MODEL 1 SUPPORT VECTOR MACHINE

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```r
# Load Packages

library(dplyr)    # for data wrangling
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(readr)    #Load dataset
library(ggplot2)  # for awesome graphics
library(rsample)  # for data splitting
library(caret)    # for classification and regression training
```

```
## Loading required package: lattice
```

```r
library(kernlab)  # for fitting SVMs
```

```
##
## Attaching package: 'kernlab'

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

```r
library(modeldata) #for Failure.binary data
library(pdp)      # for partial dependence plots, etc.
library(vip)      # for variable importance plots
```

```
##
## Attaching package: 'vip'

## The following object is masked from 'package:utils':
##
##     vi
```

```r
library(forcats)
```

SUPPORT VECTOR MACHINE

Load the data set

The data frame output of data reprocessing converted into to "csv", which will be used for entire project.

```
dt <- read_csv("normalRad.CSV")
```

```
## Rows: 197 Columns: 431
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (1): Institution
## dbl (430): Failure.binary, Failure, Entropy_cooc.W.ADC, GLNU_align.H.PET, Mi...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
View(dt)
head(dt)
```

```
## # A tibble: 6 x 431
##   Institution Failure.~1 Failure Entro~2 GLNU_~3 Min_h~4 Max_h~5 Mean_~6 Varia~7
##   <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 A                    0   1.15     12.9  -0.433  -0.270 -0.257   -0.192  0.0509
## 2 A                    1  -0.533    12.2  -1.02    0.671  0.405    0.490  0.687
## 3 A                    0   2.24     12.8   0.179  -1.41  -1.57    -1.53  -1.57
## 4 A                    1  -0.140    13.5   2.00   -0.218  0.0764  -0.153  0.0127
## 5 A                    0   0.787    12.6   0.153  -1.06  -1.15    -1.45  -1.91
## 6 A                    1  -2.80     13.2   0.391  -1.57  -1.91    -1.72  -1.84
## # ... with 422 more variables: Standard_Deviation_hist.PET <dbl>,
## #   Skewness_hist.PET <dbl>, Kurtosis_hist.PET <dbl>, Energy_hist.PET <dbl>,
## #   Entropy_hist.PET <dbl>, AUC_hist.PET <dbl>, H_suv.PET <dbl>,
## #   Volume.PET <dbl>, X3D_surface.PET <dbl>, ratio_3ds_vol.PET <dbl>,
## #   ratio_3ds_vol_norm.PET <dbl>, irregularity.PET <dbl>,
## #   tumor_length.PET <dbl>, Compactness_v1.PET <dbl>, Compactness_v2.PET <dbl>,
## #   Spherical_disproportion.PET <dbl>, Sphericity.PET <dbl>, ...
```

```
# Load Failure.binary data

dt$Failure.binary=as.factor(dt$Failure.binary)
```

CREATING THE TRAINING (80%) AND TEST (20%) SETS

```
set.seed(123)  # for reproducibility

churn_split <- initial_split(dt, prop = 0.8, strata = "Failure.binary")
split_train <- training(churn_split)
split_test  <- testing(churn_split)
```

```
caret::getModelInfo("svmLinear")$svmLinear$parameters # Linear (i.e., soft margin classifier)
```

```
##   parameter   class label
## 1         C numeric  Cost
```

```
caret::getModelInfo("svmPoly")$svmPoly$parameters # Polynomial kernel
```

```
##   parameter   class             label
## 1    degree numeric Polynomial Degree
## 2     scale numeric             Scale
## 3         C numeric              Cost
```

```
caret::getModelInfo("svmRadial")$svmRadial$parameters # Radial basis kernel
```

```
##   parameter   class label
## 1     sigma numeric Sigma
## 2         C numeric  Cost
```

