Model 1 Support Vector Machine

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Packages

```
##
## 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

## Warning: package 'ggplot2' was built under R version 4.2.2

## Warning: package 'rsample' was built under R version 4.2.2

## Loading required package: lattice

##
## Attaching package: 'kernlab'

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

##
## Attaching package: 'vip'

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

MODEL 1 SVM

Support Vector Machine (SVM) is a supervised learning technique that analyzes data and isolates patterns applicable to both classification and regression. The classifier is useful for choosing between two or more possible outcomes that depend on continuous or categorical predictor variables. Based on training and sample classification data, the SVM algorithm assigns the target data into any one of the given categories. The data is represented as points in space and categories are mapped in both linear and non-linear ways.

LOADING OF REPROCESSED DATASET

We used the reprocessed data of radiomics_complete.csv (*normalRad.csv*) in performing support vectore machine.

Radiomics Dataset 197 Rows (Observations) of 431 Columns (Variables) Failure.binary: binary property to predict
Normalized Dataset

```
radiomicsdat<- 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(radiomicsdt)
head(radiomicsdat)
```

```
## # 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

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

Create training (80%) and test (20%) sets

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

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

Classifiers

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

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

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

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

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

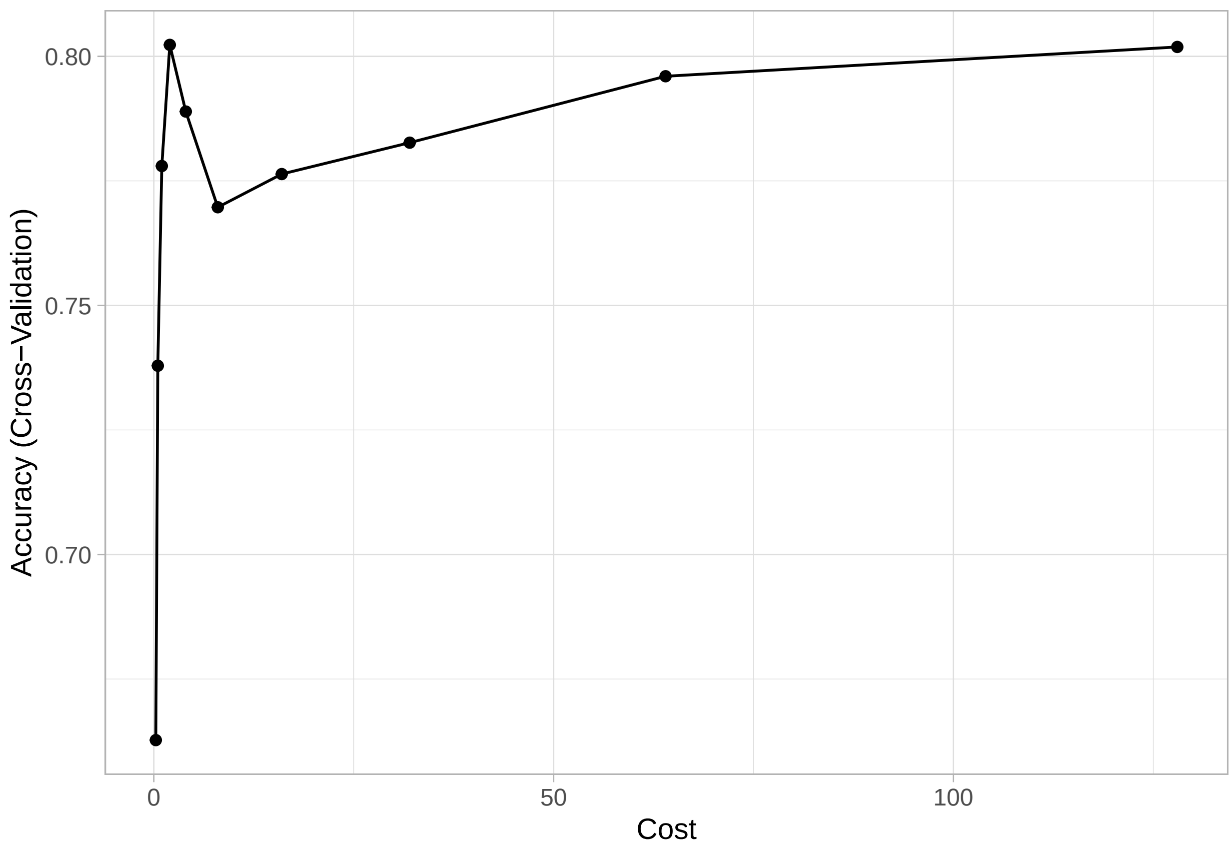
```
##   parameter   class label
## 1     sigma numeric Sigma
## 2         C numeric  Cost
```

