D698 Final Project

Coffy Andrews-Guo, Vyanna Hill

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```r
#Packages used
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.4     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.0
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(MLmetrics)
```

```
##
## Attaching package: 'MLmetrics'
##
## The following object is masked from 'package:base':
##
##     Recall
```

```r
library(ggpubr)
library(caret)
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following objects are masked from 'package:MLmetrics':
##
##     MAE, RMSE
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```r
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
##
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
library(caTools)
library(h2o)
```

```
##
## ----------------------------------------------------------------------
##
## Your next step is to start H2O:
##     > h2o.init()
##
## For H2O package documentation, ask for help:
##     > ??h2o
##
## After starting H2O, you can use the Web UI at http://localhost:54321
## For more information visit https://docs.h2o.ai
##
## ----------------------------------------------------------------------
##
##
## Attaching package: 'h2o'
##
## The following object is masked from 'package:pROC':
##
##     var
##
## The following objects are masked from 'package:lubridate':
##
##     day, hour, month, week, year
##
## The following objects are masked from 'package:stats':
##
##     cor, sd, var
##
## The following objects are masked from 'package:base':
##
##     %*%, %in%, &&, ||, apply, as.factor, as.numeric, colnames,
##     colnames<-, ifelse, is.character, is.factor, is.numeric, log,
##     log10, log1p, log2, round, signif, trunc
```

#Uploading data sets for combination

```
elevation<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/USGS_CACounties_elevation_2023 (1).cs
slope<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/SlopePercentage_Calitracts_LF2020.csv")
whp<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/WHP2020_ZipCode_Summary - zipcode_summary.c

weather<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/NOAA_CACounties_AverageTemp_2022.csv")
rainfall<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/NOAA_CACounties_AveragePercipitation_2

LF_Vegdictonary<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/LF22_EVT_230 - LF22_EVT_230.csv
cali_vegtype<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/CalifornianTracts_VegType_2022LF -
#combining the weather data set first as both on the county lvl. Only want the averages of the year
cali_cweather<-weather%>%left_join(rainfall,by=join_by(ID))
cali_cweather<-cali_cweather%>%select(-c("Rank.x","Anomaly (1901-2000 base period).x","1901-2000 Mean.x
cali_cweather<-cali_cweather%>%rename(county_Id=ID,county_name=Name.x,State=State.x,avg_tempeture=Value
```

#onto topographic data, will need to combine by county and lat/long(if possible) #Need the county ID in Slope data for left combine with elevation

```
cali_topography<-slope%>%unite("countyID",1:2,remove = FALSE,sep = "")
```

#14 rows missing slope data, can be zero slope but using mice for imputation

```
cali_topography<-cali_topography%>%rename(tract_avgSlope="_mean",tract_countSlope="_count",tract_maxSlop
cali_topography<-complete(mice(cali_topography,method = "cart",seed = 333))

elevation<-elevation%>%rename(countyID="County FIPS Code")
```

#mapping the tract data in topography by county ID and the closest match by Longitude

```
cali_topography<-cali_topography%>%inner_join(elevation,by=join_by(countyID,closest(INTPTLON<=Longitude)
```

#removing unnecessary metrics and renaming columns for readability

```
cali_topography<-cali_topography%>%select(-c("Latitude","Longitude","Bgn Decision Date","Entry Date","Co
cali_topography<-cali_topography%>%rename(tractID=NAME,land_Area=ALAND,water_Area=AWATER,latitude=INTPTL
```

#Using LandFire's vegetation type dictionary to map tract's average vegetation type #Filtering for CA tracts only

```
cali_vegetation<-cali_vegtype%>%filter(STUSPS=="CA")
lf_small<-LF_Vegdictonary%>%select("VALUE","EVT_NAME","EVT_LF","EVT_CLASS")
cali_vegetation<-cali_vegetation%>%left_join(lf_small,by=join_by(closest("_mean">=VALUE)))
```

#Cleaning up new data set

```
cali_vegetation<-cali_vegetation%>%select(-c("STATEFP","COUNTYFP","TRACTCE","AFFGEOID","NAME","NAMELSAD"
```

#Combing weather, topography, and vegetation

```r
cali_features<-cali_topography%>%left_join(cali_cweather,by=join_by(County==county_name))
cali_features<-cali_features%>%select(-c("county_Id","State"))
cali_vegetation<-cali_vegetation%>% mutate(GEOID = paste("0", GEOID, sep = ""))
```

#Census Tract 9901 does not have vegetation as it is the shoreline, replacing NAs with Water

```r
cali_features<-cali_features%>%left_join(cali_vegetation,by=join_by(GEOID))
cali_features<-cali_features%>%mutate(EVT_LF=replace_na(EVT_LF,"Water"))
```

#saving export

```r
write.csv(cali_features,"caliTracts_features.csv")
```

#Reducing predictors from NRI before the combination

```r
nri_data<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/NRI_Table_CensusTracts_Subset.csv")
nri<-nri_data%>%select("STATE","STATEABBRV","STATEFIPS","COUNTY","COUNTYTYPE","COUNTYFIPS","STCOFIPS","
```

#only CA cases, converting categorical to binary

```r
nri<-nri%>%filter(STATEABBRV=="CA")
nri<-nri%>%mutate(WFRI_R=case_when(WFIR_RISKV<13000~0,WFIR_RISKV>13000~1))
```

#Removal of extra columns

```r
nri<-nri%>%select(-c(WFIR_EVNTS,WFIR_HLRR,WFIR_EALR))
```

#combination of cali features

```r
cali_features<-read_csv("C:/Users/walki/Documents/GitHub/D698/Datasets/caliTracts_features.csv")

nri_cali<-nri%>%inner_join(cali_features,by=join_by(TRACTFIPS==GEOID))
nri_cali<-nri_cali%>%select(-c(STATE,STATEABBRV,STATEFIPS,COUNTY,COUNTYTYPE,COUNTYFIPS,STCOFIPS,TRACT,.
```

#renaming columns for reference

```r
nri_cali<-nri_cali%>%rename(TRCT_WAREA=water_Area,TRCT_SLOPE=tract_avgSlope,CNTY_ELEV=county_avgElevati

write.csv(nri_cali,"nri_cali.csv")
```

###Data Exploration ##using nri.cali Dataset

```r
cali_data<-read_csv("C:/Users/walki/Documents/GitHub/D698/nri_cali.csv")
```

```
## New names:
## Rows: 9098 Columns: 34
## -- Column specification
## -------------------------------------------------------- Delimiter: "," chr
## (2): TRACTFIPS, TRCT_VEGLF dbl (32): ...1, POPULATION, AREA, DRGT_EVNTS,
## DRGT_AFREQ, DRGT_HLRA, HWAV_EV...
## 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.
## * ‘‘ -> ‘...1‘
```

#Removing non important columns #Note: WFIR_RISKS AND WFIR_RISV holds actual percentages of the likelihood, cannot be included as predictor value

```
c_data<-cali_data%>%select(-c("...1","WFIR_RISKV","WFIR_RISKS","WFIR_HLRB"))
```

#Looking at the summary of all variables in the data set

```
summary(c_data)
```

```
##   TRACTFIPS           POPULATION         AREA             DRGT_EVNTS
##  Length:9098        Min.   :    0    Min.   :   0.008    Min.   :   0
##  Class :character   1st Qu.: 3209    1st Qu.:   0.379    1st Qu.:1148
##  Mode  :character   Median : 4194    Median :   0.693    Median :1372
##                     Mean   : 4340    Mean   :  16.190    Mean   :1330
##                     3rd Qu.: 5350    3rd Qu.:   1.644    3rd Qu.:1624
##                     Max.   :37562    Max.   :7024.460    Max.   :2261
##    DRGT_AFREQ       DRGT_HLRA          HWAV_EVNTS        HWAV_AFREQ
##  Min.   :  0.00   Min.   :0.0000121   Min.   :  0.00   Min.   : 0.000
##  1st Qu.: 52.18   1st Qu.:0.0000121   1st Qu.: 20.94   1st Qu.: 1.357
##  Median : 62.36   Median :0.0000121   Median : 35.00   Median : 2.167
##  Mean   : 60.47   Mean   :0.0006693   Mean   : 41.07   Mean   : 2.550
##  3rd Qu.: 73.82   3rd Qu.:0.0016279   3rd Qu.: 66.85   3rd Qu.: 4.139
##  Max.   :102.77   Max.   :0.0036879   Max.   :240.00   Max.   :14.861
##    HWAV_HLRA          LTNG_EVNTS       LTNG_AFREQ         SWND_EVNTS
##  Min.   :8.000e-10   Min.   :  0.0   Min.   : 0.0000   Min.   : 0.000
##  1st Qu.:4.569e-05   1st Qu.: 12.0   1st Qu.: 0.5254   1st Qu.: 2.000
##  Median :7.618e-05   Median : 17.0   Median : 0.7727   Median : 5.000
##  Mean   :7.297e-05   Mean   : 21.6   Mean   : 0.9761   Mean   : 4.387
##  3rd Qu.:1.057e-04   3rd Qu.: 24.0   3rd Qu.: 1.0909   3rd Qu.: 6.000
##  Max.   :2.357e-04   Max.   :302.0   Max.   :13.7060   Max.   :11.000
##    SWND_AFREQ        SWND_HLRA           WFIR_AFREQ          WFIR_EXPA
##  Min.   :0.00000   Min.   :3.030e-08   Min.   :0.000000   Min.   :        0
##  1st Qu.:0.02971   1st Qu.:1.078e-06   1st Qu.:0.000000   1st Qu.:        0
##  Median :0.13369   Median :1.766e-06   Median :0.000000   Median :        0
##  Mean   :0.11547   Mean   :2.775e-05   Mean   :0.002021   Mean   :   563272
##  3rd Qu.:0.17430   3rd Qu.:2.114e-05   3rd Qu.:0.001067   3rd Qu.:        0
##  Max.   :1.46035   Max.   :8.467e-04   Max.   :0.063501   Max.   :258377478
##    WFIR_EXPT          WFIR_EXP_AREA        WFIR_HLRP            WFIR_HLRA
##  Min.   :0.000e+00   Min.   : 0.00000   Min.   :1.784e-06   Min.   :4.620e-07
##  1st Qu.:0.000e+00   1st Qu.: 0.00000   1st Qu.:6.677e-06   1st Qu.:6.600e-07
##  Median :0.000e+00   Median : 0.00000   Median :1.960e-05   Median :8.470e-07
##  Mean   :1.903e+09   Mean   : 0.15782   Mean   :4.423e-05   Mean   :9.784e-04
##  3rd Qu.:1.102e+09   3rd Qu.: 0.02316   3rd Qu.:1.973e-05   3rd Qu.:5.797e-05
##  Max.   :8.390e+10   Max.   :31.74707   Max.   :9.962e-04   Max.   :2.701e-02
##    WFIR_EALT          WFIR_EALS         WFIR_ALRA            WFRI_R
##  Min.   :       0   Min.   :  0.00   Min.   :0.000e+00   Min.   :0.0000
##  1st Qu.:       0   1st Qu.:  0.00   1st Qu.:0.000e+00   1st Qu.:0.0000
##  Median :       0   Median :  0.00   Median :0.000e+00   Median :0.0000
##  Mean   :  152785   Mean   : 29.78   Mean   :7.176e-07   Mean   :0.2071
##  3rd Qu.:    2518   3rd Qu.: 76.73   3rd Qu.:0.000e+00   3rd Qu.:0.0000
##  Max.   :29548172   Max.   :100.00   Max.   :1.377e-04   Max.   :1.0000
##    TRCT_WAREA          TRCT_SLOPE        CNTY_ELEV         CNTY_TEMP
##  Min.   :0.000e+00   Min.   :0.0000   Min.   : -84.0   Min.   :45.50
```

```
##  1st Qu.:0.000e+00   1st Qu.:0.4167   1st Qu.:  27.0   1st Qu.:60.50
##  Median :0.000e+00   Median :0.7900   Median :  96.0   Median :63.70
##  Mean   :8.072e+05   Mean   :1.6222   Mean   : 193.9   Mean   :62.85
##  3rd Qu.:4.108e+03   3rd Qu.:2.4142   3rd Qu.: 234.0   3rd Qu.:64.20
##  Max.   :1.098e+09   Max.   :9.0156   Max.   :2534.0   Max.   :75.50
##   CNTY_PRECIP     TRCT_VEGLF
##  Min.   : 2.17   Length:9098
##  1st Qu.: 7.64   Class :character
##  Median : 8.64   Mode  :character
##  Mean   :11.04
##  3rd Qu.:13.45
##  Max.   :52.90
```

#checking for null values

```
colSums(is.na(c_data))
```

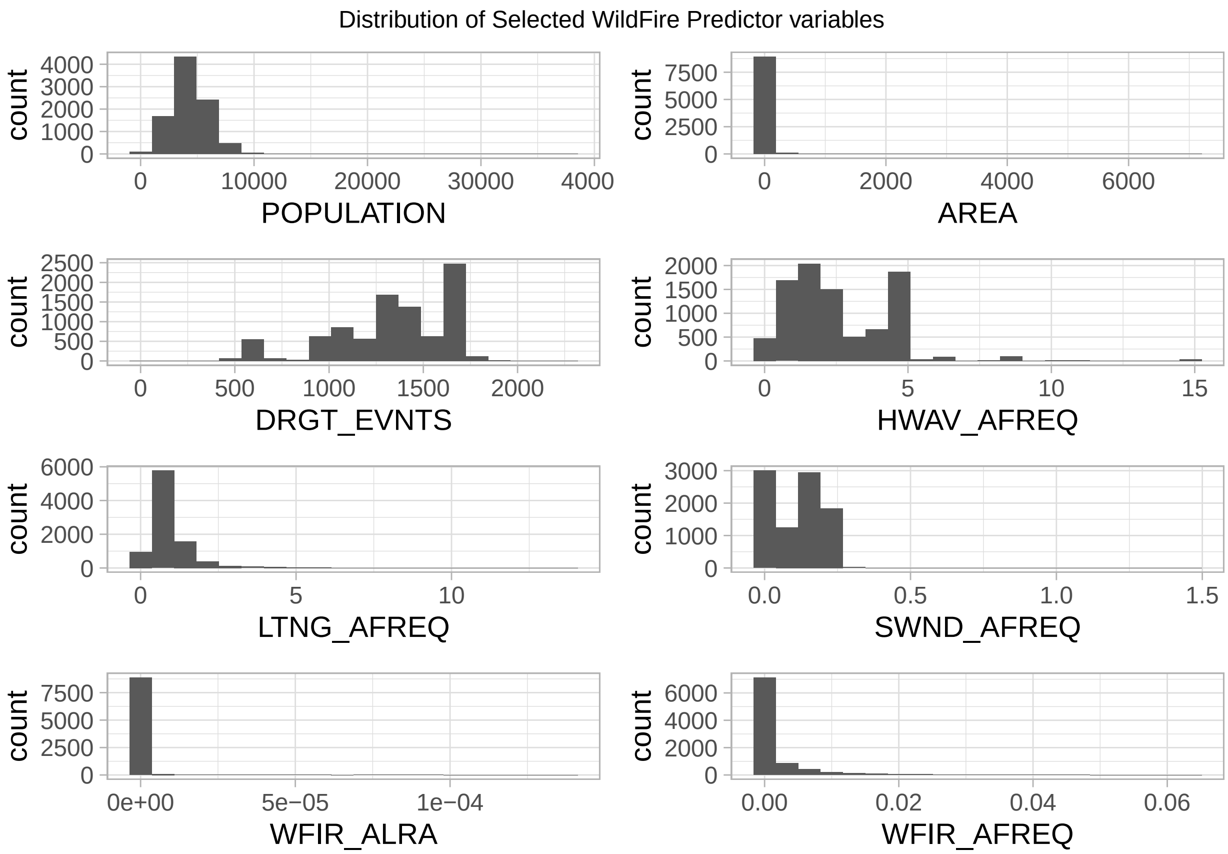
```
##     TRACTFIPS    POPULATION          AREA    DRGT_EVNTS    DRGT_AFREQ
##             0             0             0             0             0
##     DRGT_HLRA    HWAV_EVNTS    HWAV_AFREQ     HWAV_HLRA    LTNG_EVNTS
##             0             0             0             0             0
##    LTNG_AFREQ    SWND_EVNTS    SWND_AFREQ     SWND_HLRA    WFIR_AFREQ
##             0             0             0             0             0
##     WFIR_EXPA     WFIR_EXPT WFIR_EXP_AREA     WFIR_HLRP     WFIR_HLRA
##             0             0             0             0             0
##     WFIR_EALT     WFIR_EALS     WFIR_ALRA        WFRI_R    TRCT_WAREA
##             0             0             0             0             0
##    TRCT_SLOPE     CNTY_ELEV     CNTY_TEMP   CNTY_PRECIP    TRCT_VEGLF
##             0             0             0             0             0
```

#Reviewing the current distribution of the predictor values. See if there's future transformations