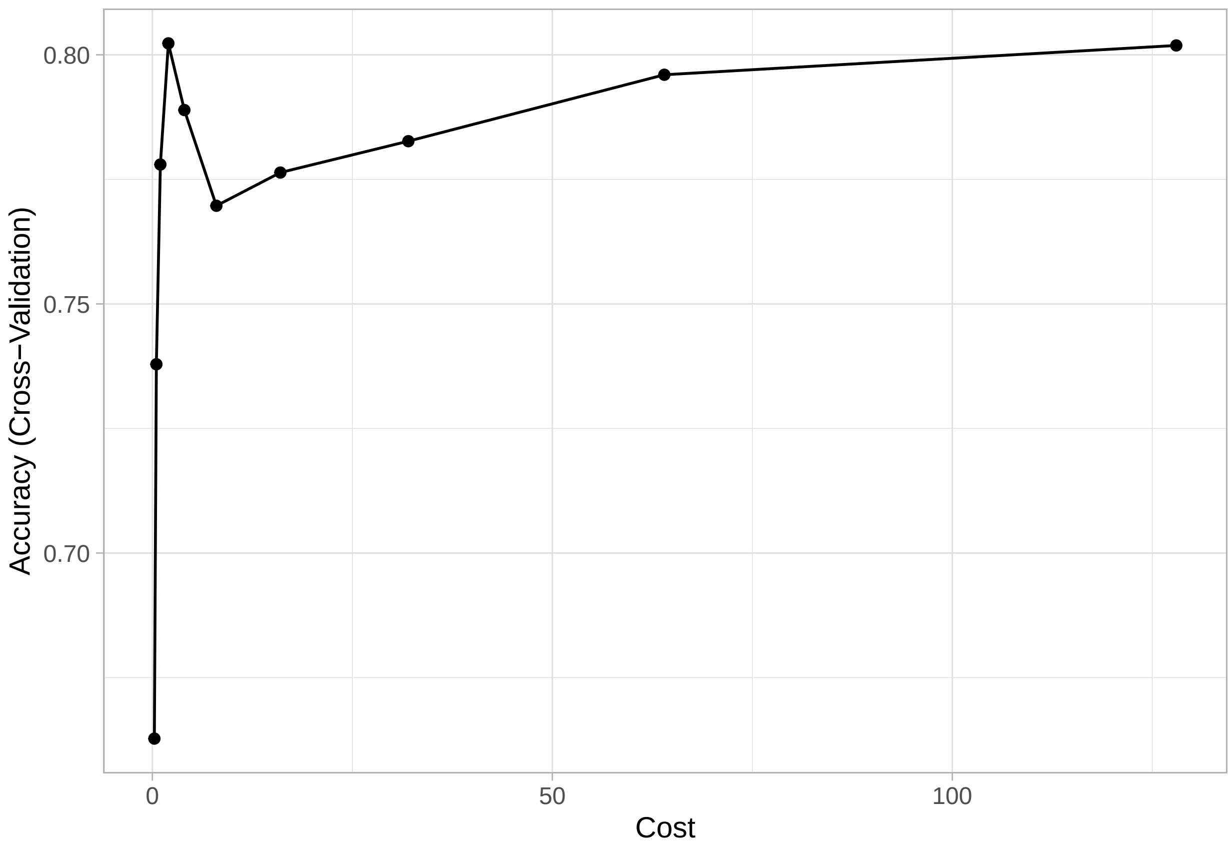
RUNNING SUPPORT VECTOR MACHINE MODEL IN TRAINING PHASE

Using **split__train**, we can tune an SVM model with radial basis kernel.

```
set.seed(1854)  # for reproducibility
split_svm <- train(
  Failure.binary ~ .,
  data = split_train,
  method = "svmRadial",
  preProcess = c("center", "scale"),
  trControl = trainControl(method = "cv", number = 10),
  tuneLength = 10
)
```

PLOT AND PRINT SVM MODEL WITH WITH RADIAL BASIS KERNEL.

```
# Plot results
ggplot(split_svm) + theme_light()
```



```
# Print results
split_svm$results
```

```
##          sigma      C  Accuracy     Kappa AccuracySD   KappaSD
## 1  0.001998749   0.25 0.6627451 0.0000000 0.01891300 0.0000000
## 2  0.001998749   0.50 0.7378922 0.2715440 0.06418046 0.2198366
## 3  0.001998749   1.00 0.7779902 0.4565954 0.07142465 0.1608304
## 4  0.001998749   2.00 0.8023039 0.5196491 0.09057479 0.2186000
## 5  0.001998749   4.00 0.7889216 0.5030643 0.07639949 0.1942976
## 6  0.001998749   8.00 0.7697059 0.4653629 0.07092559 0.1830668
## 7  0.001998749  16.00 0.7763725 0.4861127 0.06283611 0.1498343
## 8  0.001998749  32.00 0.7826716 0.4985015 0.07602914 0.1806382
## 9  0.001998749  64.00 0.7960049 0.5248585 0.07147503 0.1670975
## 10 0.001998749 128.00 0.8018873 0.5429164 0.08701199 0.2010434
```