Run SVM Model in the Training phase Using **split_train**, we can tune an SVM model with radial basis kernel.

```r
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.

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




```r
# 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
```

The accuracy of the model is **80.19%**
Control and train of parameters

```r
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")
```

Print 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 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)
```

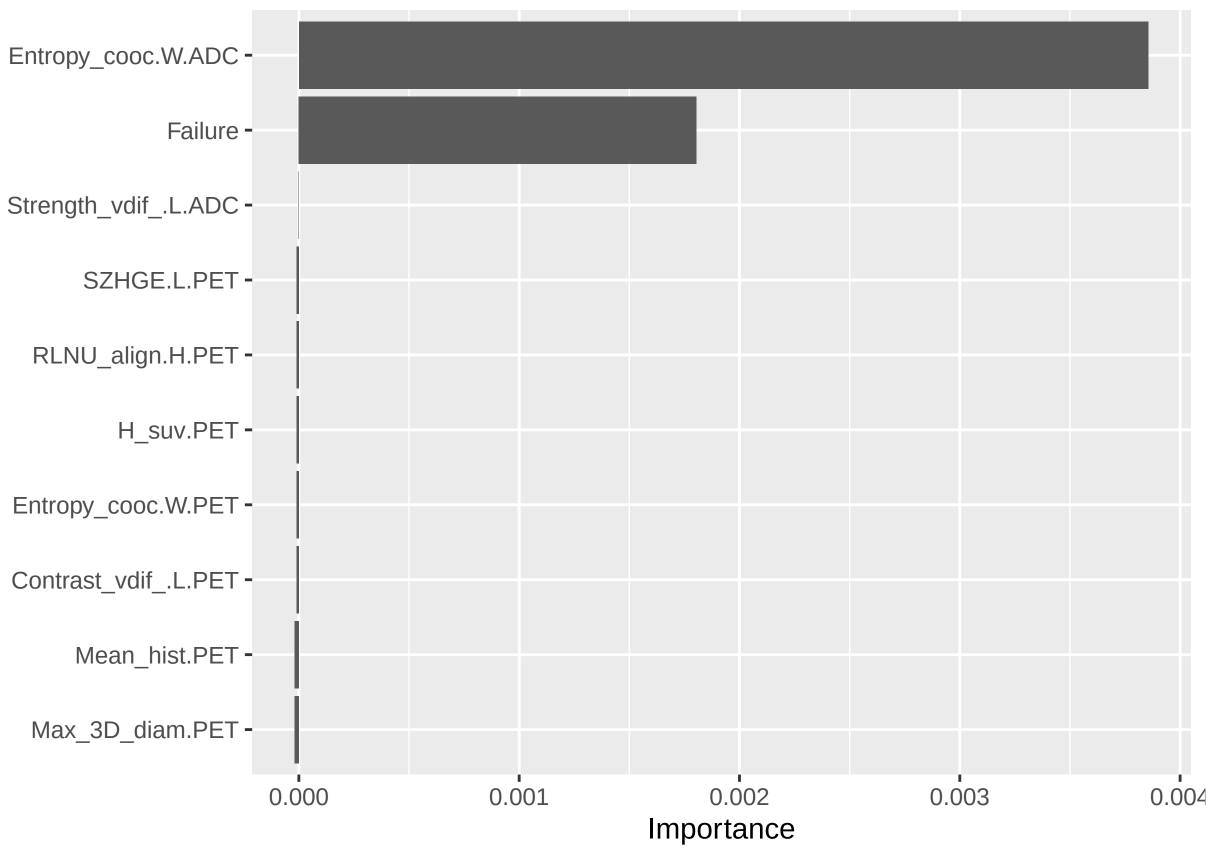
```
## Cross-Validated (10 fold) Confusion Matrix
##
## (entries are percentual average cell counts across resamples)
##
##           Reference
## Prediction   No  Yes
##        No  61.8 12.1
##        Yes  4.5 21.7
##
```

```
##  Accuracy (average) : 0.8344
```

On the average, the accuracy of the model is **83.44%**.
Print 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 = 20, train = split_train,
    target = "Failure.binary", metric = "auc", reference_class = "Yes",
    pred_wrapper = prob_yes)
```



Print 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
)

# Print 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
```

On the average, the accuracy of the model using the testing data is **62.5%**.