```
g1<-c_data%>%ggplot(aes(x=POPULATION))+geom_histogram(bins=20)+theme_light()
g2<-c_data%>%ggplot(aes(x=AREA))+geom_histogram(bins=20)+theme_light()
g3<-c_data%>%ggplot(aes(x=DRGT_EVNTS))+geom_histogram(bins=20)+theme_light()
g4<-c_data%>%ggplot(aes(x=HWAV_AFREQ))+geom_histogram(bins=20)+theme_light()
g7<-c_data%>%ggplot(aes(x=WFIR_AFREQ))+geom_histogram(bins=20)+theme_light()
g10<-c_data%>%ggplot(aes(x=WFIR_ALRA))+geom_histogram(bins=20)+theme_light()
g14<-c_data%>%ggplot(aes(x=LTNG_AFREQ))+geom_histogram(bins=20)+theme_light()
g22<-c_data%>%ggplot(aes(x=SWND_AFREQ))+geom_histogram(bins=20)+theme_light()
```

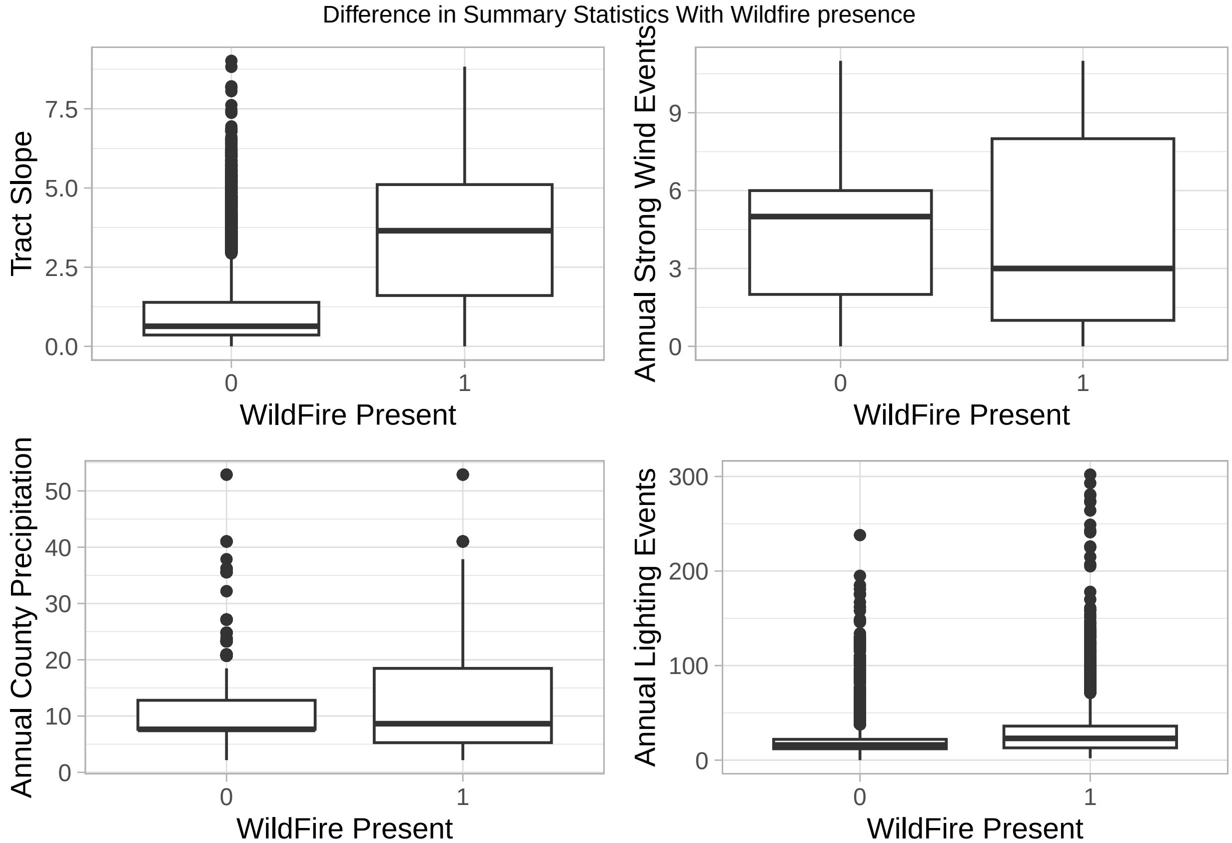
#Plot for project write up, only a selected few

```
plt1<-ggarrange(g1,g2,g3,g4,g14,g22,g10,g7,nrow =4,ncol =2,align="h",heights = 2,font.label = list(size

annotate_figure(plt1,top = text_grob("Distribution of Selected WildFire Predictor variables ",size=9))
```



#Reviewing a few variables on its boxplots in reflection with the response variable WFRI_R

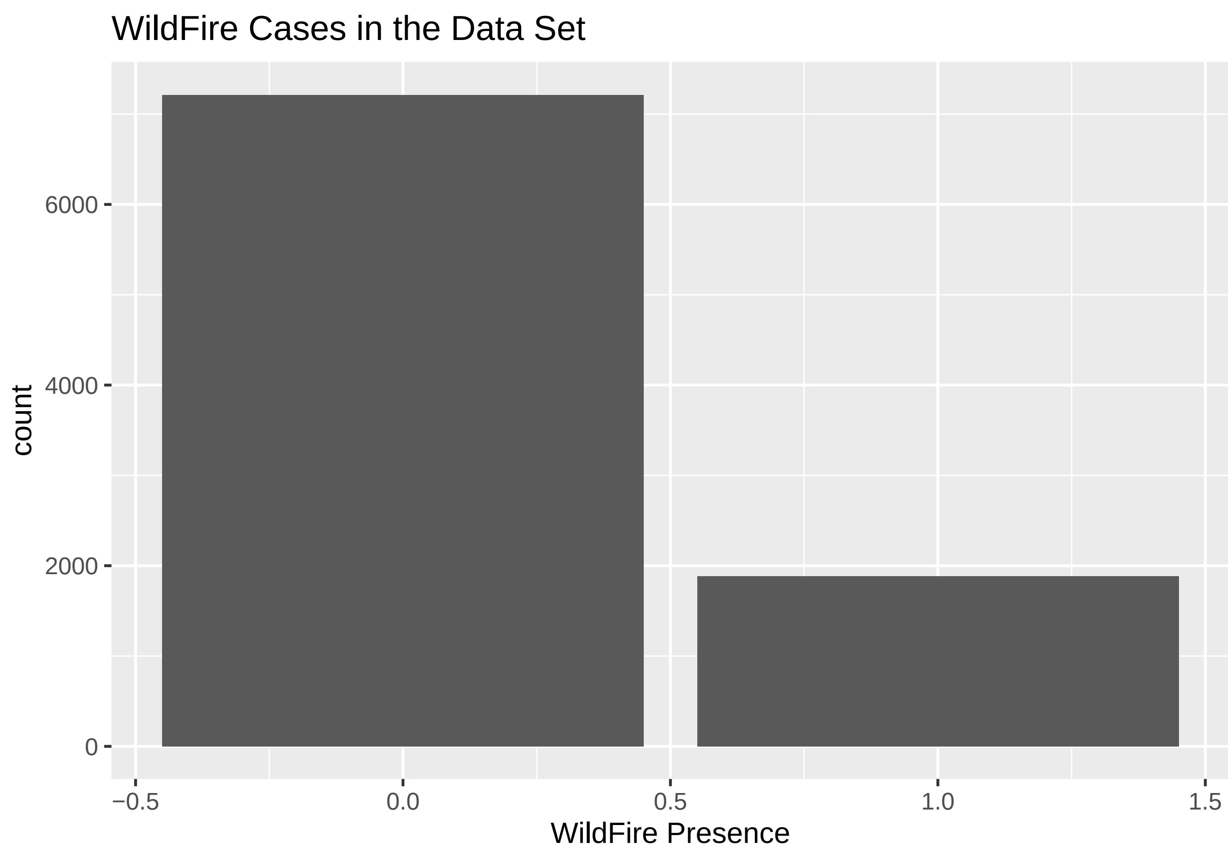
```
g1<-c_data%>%ggplot(aes(y=TRCT_SLOPE,x=factor(WFRI_R)))+geom_boxplot()+theme_light()+labs(x="WildFire Pr
g2<-c_data%>%ggplot(aes(y=SWND_EVNTS,x=factor(WFRI_R)))+geom_boxplot()+theme_light()+labs(x="WildFire Pr
g3<-c_data%>%ggplot(aes(y=CNTY_PRECIP,x=factor(WFRI_R)))+geom_boxplot()+theme_light()+labs(x="WildFire P
g4<-c_data%>%ggplot(aes(y=LTNG_EVNTS,x=factor(WFRI_R)))+geom_boxplot()+theme_light()+labs(x="WildFire Pr

plt1<-ggarrange(g1,g2,g3,g4,nrow =2,ncol =2,align="h",heights = 2,font.label = list(size =3, color = "bl

annotate_figure(plt1,top = text_grob("Difference in Summary Statistics With Wildfire presence",size=9))
```



#Checking if the data set is imbalanced

```
c_data%>%ggplot(aes(fill=WFRI_R))+geom_bar(aes(x=WFRI_R))+labs(title="WildFire Cases in the Data Set",x=
```

```
## Warning: The following aesthetics were dropped during statistical transformation: fill
## i This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## i Did you forget to specify a 'group' aesthetic or to convert a numerical
##   variable into a factor?
```



###Data Preparation

#transforming the tract vegetation life into binary dummy variables via mutate

```
unique(c_data$TRCT_VEGLF)
```

```
## [1] "Shrub"       "Tree"        "Developed"   "Herb"        "Agriculture"
## [6] "Sparse"      "Barren"      "Snow-Ice"    "Water"
```

```
c_data<-c_data%>%mutate(.isShrub=if_else(TRCT_VEGLF=="Shrub",1,0),
                        .isTree=if_else(TRCT_VEGLF=="Tree",1,0),
                        .isDeveloped=if_else(TRCT_VEGLF=="Developed",1,0),
                        .isHerb=if_else(TRCT_VEGLF=="Herb",1,0),
                        .isArgiculture=if_else(TRCT_VEGLF=="Argiculture",1,0),
                        .isSparse=if_else(TRCT_VEGLF=="Sparse",1,0),
                        .isBarren=if_else(TRCT_VEGLF=="Barren",1,0),
                        .isSnowIce=if_else(TRCT_VEGLF=="Snow-Ice",1,0),
                        )
c_data<-c_data%>%select(-c("TRCT_VEGLF"))
```

#Seeing if there's multi-collinearity in the current predictors #Drought events and drought frequency are highly correlated, Let's see with variable selection if one of the variables is dropped from the optimized predictor set

```
temp<-c_data%>%select(-c("WFRI_R","TRACTFIPS"))
temp<-cor(temp)
```

```
## Warning in stats::cor(x, ...): the standard deviation is zero
```

#setting the binary response and a few predictor variables as a factor before modeling

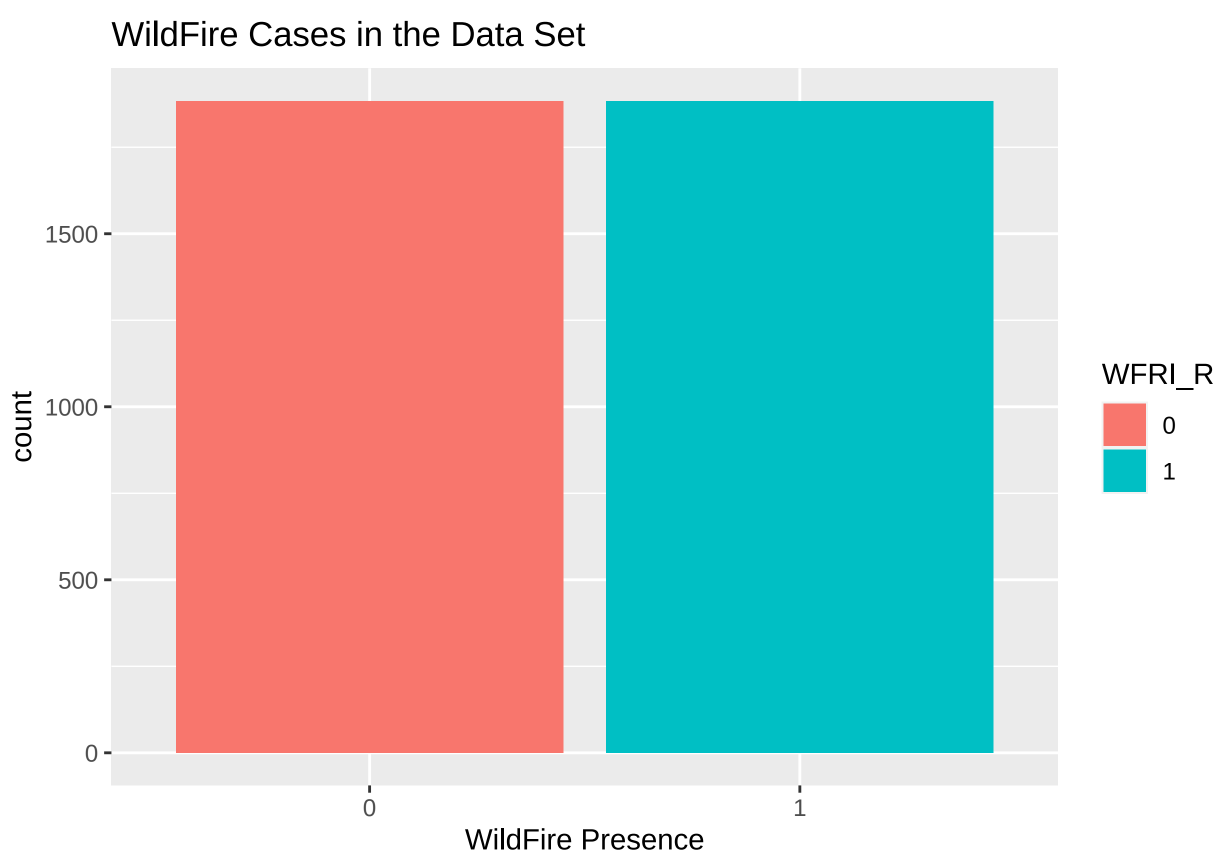
```
c_data<-c_data%>%mutate_at(c('WFRI_R',".isShrub",".isTree",".isDeveloped",".isHerb",".isArgiculture",".
```

#Downsampling the non wildfire cases so the models can predict more fire cases

```
dwn_data<-downSample(x=c_data[,-ncol(c_data)],y=c_data$WFRI_R)
```

#Seeing new distribution

```
dwn_data%>%ggplot(aes(fill=WFRI_R))+geom_bar(aes(x=WFRI_R))+labs(title="WildFire Cases in the Data Set"
```



#splitting data set into testing and training

```
temp<-sample.split(dwn_data$WFRI_R,SplitRatio = 0.7)
training_data<-subset(dwn_data,temp==TRUE)
test_data<-subset(dwn_data,temp==FALSE)
```

```r
names(test_data)
```

```
##  [1] "TRACTFIPS"      "POPULATION"     "AREA"           "DRGT_EVNTS"
##  [5] "DRGT_AFREQ"     "DRGT_HLRA"      "HWAV_EVNTS"     "HWAV_AFREQ"
##  [9] "HWAV_HLRA"      "LTNG_EVNTS"     "LTNG_AFREQ"     "SWND_EVNTS"
## [13] "SWND_AFREQ"     "SWND_HLRA"      "WFIR_AFREQ"     "WFIR_EXPA"
## [17] "WFIR_EXPT"      "WFIR_EXP_AREA"  "WFIR_HLRP"      "WFIR_HLRA"
## [21] "WFIR_EALT"      "WFIR_EALS"      "WFIR_ALRA"      "WFRI_R"
## [25] "TRCT_WAREA"     "TRCT_SLOPE"     "CNTY_ELEV"      "CNTY_TEMP"
## [29] "CNTY_PRECIP"    ".isShrub"       ".isTree"        ".isDeveloped"
## [33] ".isHerb"        ".isArgiculture" ".isSparse"      ".isBarren"
## [37] "Class"
```

```r
x_traindata <- setdiff(names(training_data), c("WFRI_R"))
names(training_data)
```