CONTROLING PARAMETER

```
class.weights = c("No" = 1, "Yes" = 10)

# Control params for SVM
ctrl <- trainControl(
  method = "cv",
  number = 10,
  classProbs = TRUE,
  summaryFunction = twoClassSummary  # also needed for AUC/ROC
)

split_train$Failure.binary=fct_recode(split_train$Failure.binary,No="0",Yes="1")
```

PRINTING THE AUC VALUES DURING TRAINING

```
# Tune an SVM
set.seed(5628)  # for reproducibility
train_svm_auc <- train(
  Failure.binary ~ .,
  data = split_train,
  method = "svmRadial",
  preProcess = c("center", "scale"),
  metric = "ROC",  # area under ROC curve (AUC)
  trControl = ctrl,
  tuneLength = 10
)

# Print the results
train_svm_auc$results
```

```
##          sigma      C       ROC      Sens      Spec      ROCSD     SensSD
## 1  0.001697891   0.25 0.8102727 0.8445455 0.5033333 0.09982583 0.12592723
## 2  0.001697891   0.50 0.8102727 0.8536364 0.5033333 0.09982583 0.12708861
## 3  0.001697891   1.00 0.8323939 0.8827273 0.5233333 0.09919217 0.11244425
## 4  0.001697891   2.00 0.8520606 0.9036364 0.6033333 0.09942461 0.09988055
## 5  0.001697891   4.00 0.8582121 0.9236364 0.6366667 0.09545946 0.09679909
## 6  0.001697891   8.00 0.8729697 0.9427273 0.5766667 0.11486557 0.06542227
## 7  0.001697891  16.00 0.8901818 0.9327273 0.6366667 0.13222606 0.07892762
## 8  0.001697891  32.00 0.8830000 0.9418182 0.5933333 0.13402578 0.06886193
## 9  0.001697891  64.00 0.8812121 0.9418182 0.6133333 0.15158268 0.05019704
## 10 0.001697891 128.00 0.8659697 0.9236364 0.6133333 0.15790577 0.08454491
##       SpecSD
## 1  0.2224721
## 2  0.2224721
## 3  0.2403958
## 4  0.2157101
## 5  0.2235792
## 6  0.1937607
## 7  0.2027283
## 8  0.2968144
## 9  0.2563755
## 10 0.3182514
```

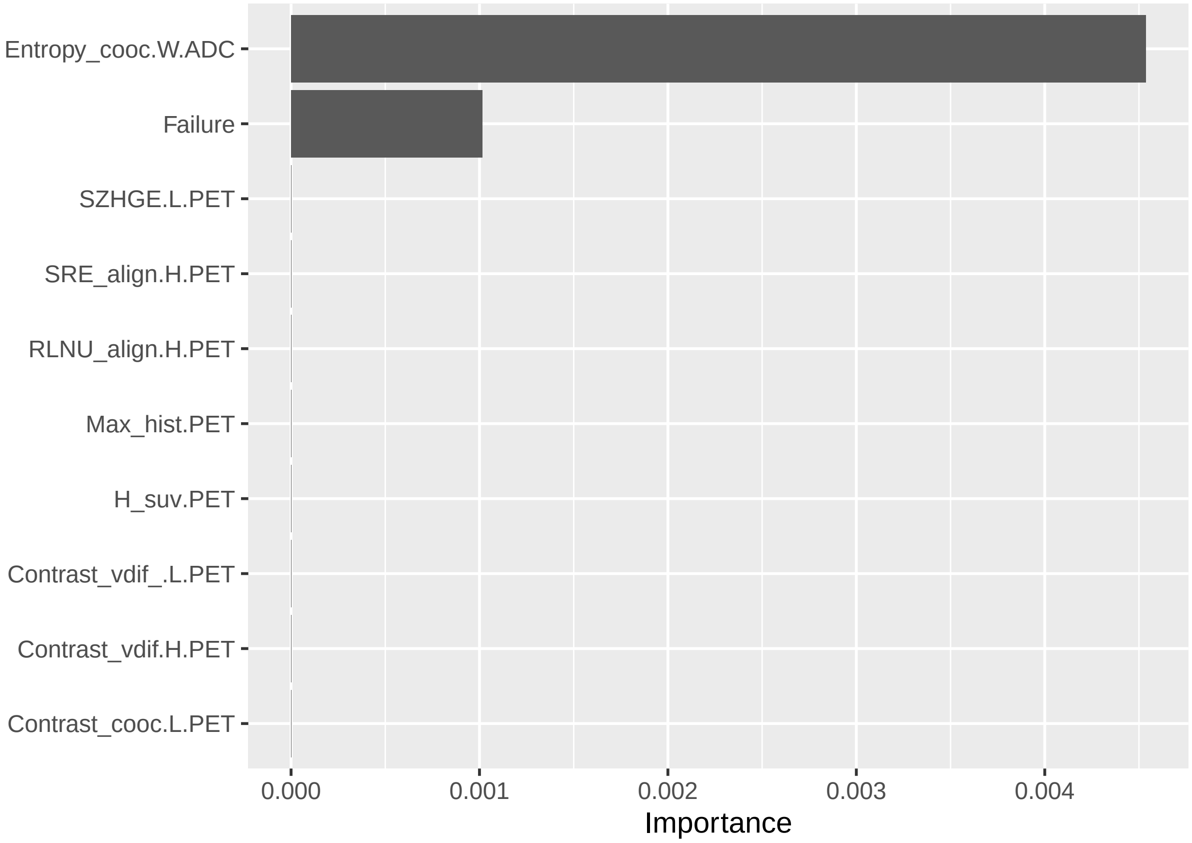
```
confusionMatrix(train_svm_auc)
```

```
## Cross-Validated (10 fold) Confusion Matrix
##
## (entries are percentual average cell counts across resamples)
##
##            Reference
## Prediction   No  Yes
##        No  61.8 12.1
##         Yes  4.5 21.7
##
##  Accuracy (average) : 0.8344
```

