- c("model\_tree", "model\_cart", "model\_cv", "model\_c5.0 ", "model\_bst",

"model\_c5.0rules", "model\_c5.0tree", "model\_ctree", "model\_ctree2", "model\_rf")

#------------------------------------------------------------------------------------------

# b. Verify model goodness of fit.

chisq.test(table(test$classe), prop.table(table(pred\_tree))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_cart))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_cv))) # pv = 0.2414

chisq.test(table(test$classe), prop.table(table(pred\_c5.0))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_bst))) # pv = 0.2650

chisq.test(table(test$classe), prop.table(table(pred\_c5.0rules))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_c5.0tree))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_ctree))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_ctree2))) # pv = 0.2202

chisq.test(table(test$classe), prop.table(table(pred\_rf))) # pv = 0.2202

conf\_tree$overall[1]

conf\_cart$overall[1]

conf\_cv$overall[1]

conf\_c5.0$overall[1]

conf\_bst$overall[1]

conf\_c5.0rules$overall[1]

conf\_c5.0tree$overall[1]

conf\_ctree$overall[1]

conf\_ctree2$overall[1]

conf\_rf$overall[1]

#-----------------------------------------------------------------------------------------

# c. Apply all the model validation techniques.

# 1

train\_control <- trainControl(method = "cv", number = 10)

cvmodel1 <- train(classe ~ ., data = train, trControl = train\_control, method = "rf")

cvpred1 <- predict(cvmodel1, test) # make prediction

cvconf1 <- confusionMatrix(test$classe, pred\_ctree) # confusion matrix

cvconf1$overall[1] # accuracy

# default

set.seed(123)

train\_control <- trainControl(method = "repeatedcv", number = 10, repeats = 3)

rf\_default <- train(classe ~ ., data = train, trControl = train\_control, method = "rf",

metric = 'Accuracy', tuneGrid = expand.grid(.mtry = sqrt(ncol(train))))

pred\_rf\_default <- predict(rf\_default, test) # make prediction

conf\_rf\_default <- confusionMatrix(test$classe, pred\_rf\_default) # confusion matrix

conf\_rf\_default$overall[1] # accuracy

varImp(rf\_default) # var importance - 20

# random search for parameters

train\_control <- trainControl(method = "repeatedcv", number = 10, repeats = 3, search = 'random')

rf\_random <- train(classe ~ ., data = train, trControl = train\_control, method = "rf",

metric = 'Accuracy', tuneLength = 15)

pred\_rf\_random <- predict(rf\_random, test) # make prediction

conf\_rf\_random <- confusionMatrix(test$classe, pred\_rf\_random) # confusion matrix

conf\_rf\_random$overall[1] # accuracy

varImp(rf\_random) # var importance - 20

# Grid Search

train\_control <- trainControl(method = "repeatedcv", number = 10, repeats = 3, search = 'grid')

rf\_grid <- train(classe ~ ., data = train, trControl = train\_control, method = "rf",

metric = 'Accuracy', tuneGrid = expand.grid(.mtry=c(1:15)))

pred\_rf\_grid <- predict(rf\_grid, test) # make prediction

conf\_rf\_grid <- confusionMatrix(test$classe, pred\_rf\_grid) # confusion matrix

conf\_rf\_grid$overall[1] # accuracy

varImp(rf\_grid) # var importance - 20

# gradient boosting

train\_control <- trainControl(method = "repeatedcv", number = 5, repeats = 3, search = 'grid')

rf\_gbm <- train(classe ~ ., data = train, trControl = train\_control, method = "gbm",

metric = 'Accuracy')

print(rf\_gbm)

plot(rf\_gbm)

pred\_rf\_gbm <- predict(rf\_gbm, test) # make prediction

conf\_rf\_gbm <- confusionMatrix(test$classe, pred\_rf\_gbm) # confusion matrix

conf\_rf\_gbm$overall[1] # accuracy

summary(rf\_gbm) # var importance - 18

# ---------------------------------------------------------------------------------------

# d. Make conclusions

# Problem was to predict how well the activity is performed

# The target variable is the 5 classe; 1 accurate and 4 type of error

# occured during the activity

# error (target) detection was done by classifying an

# execution to one of the mistake classes

# we could detect mistakes fairly accurately

# Gradient bossting model is most accurate with less number of predictors

# Model is good fit and the Accuracy is 1

plot <- plot(conf\_rf$table, col = topo.colors(6))

# -------------------------------------------------------------------------------------