```
##  [1] "TRACTFIPS"      "POPULATION"     "AREA"           "DRGT_EVNTS"
##  [5] "DRGT_AFREQ"     "DRGT_HLRA"      "HWAV_EVNTS"     "HWAV_AFREQ"
##  [9] "HWAV_HLRA"      "LTNG_EVNTS"     "LTNG_AFREQ"     "SWND_EVNTS"
## [13] "SWND_AFREQ"     "SWND_HLRA"      "WFIR_AFREQ"     "WFIR_EXPA"
## [17] "WFIR_EXPT"      "WFIR_EXP_AREA"  "WFIR_HLRP"      "WFIR_HLRA"
## [21] "WFIR_EALT"      "WFIR_EALS"      "WFIR_ALRA"      "WFRI_R"
## [25] "TRCT_WAREA"     "TRCT_SLOPE"     "CNTY_ELEV"      "CNTY_TEMP"
## [29] "CNTY_PRECIP"    ".isShrub"       ".isTree"        ".isDeveloped"
## [33] ".isHerb"        ".isArgiculture" ".isSparse"      ".isBarren"
## [37] "Class"
```

Data Analysis

#connection to h20 server

```r
h2o.init()
```

```
##  Connection successful!
##
## R is connected to the H2O cluster:
##     H2O cluster uptime:         16 minutes 6 seconds
##     H2O cluster timezone:       America/New_York
##     H2O data parsing timezone:  UTC
##     H2O cluster version:        3.42.0.2
##     H2O cluster version age:    4 months and 10 days
##     H2O cluster name:           H2O_started_from_R_walki_kmz484
##     H2O cluster total nodes:    1
##     H2O cluster total memory:   3.41 GB
##     H2O cluster total cores:    8
##     H2O cluster allowed cores:  8
##     H2O cluster healthy:        TRUE
##     H2O Connection ip:          localhost
##     H2O Connection port:        54321
##     H2O Connection proxy:       NA
##     H2O Internal Security:      FALSE
##     R Version:                  R version 4.1.2 (2021-11-01)
```

```
## Warning in h2o.clusterInfo():
## Your H2O cluster version is (4 months and 10 days) old. There may be a newer version available.
## Please download and install the latest version from: https://h2o-release.s3.amazonaws.com/h2o/latest_
```

#Uploading the data set into h2o and splitting the data set into training/test. Choosing a 70/30 split and splitting testing for a validation test

```
train.h2o<-as.h2o(training_data)
```

```
##   |                                                                                |
```

```
test.h2o<-as.h2o(test_data)
```

```
##   |                                                                                |
```

#Model 1| Random Forest

```
#removed wildfire exposure features it's possibly tied to the  likelihood response(,"WFIR_EXPA","WFIR_E
features<-c("POPULATION","AREA","DRGT_AFREQ","DRGT_HLRA","HWAV_EVNTS","HWAV_AFREQ","HWAV_HLRA","LTNG_EV
response<-c("WFRI_R")
```

##Version 1 of Random Forest

```
#V1: Stopping metrics based on AUC score as preventing for overfitting and added Cross-validation with 
rf.model<-h2o.randomForest(x = features, y =response , training_frame = train.h2o, stopping_rounds = 5,
```

```
##   |                                                                                |
```

```
#see the first version of the tree structure
rf.model@model$model_summary
```

```
#look at cross-validation results from the model, Not much difference between cases
rf.cross<-rf.model@model$cross_validation_metrics_summary%>%select(-c(mean,sd))
#rf.cross
```

```
#review the feature importance of this random forest model and using the highest gini indexes in the fi
rf.features<-h2o.varimp(rf.model)
features_v2<-rf.features$variable[1:10]%>%as.vector()
```

##Version 2| RF

```
#Shortening max depth and trees for more conservative AUC. Applying highest gini index features to the 
rf.v2<-h2o.randomForest(x = features_v2, y =response , training_frame = train.h2o, stopping_rounds = 5,
```

```
##   |                                                                                |
```

RF Verison 2 - Model Performance

```r
rf2_perf <- h2o.performance(rf.v2, test.h2o)
rf2_perf
```

```
## H2OBinomialMetrics: drf
##
## MSE:  0.03868792
## RMSE:  0.1966925
## LogLoss:  0.1467657
## Mean Per-Class Error:  0.04424779
## AUC:  0.9882356
## AUCPR:  0.9863941
## Gini:  0.9764711
## R^2:  0.8452483
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          0   1    Error      Rate
## 0      524  41 0.072566   =41/565
## 1        9 556 0.015929    =9/565
## Totals 533 597 0.044248  =50/1130
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold      value idx
## 1                       max f1  0.532212   0.956971 259
## 2                       max f2  0.485115   0.976290 269
## 3                 max f0point5  0.720246   0.957605 209
## 4                 max accuracy  0.532212   0.955752 259
## 5                max precision  0.998871   1.000000   0
## 6                   max recall  0.128207   1.000000 302
## 7              max specificity  0.998871   1.000000   0
## 8             max absolute_mcc  0.532212   0.912970 259
## 9   max min_per_class_accuracy  0.653353   0.948673 230
## 10 max mean_per_class_accuracy  0.532212   0.955752 259
## 11                     max tns  0.998871 565.000000   0
## 12                     max fns  0.998871 562.000000   0
## 13                     max fps  0.007579 565.000000 399
## 14                     max tps  0.128207 565.000000 302
## 15                     max tnr  0.998871   1.000000   0
## 16                     max fnr  0.998871   0.994690   0
## 17                     max fpr  0.007579   1.000000 399
## 18                     max tpr  0.128207   1.000000 302
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

```r
rf2_pred <- h2o.predict(rf.v2,test.h2o)
```

```
##   |                                                                                |
```

```r
pred1 <- as.data.frame(rf2_pred$predict)
pred1$predict <- factor(pred1$predict, levels = c(0, 1))
mean(pred1$predict==test_data$WFRI_R)
```

```
## [1] 0.9495575
```

```r
#plotting logloss of the revised model
plot(rf.v2)
```

RF Version2 - Predictions

```r
#from the revised model, pull results from prediction against test set
rf.pred<-h2o.predict(rf.v2,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                              |
```

```r
rf.precsnprob<-h2o.predict(rf.v2,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                              |
```

```r
rf.reclprob<-h2o.predict(rf.v2,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                              |
```

RF Version 2 - confusion matrix of rf predictions

```r
rf.con<-confusionMatrix(rf.pred,test_data$WFRI_R,positive = "1",mode = "prec_recall")

rf.con
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 531  23
##          1  34 542
##
##                Accuracy : 0.9496
##                  95% CI : (0.9351, 0.9616)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.8991
##
##  Mcnemar's Test P-Value : 0.1853
##
##               Precision : 0.9410
##                  Recall : 0.9593
##                      F1 : 0.9500
##              Prevalence : 0.5000
##          Detection Rate : 0.4796
##    Detection Prevalence : 0.5097
##       Balanced Accuracy : 0.9496
##
##        'Positive' Class : 1
##
```

RF Version 2 - storing confusion matrix results

```
confusionM<-rf.con$byClass%>%as.data.frame()%>%t()
confusionM<-as.data.frame(confusionM)
confusionM<-confusionM%>%rename(Pos_pred_value="Pos Pred Value",Neg_Pred_value="Neg Pred Value",Detecti
#confusionM
```

#creating a reference table w/ predicted probabilities, actual, and predictions all in one #see summary results of random forest model on the test data

```
rf.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-rf.pred,
      N<-rf.reclprob,
      Y<-rf.precsnprob
  )

rf.summary<-rf.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....rf.pred", N="N....rf.reclpr

rf.auc<-roc(rf.summary$obs,Y)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
test.results<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(rf.summary$pred)),y_true =as.numeric(as.character( rf
  t.mse<-MSE(as.numeric(as.character(rf.summary$pred)),as.numeric(as.character(rf.summary$obs))),
  t.RSME<-RMSE(as.numeric(as.character(rf.summary$pred)),as.numeric(as.character(rf.summary$obs))),
  t.AUC<-rf.auc$auc,
  t.ClassError<-mean(rf.summary$pred!=rf.summary$obs)

)
```

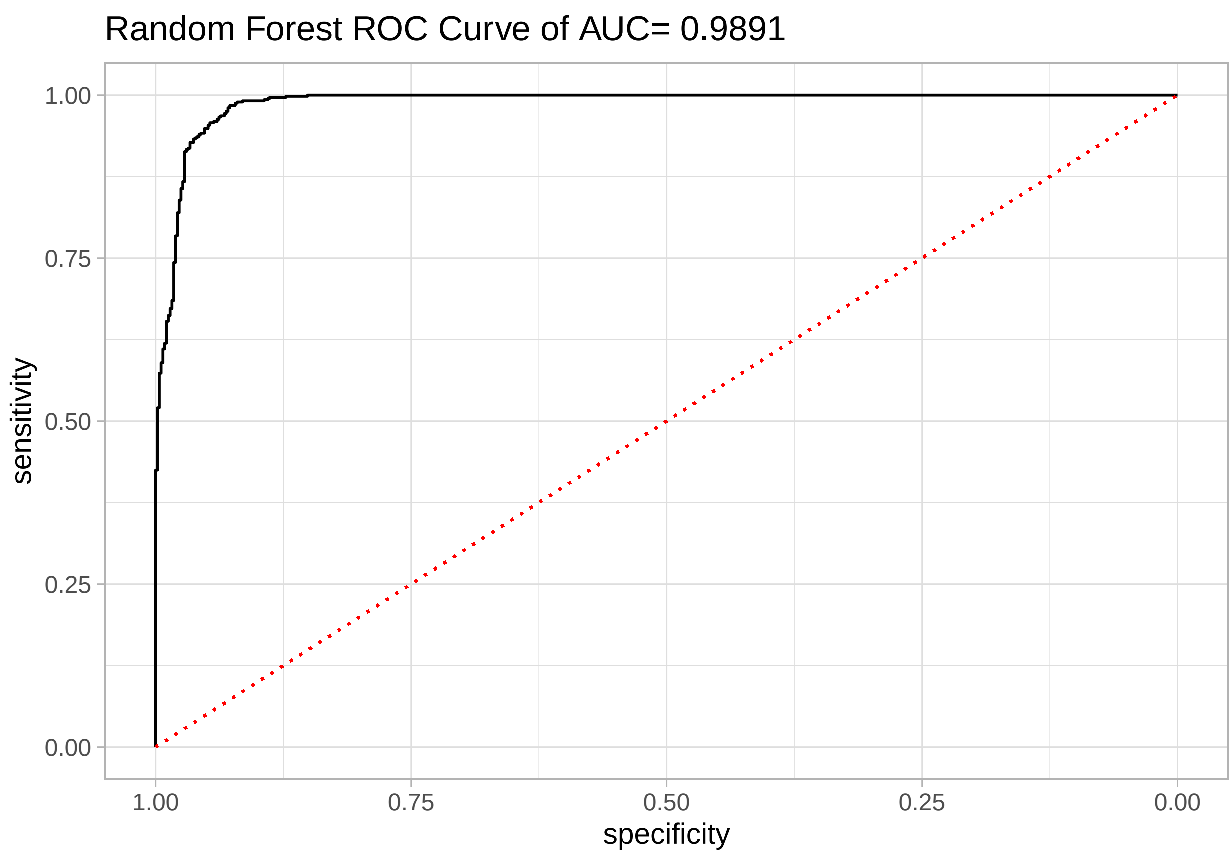
#Stores Test Performance of Models

```
test.results<-test.results%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.rf.summary.pr
test.results
```

```
##          R2        MSE     RMSE       AUC classError
## 1 0.7982301 0.05044248 0.224594 0.9882434 0.05044248
```

#plotting ROC curve of Random Forest - Version 2

```
ggroc(rf.auc)+ggtitle("Random Forest ROC Curve of AUC= 0.9891")+geom_segment(aes(x=1,y=0,xend=0,yend=1)
```



#Model 2| Gradient Boosting Decision Tree

#Version 1| #Higher learning rate, Stopping metric on AUC as logloss saw lower R^2, Cross-validation on training set

```
gb_model<-h2o.gbm(x=features,y=response,training_frame = train.h2o,learn_rate = 0.1,ntrees=1000,stoppin
```

```
##   |                                                                      |
```

#see the first version of the tree structure

```
gb_model@model$model_summary
gb.cross<-gb_model@model$cross_validation_metrics_summary%>%select(-c(mean,sd))
```

#Feature importance for gb_model

```
gb.features<-h2o.varimp(gb_model)
features_v2<-gb.features$variable[1:10]%>%as.vector()
```

#Version 2 #Lowering stopping rounds for a quicker review on the AUC score, Smaller tree size from v1

```
gb_v2<-h2o.gbm(x=features_v2,y=response,training_frame = train.h2o,learn_rate = 0.1,ntrees=45,stopping_
```

```
##   |                                                                      |
```

#see performance of prediction

```
gb.pred<-h2o.predict(gb_v2,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                              |
```

```
gb.precsnprob<-h2o.predict(gb_v2,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                              |
```

```
gb.reclprob<-h2o.predict(gb_v2,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                              |
```

#Print the confusion matrix

```
gb.con<-confusionMatrix(gb.pred,test_data$WFRI_R,positive = "1",mode = "prec_recall")

gb.con
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 530  34
##          1  35 531
##
##                Accuracy : 0.9389
##                  95% CI : (0.9234, 0.9522)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.8779
##
##  Mcnemar's Test P-Value : 1
##
##               Precision : 0.9382
##                  Recall : 0.9398
##                      F1 : 0.9390
##              Prevalence : 0.5000
##          Detection Rate : 0.4699
##    Detection Prevalence : 0.5009
##       Balanced Accuracy : 0.9389
##
##        'Positive' Class : 1
##
```

#see summary results of random forest model on the test data

```r
gb.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-gb.pred,
      N<-gb.reclprob,
      Y<-gb.precsnprob
  )

gb.summary<-gb.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....gb.pred", N="N....gb.reclpr

gb.auc<-roc(gb.summary$obs,Y)
```

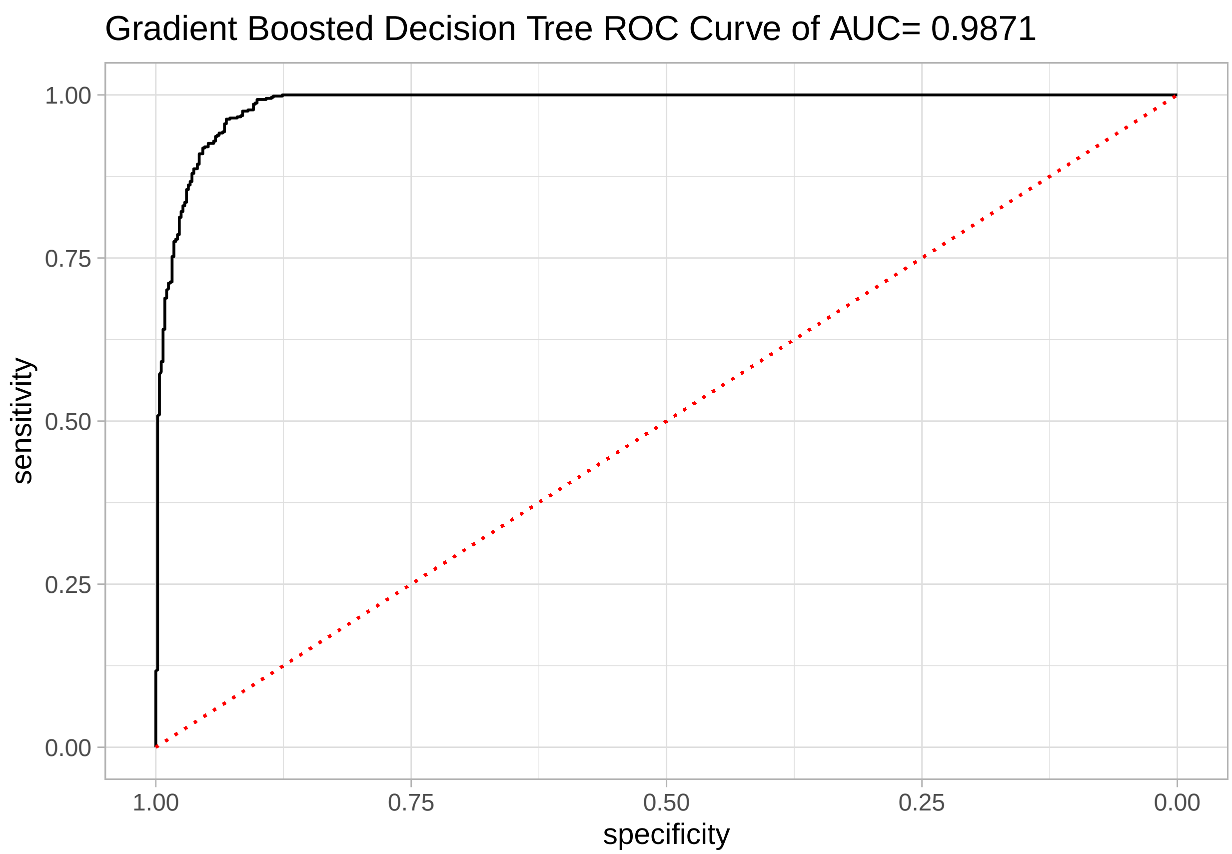
```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
temp<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(gb.summary$pred)),y_true =as.numeric(as.character( gb
  t.mse<-MSE(as.numeric(as.character(gb.summary$pred)),as.numeric(as.character(gb.summary$obs))),
  t.RSME<-RMSE(as.numeric(as.character(gb.summary$pred)),as.numeric(as.character(gb.summary$obs))),
  t.AUC<-gb.auc$auc,
  t.ClassError<-mean(gb.summary$pred!=gb.summary$obs)

)
```