PRINTING THE TOP 20 IMPORTANT FEATURES DURING TRAINING

```
prob_yes <- function(object, newdata) {
  predict(object, newdata = newdata, type = "prob")[, "Yes"]
}

# Variable importance plot
set.seed(2827)  # for reproducibility
vip(train_svm_auc, method = "permute", nsim = 5, train = split_train,
    target = "Failure.binary", metric = "auc", reference_class = "Yes",
    pred_wrapper = prob_yes)
```



PRINTING THE AUC VALUES DURING TESTING

```
split_test$Failure.binary=fct_recode(split_test$Failure.binary,No="0",Yes="1")

# Tune an SVM with radial
set.seed(5628)  # for reproducibility
```

```
test_svm_auc <- train(
  Failure.binary ~ .,
  data = split_test,
  method = "svmRadial",
  preProcess = c("center", "scale"),
  metric = "ROC",  # area under ROC curve (AUC)
  trControl = ctrl,
  tuneLength = 10
)

# Printing the results
test_svm_auc$results
```

```
##          sigma      C       ROC      Sens Spec     ROCSD    SensSD SpecSD
## 1  0.001959001   0.25 0.6750000 0.9666667    0 0.2872013 0.1054093      0
## 2  0.001959001   0.50 0.5750000 0.9333333    0 0.3320577 0.1405457      0
## 3  0.001959001   1.00 0.6250000 1.0000000    0 0.3148829 0.0000000      0
## 4  0.001959001   2.00 0.3083333 0.9000000    0 0.3168372 0.2249829      0
## 5  0.001959001   4.00 0.3500000 0.9000000    0 0.4021547 0.2249829      0
## 6  0.001959001   8.00 0.3916667 0.9000000    0 0.3889881 0.2249829      0
## 7  0.001959001  16.00 0.3083333 0.9000000    0 0.3514740 0.2249829      0
## 8  0.001959001  32.00 0.4250000 0.8333333    0 0.3976202 0.2832789      0
## 9  0.001959001  64.00 0.3750000 0.9333333    0 0.3833937 0.1405457      0
## 10 0.001959001 128.00 0.4083333 0.8666667    0 0.3937200 0.2810913      0
```

```
confusionMatrix(test_svm_auc)
```

```
## Cross-Validated (10 fold) Confusion Matrix
##
## (entries are percentual average cell counts across resamples)
##
##            Reference
## Prediction   No  Yes
##        No  62.5 35.0
##        Yes  2.5  0.0
##
##  Accuracy (average) : 0.625
```