#plotting ROC curve of gradient boosted DT

```r
ggroc(gb.auc)+ggtitle("Gradient Boosted Decision Tree ROC Curve of AUC= 0.9871")+geom_segment(aes(x=1,y=
```




```
temp<-temp%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.gb.summary.pred....",MSE="t.m
,RMSE="t.RSME....RMSE.as.numeric.as.character.gb.summary.pred....as.numeric.as.character.gb.summary.obs
,AUC="t.AUC....gb.auc.auc",classError="t.ClassError....mean.gb.summary.pred....gb.summary.obs.")
```

#adding gradient boosting to the results data frame

```
test.results[2,]<-c(R2=temp$R2,MSE=temp$MSE,RMSE=temp$RMSE,AUC=temp$AUC,classError=temp$classError)
rownames(test.results)<-c("Random Forest","Gradient Boosting")
```

#storing confusion matrix testing results

```
temp<-gb.con$byClass%>%as.data.frame()%>%t()
temp<-as.data.frame(temp)

confusionM<-confusionM%>%add_row(Sensitivity= temp$Sensitivity,Specificity=temp$Specificity, Pos_pred_va

rownames(confusionM)<-c("Random Forest","Gradient Boosting")
```

##Part 1 of analysis RF VS GB

#Current review on the two models

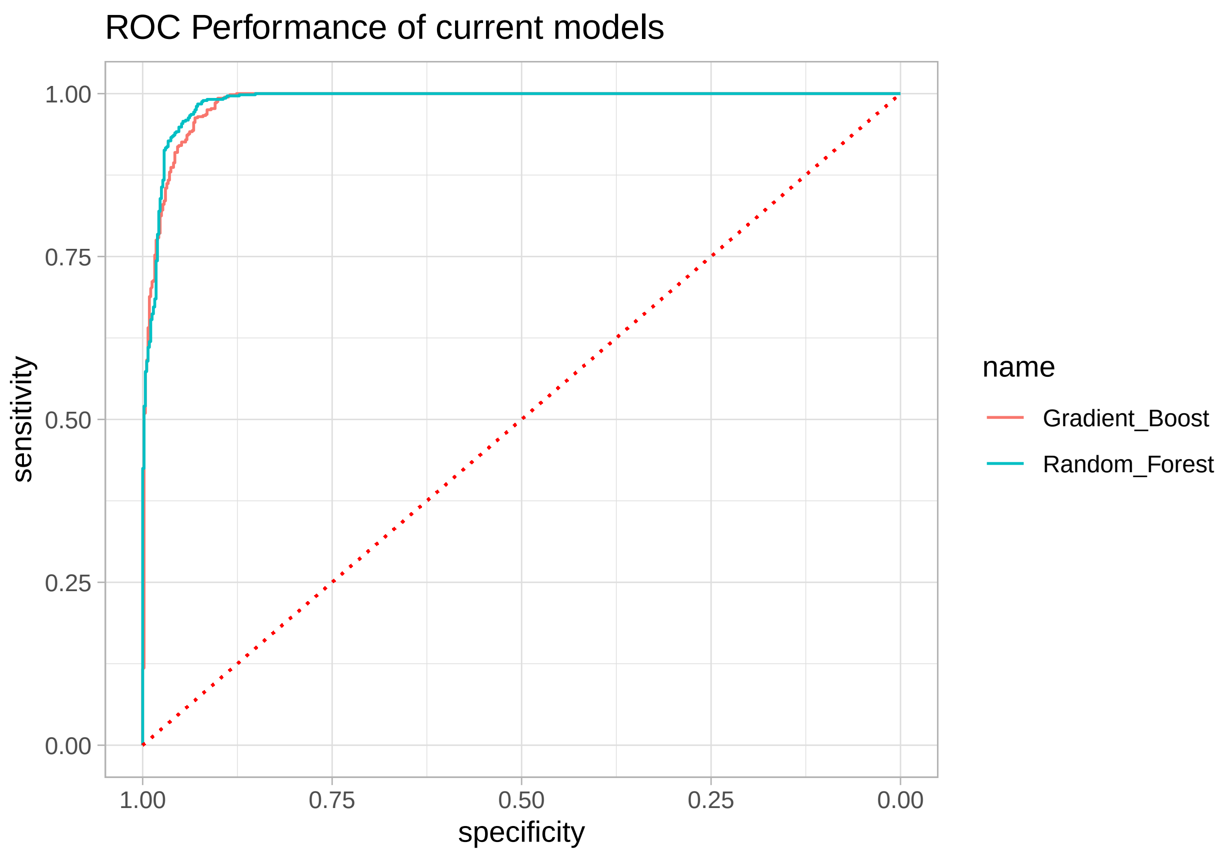
```
confusionM
```

```
##                    Sensitivity Specificity Pos_pred_value Neg_Pred_value
```

```
## Random Forest        0.959292   0.9398230      0.9409722      0.9584838
## Gradient Boosting    0.939823   0.9380531      0.9381625      0.9397163
##                   Precision   Recall         F1 Prevalence Detection_rate
## Random Forest     0.9409722 0.959292 0.9500438        0.5      0.4796460
## Gradient Boosting 0.9381625 0.939823 0.9389920        0.5      0.4699115
##                   Detection_prevalence Balanced_Accuracy
## Random Forest                0.5097345         0.9495575
## Gradient Boosting            0.5008850         0.9389381
```

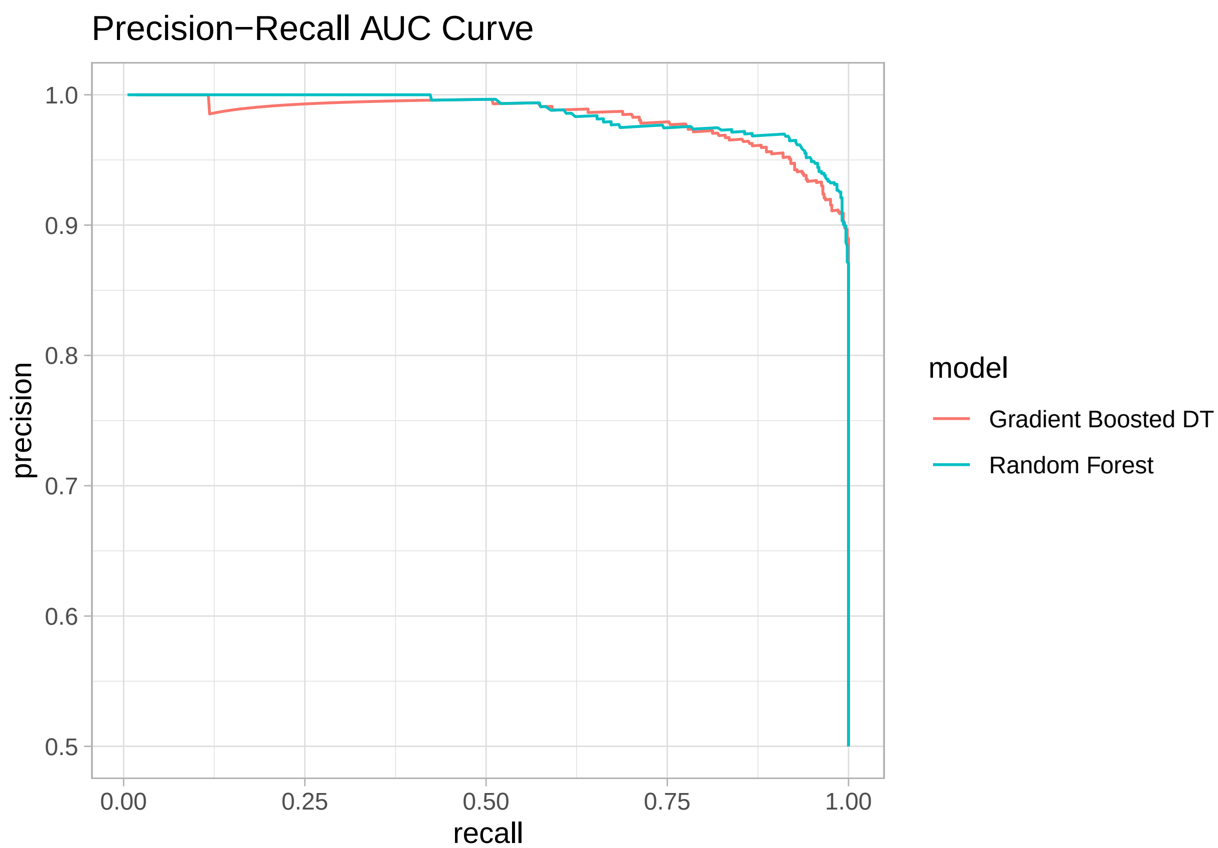
#see ROCs of gradient boosted DT and random forest

```
rocs<-list(Gradient_Boost=gb.auc,Random_Forest=rf.auc)
ggroc(rocs)+ggtitle("ROC Performance of current models")+geom_segment(aes(x=1,y=0,xend=0,yend=1),linety
```



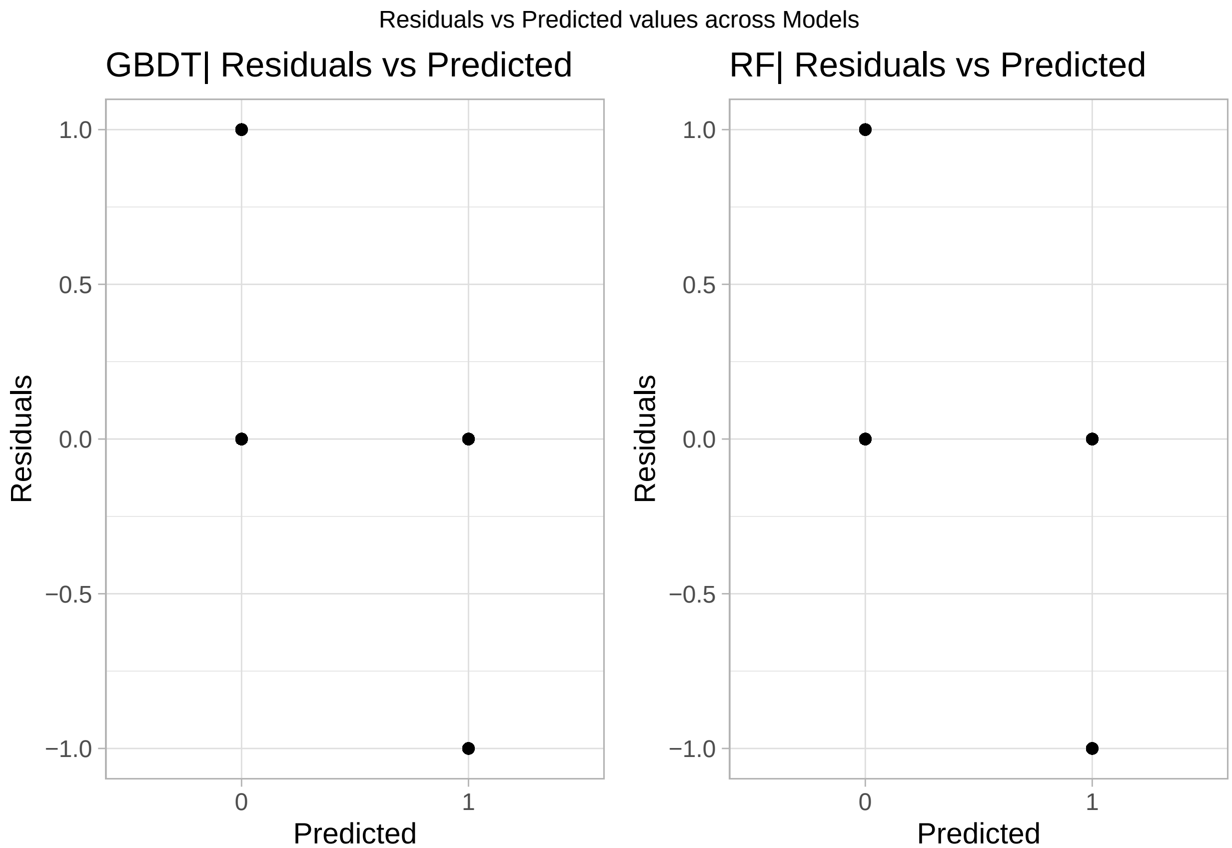
#see Precision-Recall Plots of the two models

```
rf.perf<-h2o.performance(rf.v2,test.h2o)%>%h2o.metric()%>%as.data.frame()%>%select(c(recall,precision))
rf.perf$model<-"Random Forest"
gb.perf<-h2o.performance(gb_v2,test.h2o)%>%h2o.metric()%>%as.data.frame()%>%select(c(recall,precision))
gb.perf$model<-"Gradient Boosted DT"
combine_rpplots<-rbind(rf.perf,gb.perf)

ggplot(combine_rpplots,aes(recall,precision,group=model,color=model))+geom_line()+labs(title ="Precisio
```



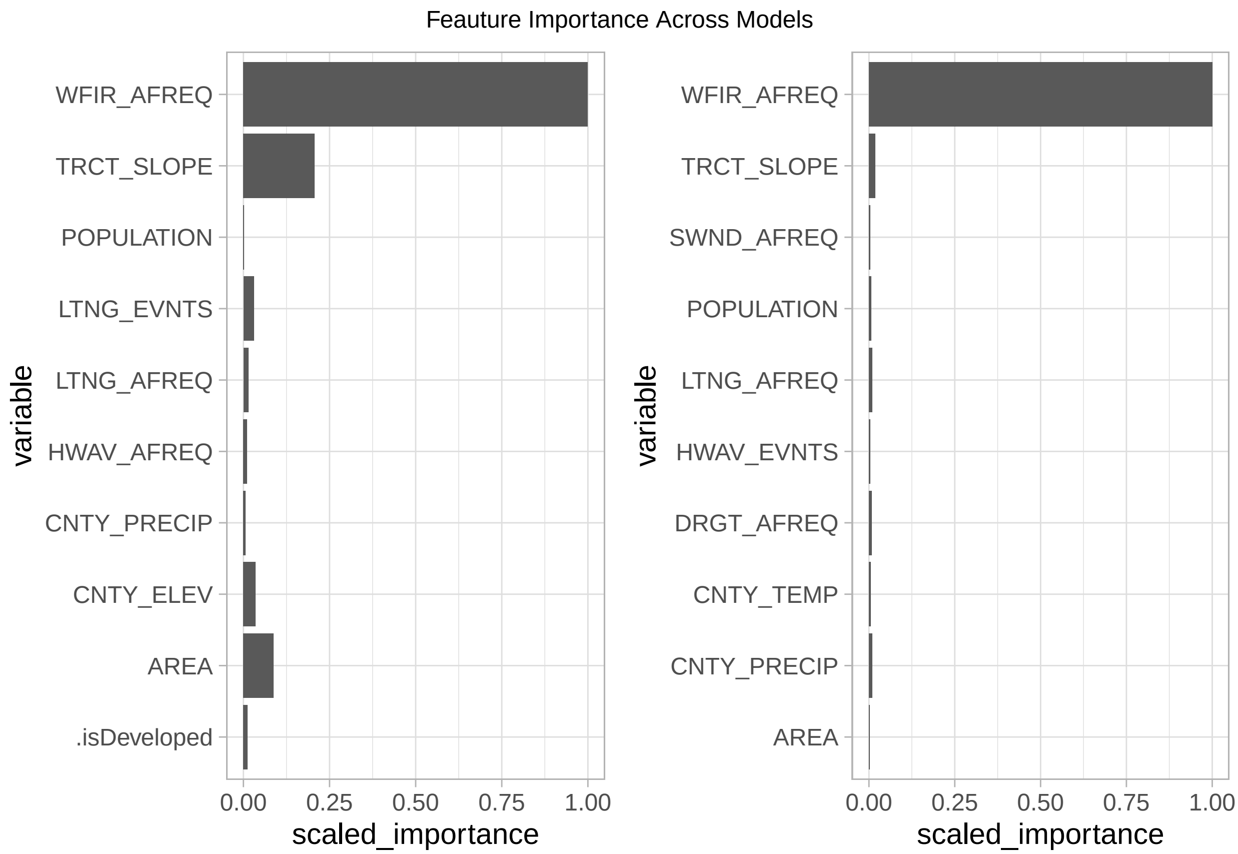
#Plotting residuals vs fitted

```
rf.summary<-rf.summary%>%mutate(resid=as.numeric(obs)-as.numeric(pred))
gb.summary<-gb.summary%>%mutate(resid=as.numeric(obs)-as.numeric(pred))
g1<-gb.summary%>%ggplot(aes(pred,resid))+geom_point()+labs(title="GBDT| Residuals vs Predicted",y="Resid
g2<-rf.summary%>%ggplot(aes(pred,resid))+geom_point()+labs(title="RF| Residuals vs Predicted",y="Residua

plt2<-ggarrange(g1,g2,ncol = 2)
annotate_figure(plt2,top = text_grob("Residuals vs Predicted values across Models",size=9))
```



#feature analysis. Plotting top ten feature by its gini score

```
rf.features<-h2o.varimp(rf.v2)%>%as.data.frame()
gb.features<-h2o.varimp(gb_v2)%>%as.data.frame()

g1<-rf.features%>%ggplot(aes(y=variable,x=scaled_importance))+geom_bar(stat="identity")+theme_light()
g2<-gb.features%>%ggplot(aes(y=variable,x=scaled_importance))+geom_bar(stat="identity")+theme_light()

plt3<-ggarrange(g1,g2,ncol = 2)
annotate_figure(plt3,top = text_grob("Feauture Importance Across Models",size=9))
```



Model 3 |Auto ML Models

Run AutoML for 5 base models using the "features" data.

```
aml <- h2o.automl(x = features, y = response,
                  training_frame = train.h2o,
                  max_models = 5,
                  seed = 1)
```

```
##   |                                                                              |
## 22:12:42.590: AutoML: XGBoost is not available; skipping it.  |
```

View the AutoML Leaderboard

```
lb <- aml@leaderboard
head(lb, n = nrow(lb))  # Print all rows instead of default (6 rows)
```

```
##                                                  model_id       auc   logloss
## 1 StackedEnsemble_BestOfFamily_1_AutoML_5_20231205_221242 0.9919661 0.1036018
## 2    StackedEnsemble_AllModels_1_AutoML_5_20231205_221242 0.9918423 0.1032283
## 3                       GBM_3_AutoML_5_20231205_221242 0.9917092 0.1083574
```

```
## 4                          GBM_2_AutoML_5_20231205_221242 0.9916690 0.1094926
## 5                          GBM_1_AutoML_5_20231205_221242 0.9912867 0.1050881
## 6                          DRF_1_AutoML_5_20231205_221242 0.9907154 0.1221969
## 7                          GLM_1_AutoML_5_20231205_221242 0.9870747 0.1694009
##       aucpr mean_per_class_error      rmse        mse
## 1 0.9909088           0.03790751 0.1724919 0.02975347
## 2 0.9905500           0.03563306 0.1719834 0.02957830
## 3 0.9905777           0.03904473 0.1750038 0.03062634
## 4 0.9905942           0.03790751 0.1764119 0.03112116
## 5 0.9890545           0.03563306 0.1725022 0.02975702
## 6 0.9891132           0.03866566 0.1810820 0.03279070
## 7 0.9821826           0.04776346 0.1996383 0.03985545
```

View the Leader Model

```r
leader_model <- aml@leader
leader_model
```

```
## Model Details:
## ==============
##
## H2OBinomialModel: stackedensemble
## Model ID:  StackedEnsemble_BestOfFamily_1_AutoML_5_20231205_221242
## Model Summary for Stacked Ensemble:
##                                      key            value
## 1                      Stacking strategy cross_validation
## 2  Number of base models (used / total)               3/3
## 3      # GBM base models (used / total)               1/1
## 4      # DRF base models (used / total)               1/1
## 5      # GLM base models (used / total)               1/1
## 6                  Metalearner algorithm              GLM
## 7    Metalearner fold assignment scheme           Random
## 8                     Metalearner nfolds                5
## 9                Metalearner fold_column               NA
## 10   Custom metalearner hyperparameters             None
##
##
## H2OBinomialMetrics: stackedensemble
## ** Reported on training data. **
##
## MSE:  0.00484105
## RMSE:  0.06957766
## LogLoss:  0.02698711
## Mean Per-Class Error:  0.001137225
## AUC:  0.9999632
## AUCPR:  0.9999627
## Gini:  0.9999264
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##           0    1    Error     Rate
## 0      1317    2 0.001516  =2/1319
## 1         1 1318 0.000758  =1/1319
```

```
## Totals 1318 1320 0.001137  =3/2638
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.605071    0.998863 231
## 2                       max f2  0.525650    0.999242 235
## 3                 max f0point5  0.605071    0.998636 231
## 4                 max accuracy  0.605071    0.998863 231
## 5                max precision  0.999993    1.000000   0
## 6                   max recall  0.525650    1.000000 235
## 7              max specificity  0.999993    1.000000   0
## 8             max absolute_mcc  0.605071    0.997726 231
## 9   max min_per_class_accuracy  0.605939    0.998484 230
## 10 max mean_per_class_accuracy  0.605071    0.998863 231
## 11                     max tns  0.999993 1319.000000   0
## 12                     max fns  0.999993  659.000000   0
## 13                     max fps  0.000328 1319.000000 399
## 14                     max tps  0.525650 1319.000000 235
## 15                     max tnr  0.999993    1.000000   0
## 16                     max fnr  0.999993    0.499621   0
## 17                     max fpr  0.000328    1.000000 399
## 18                     max tpr  0.525650    1.000000 235
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F
##
## H2OBinomialMetrics: stackedensemble
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **
##
## MSE:  0.02975347
## RMSE:  0.1724919
## LogLoss:  0.1036018
## Mean Per-Class Error:  0.03790751
## AUC:  0.9919661
## AUCPR:  0.9909088
## Gini:  0.9839323
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##           0    1    Error       Rate
## 0      1250   69 0.052312   =69/1319
## 1        31 1288 0.023503   =31/1319
## Totals 1281 1357 0.037908  =100/2638
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.468777    0.962631 245
## 2                       max f2  0.071618    0.981253 317
## 3                 max f0point5  0.723463    0.962579 190
## 4                 max accuracy  0.468777    0.962092 245
## 5                max precision  0.999992    1.000000   0
## 6                   max recall  0.071618    1.000000 317
## 7              max specificity  0.999992    1.000000   0
## 8             max absolute_mcc  0.468777    0.924569 245
## 9   max min_per_class_accuracy  0.622742    0.960576 215
```

```
## 10 max mean_per_class_accuracy  0.468777    0.962092 245
## 11                      max tns  0.999992 1319.000000   0
## 12                      max fns  0.999992  933.000000   0
## 13                      max fps  0.000009 1319.000000 399
## 14                      max tps  0.071618 1319.000000 317
## 15                      max tnr  0.999992    1.000000   0
## 16                      max fnr  0.999992    0.707354   0
## 17                      max fpr  0.000009    1.000000 399
## 18                      max tpr  0.071618    1.000000 317
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F
## Cross-Validation Metrics Summary:
##                mean       sd cv_1_valid cv_2_valid cv_3_valid cv_4_valid
## accuracy   0.965853 0.005085   0.970205   0.962617   0.965714   0.971429
## auc        0.992218 0.002271   0.992883   0.991571   0.992871   0.994975
## err        0.034147 0.005085   0.029795   0.037383   0.034286   0.028571
## err_count 18.000000 2.549510  16.000000  20.000000  18.000000  15.000000
## f0point5   0.959790 0.004820   0.961680   0.957370   0.952738   0.965167
##           cv_5_valid
## accuracy    0.959302
## auc         0.988791
## err         0.040698
## err_count  21.000000
## f0point5    0.961995
##
## ---
##                         mean        sd cv_1_valid cv_2_valid cv_3_valid
## precision           0.955619  0.007621   0.956044   0.953237   0.944238
## r2                  0.881143  0.013881   0.883568   0.870539   0.883302
## recall              0.977125  0.014526   0.984906   0.974265   0.988327
## residual_deviance 109.191140 13.522715 109.657555 117.658590 106.122130
## rmse                0.172105  0.010243   0.170596   0.179878   0.170768
## specificity         0.954573  0.007967   0.955882   0.950570   0.944030
##                   cv_4_valid cv_5_valid
## precision           0.960289   0.964286
## r2                  0.901896   0.866411
## recall              0.985185   0.952941
## residual_deviance  88.469350 124.048080
## rmse                0.156544   0.182737
## specificity         0.956863   0.965517
```

AutoML Leader-Board Predictions

```r
# Make predictions on the validation set
pred <- h2o.predict(aml@leader, test.h2o)
```

```
##   |                                                                              |
```

```r
# Convert H2O frame to a data frame
predictions_df <- as.data.frame(pred)

head(predictions_df)
```

```
##   predict        p0           p1
## 1       0 0.9676080 0.0323919795
## 2       0 0.9840842 0.0159158428
## 3       0 0.9996577 0.0003422652
## 4       0 0.8036897 0.1963102573
## 5       0 0.9707758 0.0292241819
## 6       0 0.9995839 0.0004161366
```

Top model with the "AUC" metric

```r
# Get the best model using a non-default metric
m <- h2o.get_best_model(aml, criterion = "auc")
m
```

```
## Model Details:
## ==============
##
## H2OBinomialModel: stackedensemble
## Model ID:  StackedEnsemble_BestOfFamily_1_AutoML_5_20231205_221242
## Model Summary for Stacked Ensemble:
##                                     key            value
## 1                     Stacking strategy cross_validation
## 2  Number of base models (used / total)              3/3
## 3      # GBM base models (used / total)              1/1
## 4      # DRF base models (used / total)              1/1
## 5      # GLM base models (used / total)              1/1
## 6                 Metalearner algorithm              GLM
## 7    Metalearner fold assignment scheme           Random
## 8                    Metalearner nfolds                5
## 9               Metalearner fold_column               NA
## 10   Custom metalearner hyperparameters             None
##
##
## H2OBinomialMetrics: stackedensemble
## ** Reported on training data. **
##
## MSE:  0.00484105
## RMSE:  0.06957766
## LogLoss:  0.02698711
## Mean Per-Class Error:  0.001137225
## AUC:  0.9999632
## AUCPR:  0.9999627
## Gini:  0.9999264
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##           0    1    Error     Rate
## 0      1317    2 0.001516  =2/1319
## 1         1 1318 0.000758  =1/1319
## Totals 1318 1320 0.001137  =3/2638
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.605071    0.998863 231
## 2                       max f2  0.525650    0.999242 235
```

```
## 3                 max f0point5  0.605071    0.998636 231
## 4                 max accuracy  0.605071    0.998863 231
## 5                max precision  0.999993    1.000000   0
## 6                   max recall  0.525650    1.000000 235
## 7              max specificity  0.999993    1.000000   0
## 8             max absolute_mcc  0.605071    0.997726 231
## 9   max min_per_class_accuracy  0.605939    0.998484 230
## 10 max mean_per_class_accuracy  0.605071    0.998863 231
## 11                     max tns  0.999993 1319.000000   0
## 12                     max fns  0.999993  659.000000   0
## 13                     max fps  0.000328 1319.000000 399
## 14                     max tps  0.525650 1319.000000 235
## 15                     max tnr  0.999993    1.000000   0
## 16                     max fnr  0.999993    0.499621   0
## 17                     max fpr  0.000328    1.000000 399
## 18                     max tpr  0.525650    1.000000 235
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F
##
## H2OBinomialMetrics: stackedensemble
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **
##
## MSE:  0.02975347
## RMSE:  0.1724919
## LogLoss:  0.1036018
## Mean Per-Class Error:  0.03790751
## AUC:  0.9919661
## AUCPR:  0.9909088
## Gini:  0.9839323
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##           0    1    Error       Rate
## 0      1250   69 0.052312   =69/1319
## 1        31 1288 0.023503   =31/1319
## Totals 1281 1357 0.037908  =100/2638
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold       value idx
## 1                       max f1  0.468777    0.962631 245
## 2                       max f2  0.071618    0.981253 317
## 3                 max f0point5  0.723463    0.962579 190
## 4                 max accuracy  0.468777    0.962092 245
## 5                max precision  0.999992    1.000000   0
## 6                   max recall  0.071618    1.000000 317
## 7              max specificity  0.999992    1.000000   0
## 8             max absolute_mcc  0.468777    0.924569 245
## 9   max min_per_class_accuracy  0.622742    0.960576 215
## 10 max mean_per_class_accuracy  0.468777    0.962092 245
## 11                     max tns  0.999992 1319.000000   0
## 12                     max fns  0.999992  933.000000   0
## 13                     max fps  0.000009 1319.000000 399
## 14                     max tps  0.071618 1319.000000 317
## 15                     max tnr  0.999992    1.000000   0
```

```
## 16                        max fnr  0.999992    0.707354   0
## 17                        max fpr  0.000009    1.000000 399
## 18                        max tpr  0.071618    1.000000 317
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F
## Cross-Validation Metrics Summary:
##                mean       sd cv_1_valid cv_2_valid cv_3_valid cv_4_valid
## accuracy   0.965853 0.005085   0.970205   0.962617   0.965714   0.971429
## auc        0.992218 0.002271   0.992883   0.991571   0.992871   0.994975
## err        0.034147 0.005085   0.029795   0.037383   0.034286   0.028571
## err_count 18.000000 2.549510  16.000000  20.000000  18.000000  15.000000
## f0point5   0.959790 0.004820   0.961680   0.957370   0.952738   0.965167
##           cv_5_valid
## accuracy    0.959302
## auc         0.988791
## err         0.040698
## err_count  21.000000
## f0point5    0.961995
##
## ---
##                         mean        sd cv_1_valid cv_2_valid cv_3_valid
## precision           0.955619  0.007621   0.956044   0.953237   0.944238
## r2                  0.881143  0.013881   0.883568   0.870539   0.883302
## recall              0.977125  0.014526   0.984906   0.974265   0.988327
## residual_deviance 109.191140 13.522715 109.657555 117.658590 106.122130
## rmse                0.172105  0.010243   0.170596   0.179878   0.170768
## specificity         0.954573  0.007967   0.955882   0.950570   0.944030
##                   cv_4_valid cv_5_valid
## precision           0.960289   0.964286
## r2                  0.901896   0.866411
## recall              0.985185   0.952941
## residual_deviance  88.469350 124.048080
## rmse                0.156544   0.182737
## specificity         0.956863   0.965517
```

AutoML Performance

```r
# Extract actual values from the test set
perf <- h2o.performance(leader_model, test.h2o )
perf
```

```
## H2OBinomialMetrics: stackedensemble
##
## MSE:  0.03926883
## RMSE:  0.1981637
## LogLoss:  0.1372975
## Mean Per-Class Error:  0.04867257
## AUC:  0.9872692
## AUCPR:  0.9836436
## Gini:  0.9745383
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
```

```
##          0   1    Error      Rate
## 0      532  33 0.058407   =33/565
## 1       22 543 0.038938   =22/565
## Totals 554 576 0.048673  =55/1130
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold      value idx
## 1                       max f1  0.530993   0.951797 265
## 2                       max f2  0.048111   0.976833 320
## 3                 max f0point5  0.645673   0.949592 252
## 4                 max accuracy  0.574580   0.951327 259
## 5                max precision  0.991132   0.995781  24
## 6                   max recall  0.048111   1.000000 320
## 7              max specificity  0.999994   0.998230   0
## 8             max absolute_mcc  0.530993   0.902826 265
## 9   max min_per_class_accuracy  0.633232   0.948673 254
## 10 max mean_per_class_accuracy  0.574580   0.951327 259
## 11                     max tns  0.999994 564.000000   0
## 12                     max fns  0.999994 404.000000   0
## 13                     max fps  0.000316 565.000000 399
## 14                     max tps  0.048111 565.000000 320
## 15                     max tnr  0.999994   0.998230   0
## 16                     max fnr  0.999994   0.715044   0
## 17                     max fpr  0.000316   1.000000 399
## 18                     max tpr  0.048111   1.000000 320
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

```r
#Generate predictions on a test set, you can make predictions directly on the `H2OAutoML` object
aml_pred <- h2o.predict(leader_model, test.h2o)
```

```
##   |                                                                              |
```

```r
#Accuracy measure on the test data
amlpred_df <- as.data.frame(aml_pred$predict)
amlpred_df$predict <- factor(amlpred_df$predict, levels = c(0,1))
```

#Print the confusion matrix

```r
#Accuracy measure on the test data
aml_cm<-confusionMatrix(amlpred_df$predict,test_data$WFRI_R,positive = "1",mode = "prec_recall")

aml_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 528  22
##          1  37 543
##
##                Accuracy : 0.9478
```

```
##                  95% CI : (0.9332, 0.96)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.8956
##
##  Mcnemar's Test P-Value : 0.06836
##
##               Precision : 0.9362
##                  Recall : 0.9611
##                      F1 : 0.9485
##              Prevalence : 0.5000
##          Detection Rate : 0.4805
##    Detection Prevalence : 0.5133
##       Balanced Accuracy : 0.9478
##
##        'Positive' Class : 1
##
```

Model 4 - Naive-Bayes

```r
# Build and train the model:
pros_nb <- h2o.naiveBayes(x = features,
                          y = response,
                          training_frame = train.h2o,
                          laplace = 0,
                          nfolds = 5,
                          seed = 1234,
                          keep_cross_validation_predictions = TRUE)
```

```
##   |                                                                              |
```

```r
nb_perf <- h2o.performance(pros_nb, test.h2o)
nb_perf
```

```
## H2OBinomialMetrics: naivebayes
##
## MSE:  0.1384367
## RMSE:  0.3720708
## LogLoss:  1.207416
## Mean Per-Class Error:  0.1106195
## AUC:  0.9436307
## AUCPR:  0.929643
## Gini:  0.8872613
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          0   1    Error       Rate
## 0      478  87 0.153982    =87/565
## 1       38 527 0.067257    =38/565
## Totals 516 614 0.110619  =125/1130
```

```
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold      value idx
## 1                       max f1  0.001184   0.893978 258
## 2                       max f2  0.000361   0.929234 294
## 3                 max f0point5  0.017826   0.890688 185
## 4                 max accuracy  0.001581   0.889381 250
## 5                max precision  1.000000   0.958730   0
## 6                   max recall  0.000000   1.000000 399
## 7              max specificity  1.000000   0.976991   0
## 8             max absolute_mcc  0.001184   0.781706 258
## 9   max min_per_class_accuracy  0.006278   0.879646 211
## 10 max mean_per_class_accuracy  0.001581   0.889381 250
## 11                     max tns  1.000000 552.000000   0
## 12                     max fns  1.000000 263.000000   0
## 13                     max fps  0.000000 565.000000 399
## 14                     max tps  0.000000 565.000000 399
## 15                     max tnr  1.000000   0.976991   0
## 16                     max fnr  1.000000   0.465487   0
## 17                     max fpr  0.000000   1.000000 399
## 18                     max tpr  0.000000   1.000000 399
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

```r
#Generate predictions on a test set, you can make predictions directly on the `H2OAutoML` object
nb_pred <- h2o.predict(pros_nb, test.h2o)
```

```
##   |                                                                              |
```

```r
#Accuracy measure on the test data
nbpred_df <- as.data.frame(nb_pred$predict)
nbpred_df$predict <- factor(nbpred_df$predict, levels = c(0,1))
```

```r
#Accuracy measure on the test data
nb_cm<-confusionMatrix(nbpred_df$predict,test_data$WFRI_R,positive = "1",mode = "prec_recall")

nb_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 483  45
##          1  82 520
##
##                Accuracy : 0.8876
##                  95% CI : (0.8677, 0.9054)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7752
##
```

```
## Mcnemar's Test P-Value : 0.001401
##
##               Precision : 0.8638
##                  Recall : 0.9204
##                      F1 : 0.8912
##              Prevalence : 0.5000
##          Detection Rate : 0.4602
##    Detection Prevalence : 0.5327
##       Balanced Accuracy : 0.8876
##
##        'Positive' Class : 1
##
```

Model 5 - SVM Model

```r
# Build and train the model:
svm_model <- h2o.psvm(gamma = 0.01,
                      rank_ratio = 0.1,
                      x = features,
                      y = response,
                      training_frame = train.h2o,
                      disable_training_metrics = FALSE,
                      seed = 1)
```

```
##   |                                                                              |
```

```r
svm_perf <- h2o.performance(svm_model, test.h2o)
svm_perf
```

```
## H2OBinomialMetrics: psvm
##
## MSE:  0.4433628
## RMSE:  0.665855
## LogLoss:  NaN
## Mean Per-Class Error:  0.4433628
## AUC:  NaN
## AUCPR:  NaN
## Gini:  NaN
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##         0    1    Error       Rate
## 0      74  491 0.869027   =491/565
## 1      10  555 0.017699    =10/565
## Totals 84 1046 0.443363  =501/1130
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                            metric threshold      value idx
## 1                          max f1  1.000000   0.689013   0
```

```
## 2                       max f2  1.000000   0.839383   0
## 3                 max f0point5  1.000000   0.584334   0
## 4                 max accuracy  1.000000   0.556637   0
## 5                max precision  1.000000   0.530593   0
## 6                   max recall  1.000000   0.982301   0
## 7              max specificity  1.000000   0.130973   0
## 8             max absolute_mcc  1.000000   0.215911   0
## 9   max min_per_class_accuracy  1.000000   0.130973   0
## 10 max mean_per_class_accuracy  1.000000   0.556637   0
## 11                     max tns  1.000000  74.000000   0
## 12                     max fns  1.000000  10.000000   0
## 13                     max fps  1.000000 491.000000   0
## 14                     max tps  1.000000 555.000000   0
## 15                     max tnr  1.000000   0.130973   0
## 16                     max fnr  1.000000   0.017699   0
## 17                     max fpr  1.000000   0.869027   0
## 18                     max tpr  1.000000   0.982301   0
##
## Gains/Lift Table: Extract with 'h2o.gainsLift(<model>, <data>)' or 'h2o.gainsLift(<model>, valid=<T/F
```

```
#Generate predictions on a test set, you can make predictions directly on the `H2OAutoML` object
svm_pred <- h2o.predict(svm_model, test.h2o)
```

```
##   |                                                                              |
```

```
#Accuracy measure on the test data
svmpred_df <- as.data.frame(svm_pred$predict)
svmpred_df$predict <- factor(svmpred_df$predict, levels = c(0,1))
```

```
#Accuracy measure on the test data
svm_cm<-confusionMatrix(svmpred_df$predict,test_data$WFRI_R,positive = "1",mode = "prec_recall")

svm_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  74  10
##          1 491 555
##
##                Accuracy : 0.5566
##                  95% CI : (0.5271, 0.5859)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : 7.787e-05
##
##                   Kappa : 0.1133
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##               Precision : 0.5306
##                  Recall : 0.9823
```

```
##                       F1 : 0.6890
##               Prevalence : 0.5000
##           Detection Rate : 0.4912
##     Detection Prevalence : 0.9257
##        Balanced Accuracy : 0.5566
##
##         'Positive' Class : 1
##
```

Model 6 - Deep Learning

```r
# Build and train the model:
dl <- h2o.deeplearning(x = features,
                       y = response,
                       distribution = "AUTO",
                       hidden = c(1),
                       epochs = 1000,
                       train_samples_per_iteration = -1,
                       reproducible = TRUE,
                       activation = "Tanh",
                       single_node_mode = FALSE,
                       balance_classes = FALSE,
                       force_load_balance = FALSE,
                       seed = 23123,
                       score_training_samples = 0,
                       score_validation_samples = 0,
                       training_frame = train.h2o,
                       stopping_rounds = 0,
                       keep_cross_validation_predictions = TRUE)
```

```
##   |                                                                              |
```

```r
dl_perf <- h2o.performance(dl, test.h2o)
dl_perf
```

```
## H2OBinomialMetrics: deeplearning
##
## MSE:  0.04250999
## RMSE:  0.2061795
## LogLoss:  0.1624409
## Mean Per-Class Error:  0.04778761
## AUC:  0.9781392
## AUCPR:  0.9665388
## Gini:  0.9562785
##
## Confusion Matrix (vertical: actual; across: predicted) for F1-optimal threshold:
##          0   1    Error      Rate
## 0      521  44 0.077876   =44/565
```

```
## 1       10 555 0.017699   =10/565
## Totals 531 599 0.047788  =54/1130
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##                         metric threshold      value idx
## 1                       max f1  0.294898   0.953608 216
## 2                       max f2  0.088587   0.973958 237
## 3                 max f0point5  0.803380   0.944868 165
## 4                 max accuracy  0.294898   0.952212 216
## 5                max precision  0.984779   0.979424   2
## 6                   max recall  0.001645   1.000000 385
## 7              max specificity  0.984812   0.991150   0
## 8             max absolute_mcc  0.294898   0.906067 216
## 9   max min_per_class_accuracy  0.678508   0.939823 182
## 10 max mean_per_class_accuracy  0.294898   0.952212 216
## 11                     max tns  0.984812 560.000000   0
## 12                     max fns  0.984812 378.000000   0
## 13                     max fps  0.000525 565.000000 399
## 14                     max tps  0.001645 565.000000 385
## 15                     max tnr  0.984812   0.991150   0
## 16                     max fnr  0.984812   0.669027   0
## 17                     max fpr  0.000525   1.000000 399
## 18                     max tpr  0.001645   1.000000 385
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

```r
#Generate predictions on a test set, you can make predictions directly on the `H2OAutoML` object
dl_pred <- h2o.predict(dl, test.h2o)
```

```
##   |                                                                               |
```

```r
#Accuracy measure on the test data
dlpred_df <- as.data.frame(dl_pred$predict)
dlpred_df$predict <- factor(dlpred_df$predict, levels = c(0,1))
```

```r
#Accuracy measure on the test data
dl_cm<-confusionMatrix(dlpred_df$predict,test_data$WFRI_R,positive = "1",mode = "prec_recall")

dl_cm
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 521  10
##          1  44 555
##
##                Accuracy : 0.9522
##                  95% CI : (0.9381, 0.9639)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : < 2.2e-16
##
```

```
##                   Kappa : 0.9044
##
##  Mcnemar's Test P-Value : 7.098e-06
##
##               Precision : 0.9265
##                  Recall : 0.9823
##                      F1 : 0.9536
##              Prevalence : 0.5000
##          Detection Rate : 0.4912
##    Detection Prevalence : 0.5301
##       Balanced Accuracy : 0.9522
##
##        'Positive' Class : 1
##
```

Part 2 Analysis| Comparison of Top LM model compared to other two models

#Retrieve Top performing model and save separately #saving name: GBM_1_AutoML_1_20231119_133450

```
winining_aml<-aml@leader
winining_aml@model$model_summary
```

#Retrieving Top performing Auto model and save its prediction separately for performance

```
automl.pred<-h2o.predict(leader_model,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                              |
```

```
automl.precsnprob<-h2o.predict(leader_model,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                              |
```

```
automl.reclprob<-h2o.predict(aml@leader,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                              |
```

```
#Print the confusion matrix
automl.con<-confusionMatrix(automl.pred,test_data$WFRI_R,positive = "1",mode = "prec_recall")

automl.con
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 528  22
##          1  37 543
##
```

```
##                Accuracy : 0.9478
##                  95% CI : (0.9332, 0.96)
##     No Information Rate : 0.5
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.8956
##
##  Mcnemar's Test P-Value : 0.06836
##
##               Precision : 0.9362
##                  Recall : 0.9611
##                      F1 : 0.9485
##              Prevalence : 0.5000
##          Detection Rate : 0.4805
##    Detection Prevalence : 0.5133
##       Balanced Accuracy : 0.9478
##
##        'Positive' Class : 1
##
```

#see summary results of automled ensemble model on the test data

```
automl.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-automl.pred,
      N<-automl.reclprob,
      Y<-automl.precsnprob
  )


automl.summary<-automl.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....automl.pred", N="N.

automl.auc<-roc(automl.summary$obs,Y)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
temp<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(automl.summary$pred)),y_true =as.numeric(as.character
  t.mse<-MSE(as.numeric(as.character(automl.summary$pred)),as.numeric(as.character(automl.summary$obs))
  t.RSME<-RMSE(as.numeric(as.character(automl.summary$pred)),as.numeric(as.character(automl.summary$obs
  t.AUC<-automl.auc$auc,
  t.ClassError<-mean(automl.summary$pred!=automl.summary$obs)

)

automl.summary
```

```
##      obs pred            N            Y
## 1      0    0 9.676080e-01 0.0323919795
## 2      0    0 9.840842e-01 0.0159158428
```

```
## 3       0     0 9.996577e-01 0.0003422652
## 4       0     0 8.036897e-01 0.1963102573
## 5       0     0 9.707758e-01 0.0292241819
## 6       0     0 9.995839e-01 0.0004161366
## 7       0     0 9.856802e-01 0.0143198363
## 8       0     0 9.923463e-01 0.0076536986
## 9       0     0 9.862869e-01 0.0137130539
## 10      0     0 9.974926e-01 0.0025073802
## 11      0     0 9.744232e-01 0.0255768364
## 12      0     0 9.996485e-01 0.0003515084
## 13      0     0 9.996668e-01 0.0003331694
## 14      0     0 9.860773e-01 0.0139226702
## 15      0     0 9.996854e-01 0.0003145621
## 16      0     0 9.996933e-01 0.0003066597
## 17      0     0 9.996725e-01 0.0003274555
## 18      0     0 9.995553e-01 0.0004446769
## 19      0     0 9.995701e-01 0.0004298915
## 20      0     0 9.996274e-01 0.0003725508
## 21      0     0 9.993222e-01 0.0006777669
## 22      0     0 9.996437e-01 0.0003562592
## 23      0     0 9.996655e-01 0.0003344614
## 24      0     0 9.918938e-01 0.0081061854
## 25      0     0 9.995671e-01 0.0004328536
## 26      0     0 6.029191e-01 0.3970808866
## 27      0     0 9.996310e-01 0.0003689695
## 28      0     0 9.994906e-01 0.0005093917
## 29      0     0 9.995973e-01 0.0004026567
## 30      0     0 9.996279e-01 0.0003720755
## 31      0     0 9.996857e-01 0.0003143422
## 32      0     0 9.995905e-01 0.0004094675
## 33      0     0 9.996466e-01 0.0003533962
## 34      0     0 9.782340e-01 0.0217660268
## 35      0     0 9.877464e-01 0.0122535908
## 36      0     0 9.996230e-01 0.0003769521
## 37      0     0 9.995594e-01 0.0004405636
## 38      0     0 9.996834e-01 0.0003165704
## 39      0     0 9.996271e-01 0.0003728943
## 40      0     0 9.996497e-01 0.0003502803
## 41      0     0 9.879470e-01 0.0120530447
## 42      0     0 9.996689e-01 0.0003310733
## 43      0     0 9.886028e-01 0.0113971969
## 44      0     0 9.996297e-01 0.0003703129
## 45      0     0 9.995902e-01 0.0004098262
## 46      0     0 9.996362e-01 0.0003637611
## 47      0     0 9.996523e-01 0.0003476515
## 48      0     0 9.865789e-01 0.0134210654
## 49      0     0 9.996535e-01 0.0003464768
## 50      0     0 9.996737e-01 0.0003262943
## 51      0     0 9.996166e-01 0.0003834114
## 52      0     0 9.831708e-01 0.0168292363
## 53      0     0 9.996848e-01 0.0003151729
## 54      0     0 9.996570e-01 0.0003429885
## 55      0     0 9.879099e-01 0.0120901157
## 56      0     0 9.994980e-01 0.0005019878
```

```
## 57      0     0 9.994423e-01 0.0005576557
## 58      0     1 1.789829e-01 0.8210171254
## 59      0     0 9.937827e-01 0.0062172879
## 60      0     0 9.996384e-01 0.0003615615
## 61      0     0 9.996293e-01 0.0003706842
## 62      0     0 9.996743e-01 0.0003256606
## 63      0     0 9.995120e-01 0.0004880377
## 64      0     0 9.809187e-01 0.0190812635
## 65      0     0 9.995904e-01 0.0004095780
## 66      0     0 9.927333e-01 0.0072667209
## 67      0     0 9.947376e-01 0.0052624392
## 68      0     0 9.996459e-01 0.0003541294
## 69      0     0 9.996621e-01 0.0003378616
## 70      0     0 9.996833e-01 0.0003167118
## 71      0     0 9.996345e-01 0.0003655256
## 72      0     0 8.600808e-01 0.1399192235
## 73      0     0 9.995767e-01 0.0004233353
## 74      0     0 9.996919e-01 0.0003080952
## 75      0     0 9.997207e-01 0.0002792912
## 76      0     0 9.898861e-01 0.0101138701
## 77      0     0 9.995807e-01 0.0004193034
## 78      0     0 9.995803e-01 0.0004196838
## 79      0     0 9.996066e-01 0.0003934363
## 80      0     0 9.996592e-01 0.0003407707
## 81      0     0 9.388218e-01 0.0611781977
## 82      0     0 9.996713e-01 0.0003286667
## 83      0     0 9.878803e-01 0.0121197445
## 84      0     0 9.996667e-01 0.0003332917
## 85      0     0 9.996256e-01 0.0003743552
## 86      0     0 9.893974e-01 0.0106025701
## 87      0     0 9.996662e-01 0.0003337957
## 88      0     1 1.961270e-01 0.8038730295
## 89      0     0 9.996195e-01 0.0003805429
## 90      0     0 9.996534e-01 0.0003466319
## 91      0     0 9.996790e-01 0.0003209502
## 92      0     0 9.996376e-01 0.0003623995
## 93      0     0 9.935250e-01 0.0064750342
## 94      0     0 9.911894e-01 0.0088106403
## 95      0     0 9.996907e-01 0.0003093053
## 96      0     0 9.438134e-01 0.0561866327
## 97      0     0 9.915869e-01 0.0084130944
## 98      0     0 9.996935e-01 0.0003064620
## 99      0     0 9.996458e-01 0.0003542437
## 100     0     0 9.996347e-01 0.0003653063
## 101     0     0 9.996193e-01 0.0003807245
## 102     0     1 1.668056e-02 0.9833194430
## 103     0     0 9.996280e-01 0.0003719722
## 104     0     0 9.996046e-01 0.0003953651
## 105     0     1 3.317095e-02 0.9668290466
## 106     0     0 8.525988e-01 0.1474011654
## 107     0     0 9.906594e-01 0.0093406087
## 108     0     0 9.994302e-01 0.0005698128
## 109     0     0 9.996362e-01 0.0003638432
## 110     0     0 9.586980e-01 0.0413019744
```

```
## 111    0    1 1.199968e-01 0.8800032260
## 112    0    0 9.996380e-01 0.0003620193
## 113    0    0 9.995777e-01 0.0004223433
## 114    0    0 9.996462e-01 0.0003538196
## 115    0    0 9.996321e-01 0.0003678782
## 116    0    1 9.719600e-02 0.9028039965
## 117    0    0 9.996241e-01 0.0003758527
## 118    0    1 4.310503e-01 0.5689497150
## 119    0    0 9.996398e-01 0.0003602086
## 120    0    0 6.002852e-01 0.3997148271
## 121    0    0 9.914087e-01 0.0085912761
## 122    0    0 9.995771e-01 0.0004229154
## 123    0    0 9.996865e-01 0.0003135268
## 124    0    0 9.928256e-01 0.0071744196
## 125    0    0 9.947271e-01 0.0052728611
## 126    0    1 1.638317e-01 0.8361682998
## 127    0    0 9.495087e-01 0.0504912866
## 128    0    0 9.945508e-01 0.0054492406
## 129    0    0 9.150151e-01 0.0849849493
## 130    0    0 9.994627e-01 0.0005372856
## 131    0    0 9.848147e-01 0.0151852626
## 132    0    1 1.912070e-01 0.8087930306
## 133    0    0 9.996624e-01 0.0003375569
## 134    0    0 9.997047e-01 0.0002952630
## 135    0    0 9.994455e-01 0.0005544841
## 136    0    0 9.912845e-01 0.0087154892
## 137    0    0 9.996351e-01 0.0003649435
## 138    0    0 9.996361e-01 0.0003638894
## 139    0    1 4.717634e-01 0.5282365815
## 140    0    0 9.996810e-01 0.0003189924
## 141    0    0 9.892676e-01 0.0107323844
## 142    0    0 9.871989e-01 0.0128010507
## 143    0    0 9.996539e-01 0.0003461481
## 144    0    0 9.936914e-01 0.0063085797
## 145    0    1 5.426896e-01 0.4573104228
## 146    0    0 9.939432e-01 0.0060568406
## 147    0    0 9.996707e-01 0.0003292789
## 148    0    0 9.996951e-01 0.0003048572
## 149    0    0 9.650974e-01 0.0349025540
## 150    0    0 9.996371e-01 0.0003628940
## 151    0    0 9.810283e-01 0.0189717250
## 152    0    0 9.996377e-01 0.0003622936
## 153    0    0 9.996523e-01 0.0003477271
## 154    0    0 9.996536e-01 0.0003464006
## 155    0    0 9.996803e-01 0.0003196832
## 156    0    0 9.996866e-01 0.0003134131
## 157    0    0 9.996048e-01 0.0003952155
## 158    0    0 9.930375e-01 0.0069624586
## 159    0    0 9.996807e-01 0.0003193303
## 160    0    0 9.996338e-01 0.0003661648
## 161    0    0 9.941400e-01 0.0058600046
## 162    0    1 1.269195e-01 0.8730804540
## 163    0    0 9.996675e-01 0.0003325457
## 164    0    0 9.803693e-01 0.0196306666
```

```
## 165    0     0 9.996073e-01 0.0003927284
## 166    0     0 9.996208e-01 0.0003791986
## 167    0     0 9.921710e-01 0.0078290393
## 168    0     0 9.995835e-01 0.0004164526
## 169    0     0 9.996252e-01 0.0003747504
## 170    0     0 9.996797e-01 0.0003202925
## 171    0     0 9.952714e-01 0.0047286064
## 172    0     0 9.995708e-01 0.0004292478
## 173    0     1 9.213139e-02 0.9078686098
## 174    0     0 9.996314e-01 0.0003685824
## 175    0     0 9.996092e-01 0.0003907613
## 176    0     0 9.995742e-01 0.0004258099
## 177    0     0 9.996315e-01 0.0003684890
## 178    0     0 9.887419e-01 0.0112580822
## 179    0     0 9.995809e-01 0.0004191004
## 180    0     0 9.878056e-01 0.0121943832
## 181    0     0 9.996238e-01 0.0003762068
## 182    0     0 9.873788e-01 0.0126211898
## 183    0     1 9.282104e-03 0.9907178961
## 184    0     0 9.948538e-01 0.0051462180
## 185    0     0 9.996332e-01 0.0003668028
## 186    0     0 9.631778e-01 0.0368221909
## 187    0     0 9.996551e-01 0.0003448545
## 188    0     0 9.924850e-01 0.0075149877
## 189    0     0 9.996650e-01 0.0003349913
## 190    0     0 9.996520e-01 0.0003479801
## 191    0     0 9.996495e-01 0.0003504616
## 192    0     0 9.996173e-01 0.0003827061
## 193    0     0 9.996135e-01 0.0003865073
## 194    0     0 9.726624e-01 0.0273376156
## 195    0     0 9.859668e-01 0.0140331951
## 196    0     0 9.786228e-01 0.0213771664
## 197    0     0 9.931058e-01 0.0068942057
## 198    0     0 9.996534e-01 0.0003465672
## 199    0     0 9.995796e-01 0.0004203624
## 200    0     0 9.995742e-01 0.0004258414
## 201    0     0 9.763645e-01 0.0236354623
## 202    0     0 9.996143e-01 0.0003856794
## 203    0     0 9.995669e-01 0.0004331447
## 204    0     0 9.996409e-01 0.0003590794
## 205    0     0 7.638197e-01 0.2361802664
## 206    0     0 9.995997e-01 0.0004003022
## 207    0     0 9.996188e-01 0.0003812446
## 208    0     0 9.995608e-01 0.0004392111
## 209    0     0 9.932409e-01 0.0067591500
## 210    0     0 9.939630e-01 0.0060369763
## 211    0     0 6.480496e-01 0.3519503992
## 212    0     0 8.226613e-01 0.1773387151
## 213    0     0 9.856649e-01 0.0143350973
## 214    0     0 9.914443e-01 0.0085557460
## 215    0     0 9.596125e-01 0.0403875256
## 216    0     0 9.996912e-01 0.0003087646
## 217    0     0 9.995759e-01 0.0004240851
## 218    0     0 9.464860e-01 0.0535139964
```

```
## 219    0     0 9.938637e-01 0.0061362848
## 220    0     0 6.038563e-01 0.3961437449
## 221    0     0 9.996856e-01 0.0003144280
## 222    0     0 9.800519e-01 0.0199481391
## 223    0     0 9.996323e-01 0.0003676890
## 224    0     0 9.995194e-01 0.0004805697
## 225    0     0 9.995902e-01 0.0004098117
## 226    0     0 9.699245e-01 0.0300755063
## 227    0     0 9.996786e-01 0.0003213588
## 228    0     0 9.996925e-01 0.0003074896
## 229    0     0 9.996767e-01 0.0003232974
## 230    0     0 6.625523e-01 0.3374476547
## 231    0     0 9.996766e-01 0.0003234230
## 232    0     0 9.996248e-01 0.0003751534
## 233    0     0 9.996437e-01 0.0003563183
## 234    0     0 9.996738e-01 0.0003261905
## 235    0     0 9.996539e-01 0.0003461265
## 236    0     0 9.890763e-01 0.0109237012
## 237    0     0 9.995568e-01 0.0004431946
## 238    0     0 9.789292e-01 0.0210708318
## 239    0     0 9.996250e-01 0.0003750398
## 240    0     0 6.047984e-01 0.3952016109
## 241    0     0 9.996523e-01 0.0003476737
## 242    0     1 2.083388e-01 0.7916612393
## 243    0     1 1.024292e-01 0.8975707985
## 244    0     0 5.904204e-01 0.4095795894
## 245    0     0 9.995518e-01 0.0004482338
## 246    0     0 9.996631e-01 0.0003369275
## 247    0     0 9.995435e-01 0.0004564916
## 248    0     0 9.590395e-01 0.0409605181
## 249    0     0 9.908281e-01 0.0091719384
## 250    0     0 9.950122e-01 0.0049877687
## 251    0     0 9.996574e-01 0.0003425665
## 252    0     0 9.821070e-01 0.0178930372
## 253    0     0 9.996490e-01 0.0003510104
## 254    0     0 9.995960e-01 0.0004039935
## 255    0     0 9.995960e-01 0.0004039898
## 256    0     0 9.996539e-01 0.0003460982
## 257    0     1 1.991681e-01 0.8008319354
## 258    0     0 9.932200e-01 0.0067800038
## 259    0     0 9.996069e-01 0.0003931013
## 260    0     0 9.996072e-01 0.0003927830
## 261    0     1 1.493408e-01 0.8506591996
## 262    0     0 9.651388e-01 0.0348611793
## 263    0     0 9.996020e-01 0.0003979625
## 264    0     0 9.996687e-01 0.0003312778
## 265    0     0 7.255612e-01 0.2744387788
## 266    0     0 9.996867e-01 0.0003132880
## 267    0     0 9.996760e-01 0.0003240187
## 268    0     0 9.942445e-01 0.0057554619
## 269    0     0 9.996784e-01 0.0003216159
## 270    0     0 5.722179e-01 0.4277820986
## 271    0     0 9.799101e-01 0.0200899270
## 272    0     0 9.996361e-01 0.0003638563
```

```
## 273    0     1 3.830526e-01 0.6169473647
## 274    0     0 9.996743e-01 0.0003256517
## 275    0     0 9.996502e-01 0.0003498457
## 276    0     0 9.856522e-01 0.0143477756
## 277    0     0 9.995563e-01 0.0004436666
## 278    0     0 9.874848e-01 0.0125151691
## 279    0     0 9.948381e-01 0.0051619067
## 280    0     0 9.928777e-01 0.0071222754
## 281    0     0 9.746697e-01 0.0253303296
## 282    0     0 9.939319e-01 0.0060681111
## 283    0     0 7.220895e-01 0.2779104913
## 284    0     0 9.887028e-01 0.0112972152
## 285    0     0 9.912351e-01 0.0087649057
## 286    0     1 3.557890e-01 0.6442110294
## 287    0     0 9.952099e-01 0.0047901185
## 288    0     0 9.996530e-01 0.0003470343
## 289    0     0 9.996526e-01 0.0003473891
## 290    0     0 9.995599e-01 0.0004401032
## 291    0     0 9.996536e-01 0.0003464267
## 292    0     0 9.996233e-01 0.0003767428
## 293    0     0 9.996518e-01 0.0003481505
## 294    0     0 9.230273e-01 0.0769727292
## 295    0     0 9.941057e-01 0.0058943050
## 296    0     0 9.994472e-01 0.0005528077
## 297    0     0 9.945510e-01 0.0054489705
## 298    0     0 9.996337e-01 0.0003663498
## 299    0     0 9.996980e-01 0.0003020002
## 300    0     0 9.996007e-01 0.0003993418
## 301    0     1 1.566329e-05 0.9999843367
## 302    0     0 9.996437e-01 0.0003563062
## 303    0     0 9.348219e-01 0.0651780557
## 304    0     0 9.996731e-01 0.0003268774
## 305    0     0 9.924045e-01 0.0075955080
## 306    0     0 9.996188e-01 0.0003812159
## 307    0     0 9.943349e-01 0.0056651253
## 308    0     0 9.995907e-01 0.0004093391
## 309    0     0 9.877627e-01 0.0122372821
## 310    0     0 9.851887e-01 0.0148113185
## 311    0     0 9.996416e-01 0.0003583672
## 312    0     0 9.996300e-01 0.0003700116
## 313    0     0 9.918415e-01 0.0081584556
## 314    0     0 9.995869e-01 0.0004131307
## 315    0     0 9.996654e-01 0.0003346340
## 316    0     0 9.947875e-01 0.0052125156
## 317    0     0 9.996422e-01 0.0003577962
## 318    0     0 9.995760e-01 0.0004240304
## 319    0     0 9.397293e-01 0.0602707019
## 320    0     0 9.996969e-01 0.0003030911
## 321    0     0 9.996772e-01 0.0003228117
## 322    0     0 9.995469e-01 0.0004531245
## 323    0     0 9.996403e-01 0.0003596783
## 324    0     0 9.872106e-01 0.0127893920
## 325    0     0 9.996484e-01 0.0003516155
## 326    0     0 9.996272e-01 0.0003727848
```

```
## 327    0    1 2.275233e-01 0.7724767486
## 328    0    0 9.996689e-01 0.0003310647
## 329    0    0 8.430075e-01 0.1569924657
## 330    0    0 9.996637e-01 0.0003363021
## 331    0    0 9.995625e-01 0.0004374662
## 332    0    0 9.994060e-01 0.0005939965
## 333    0    0 9.935764e-01 0.0064236439
## 334    0    0 9.948529e-01 0.0051470551
## 335    0    0 9.919393e-01 0.0080607119
## 336    0    0 9.939921e-01 0.0060078877
## 337    0    1 4.276722e-01 0.5723278022
## 338    0    1 5.833325e-02 0.9416667490
## 339    0    0 9.996303e-01 0.0003697371
## 340    0    0 9.946062e-01 0.0053938067
## 341    0    0 9.996188e-01 0.0003812475
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## 371    0    1 5.284546e-02 0.9471545392
## 372    0    0 9.917017e-01 0.0082982607
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## 379    0    0 9.579621e-01 0.0420378726
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## 679    1     1 3.679456e-02 0.9632054382
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## 1062    1     1 3.177903e-01 0.6822096620
## 1063    1     1 1.013097e-05 0.9999898690
## 1064    1     1 2.887027e-01 0.7112972756
## 1065    1     1 8.014722e-03 0.9919852782
## 1066    1     0 6.348975e-01 0.3651024512
## 1067    1     1 5.157896e-06 0.9999948421
## 1068    1     1 2.911067e-01 0.7088933164
## 1069    1     1 1.816704e-01 0.8183295715
## 1070    1     1 1.129100e-02 0.9887090037
## 1071    1     1 2.886723e-03 0.9971132767
## 1072    1     1 8.457348e-03 0.9915426519
## 1073    1     1 1.390695e-02 0.9860930506
## 1074    1     1 1.132030e-02 0.9886797018
## 1075    1     1 3.840353e-02 0.9615964661
## 1076    1     1 3.784602e-06 0.9999962154
## 1077    1     1 9.902620e-03 0.9900973803
## 1078    1     0 9.477443e-01 0.0522557275
## 1079    1     1 6.805308e-02 0.9319469223
## 1080    1     1 1.530601e-02 0.9846939857
## 1081    1     1 5.861330e-02 0.9413866985
## 1082    1     1 8.809443e-03 0.9911905567
```
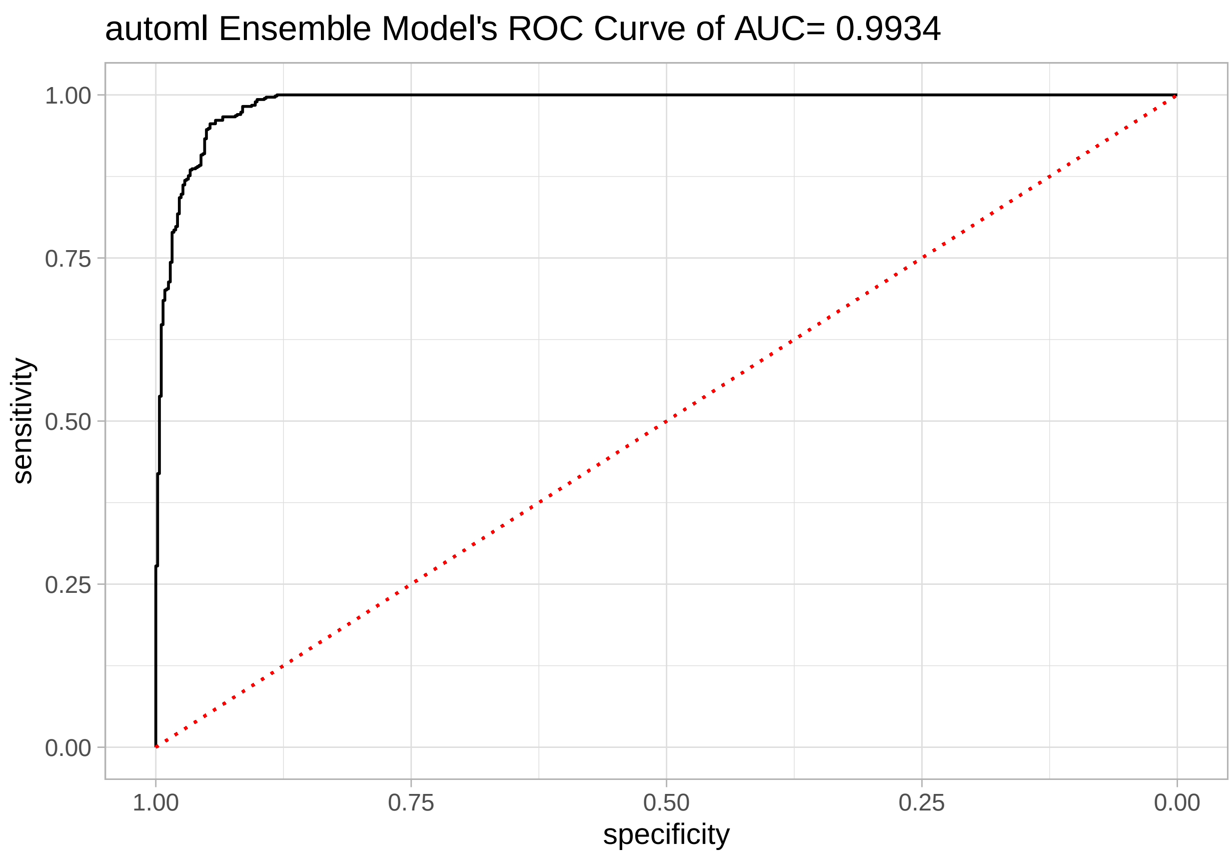

```
## 1083    1     1 7.275384e-03 0.9927246158
## 1084    1     1 5.500715e-03 0.9944992846
## 1085    1     1 5.961142e-02 0.9403885780
## 1086    1     1 7.085289e-06 0.9999929147
## 1087    1     1 5.407754e-02 0.9459224633
## 1088    1     1 2.216889e-01 0.7783111413
## 1089    1     1 9.780024e-06 0.9999902200
## 1090    1     1 1.132231e-01 0.8867768788
## 1091    1     1 3.318591e-02 0.9668140892
## 1092    1     1 6.476530e-06 0.9999935235
## 1093    1     0 5.585080e-01 0.4414919832
## 1094    1     1 1.050939e-05 0.9999894906
## 1095    1     1 1.276114e-02 0.9872388581
## 1096    1     1 9.366235e-02 0.9063376518
## 1097    1     1 9.984705e-03 0.9900152954
## 1098    1     1 3.958442e-02 0.9604155809
## 1099    1     1 9.971424e-03 0.9900285757
## 1100    1     1 2.660078e-02 0.9733992238
## 1101    1     1 4.028436e-06 0.9999959716
## 1102    1     1 2.223622e-06 0.9999977764
## 1103    1     1 4.155271e-02 0.9584472934
## 1104    1     1 7.529671e-06 0.9999924703
## 1105    1     1 1.158061e-05 0.9999884194
## 1106    1     1 6.980870e-02 0.9301913027
## 1107    1     1 9.978140e-02 0.9002185962
## 1108    1     0 6.721807e-01 0.3278193116
## 1109    1     1 3.913374e-06 0.9999960866
## 1110    1     1 2.613816e-02 0.9738618392
## 1111    1     1 2.721232e-02 0.9727876834
## 1112    1     1 9.880916e-02 0.9011908370
## 1113    1     1 9.374292e-03 0.9906257078
## 1114    1     0 8.438506e-01 0.1561494400
## 1115    1     1 2.108341e-01 0.7891659436
## 1116    1     1 2.268951e-06 0.9999977310
## 1117    1     1 3.890728e-02 0.9610927229
## 1118    1     1 3.589397e-03 0.9964106031
## 1119    1     1 4.466825e-06 0.9999955332
## 1120    1     1 8.437567e-03 0.9915624327
## 1121    1     1 3.529872e-02 0.9647012830
## 1122    1     1 1.371034e-02 0.9862896646
## 1123    1     1 1.083290e-01 0.8916709527
## 1124    1     1 1.190253e-02 0.9880974671
## 1125    1     1 1.557453e-01 0.8442546588
## 1126    1     1 2.903756e-01 0.7096243996
## 1127    1     1 5.245527e-06 0.9999947545
## 1128    1     1 4.549276e-06 0.9999954507
## 1129    1     1 1.117380e-02 0.9888262042
## 1130    1     1 1.319923e-02 0.9868007696
```

#plotting ROC curve of gradient boosted DT

```
ggroc(automl.auc)+ggtitle("automl Ensemble Model's ROC Curve of AUC= 0.9934")+geom_segment(aes(x=1,y=0,
```




```
temp<-temp%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.automl.summary.pred....",MSE=
,RMSE="t.RSME....RMSE.as.numeric.as.character.automl.summary.pred...."
,AUC="t.AUC....automl.auc.auc",classError="t.ClassError....mean.automl.summary.pred....automl.summary.o
```

#adding automled ensemble to the results data frame

```
test.results[3,]<-c(R2=temp$R2,MSE=temp$MSE,RMSE=temp$RMSE,AUC=temp$AUC,classError=temp$classError)
rownames(test.results)<-c("Random Forest","Gradient Boosting","automled Ensemble")
```

#storing confusion matrix testing results

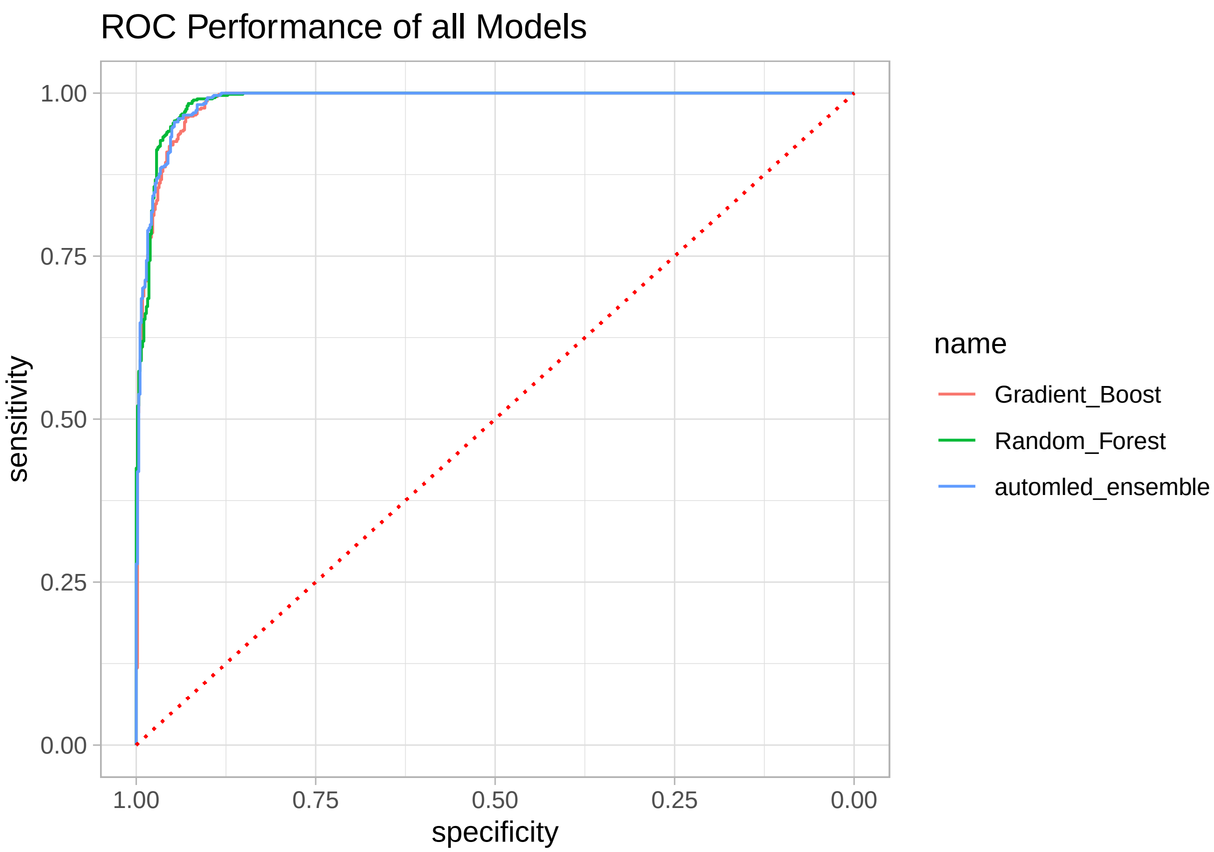
```
temp<-automl.con$byClass%>%as.data.frame()%>%t()
temp<-as.data.frame(temp)

confusionM<-confusionM%>%add_row(Sensitivity= temp$Sensitivity,Specificity=temp$Specificity, Pos_pred_v

rownames(confusionM)<-c("Random Forest","Gradient Boosting","automled Ensemble")
```

#See precision and recall for all three models

```
automl.perf<-h2o.performance(leader_model,test.h2o)%>%h2o.metric()%>%as.data.frame()%>%select(c(recall,
automl.perf$model<-"automled Ensemble"
combine_rpplots<-rbind(rf.perf,gb.perf,automl.perf)

ggplot(combine_rpplots,aes(recall,precision,group=model,color=model))+geom_line()+labs(title ="Precisio
```

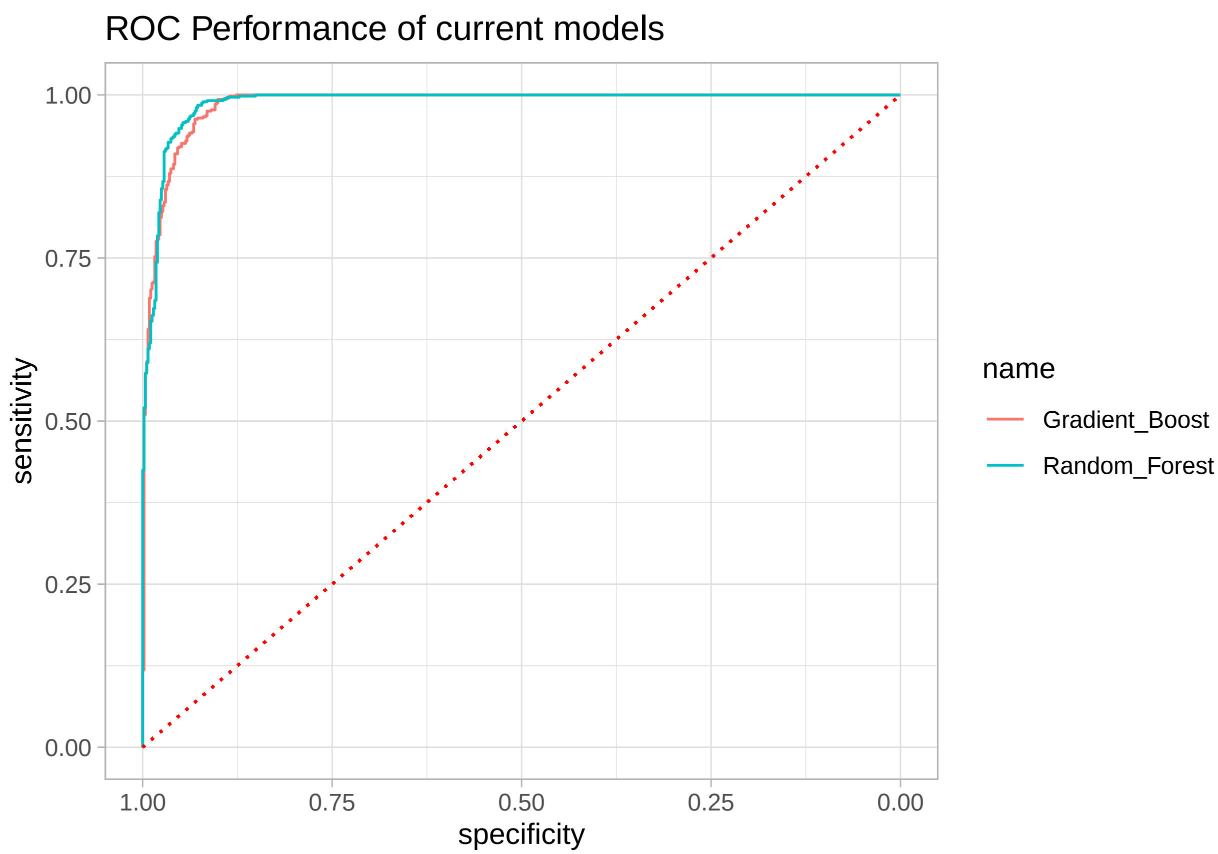
#see ROCs of all models

```
rocs<-list(Gradient_Boost=gb.auc,Random_Forest=rf.auc,automled_ensemble=automl.auc)
ggroc(rocs)+ggtitle("ROC Performance of all Models")+geom_segment(aes(x=1,y=0,xend=0,yend=1),linetype="d
```



```
library(pROC)
library(ggplot2)
```

```
rocs<-list(Gradient_Boost=gb.auc,Random_Forest=rf.auc)
ggroc(rocs)+ggtitle("ROC Performance of current models")+geom_segment(aes(x=1,y=0,xend=0,yend=1),linetyp
```



###Include NB, DPL, and SVM

```
#Including NB, DPL,SVM models in the roc graph

nb.pred<-h2o.predict(pros_nb,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                         |
```

```
nb.precsnprob<-h2o.predict(pros_nb,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                         |
```

```
nb.reclprob<-h2o.predict(pros_nb,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                         |
```

```
nb.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-nb.pred,
      N<-nb.reclprob,
      Y<-nb.precsnprob
  )

svm.pred<-h2o.predict(svm_model,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                              |
```

```r
svm.precsnprob<-h2o.predict(svm_model,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                              |
```

```r
svm.reclprob<-h2o.predict(svm_model,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                              |
```

```r
svm.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-svm.pred,
      N<-svm.reclprob,
      Y<-svm.precsnprob
  )


dl.pred<-h2o.predict(dl,test.h2o)%>%as.data.frame()%>%pull(predict)
```

```
##   |                                                                              |
```

```r
dl.precsnprob<-h2o.predict(dl,test.h2o)%>%as.data.frame()%>%pull(p1)
```

```
##   |                                                                              |
```

```r
dl.reclprob<-h2o.predict(dl,test.h2o)%>%as.data.frame()%>%pull(p0)
```

```
##   |                                                                              |
```

```r
dl.summary<-data.frame(
      obs<-test_data$WFRI_R,
      pred<-dl.pred,
      N<-dl.reclprob,
      Y<-dl.precsnprob
  )

nb.summary<-nb.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....nb.pred", N="N....nb.reclpr

nb.auc<-roc(nb.summary$obs,Y)
```

```
## Setting levels: control = 0, case = 1

## Setting direction: controls < cases
```

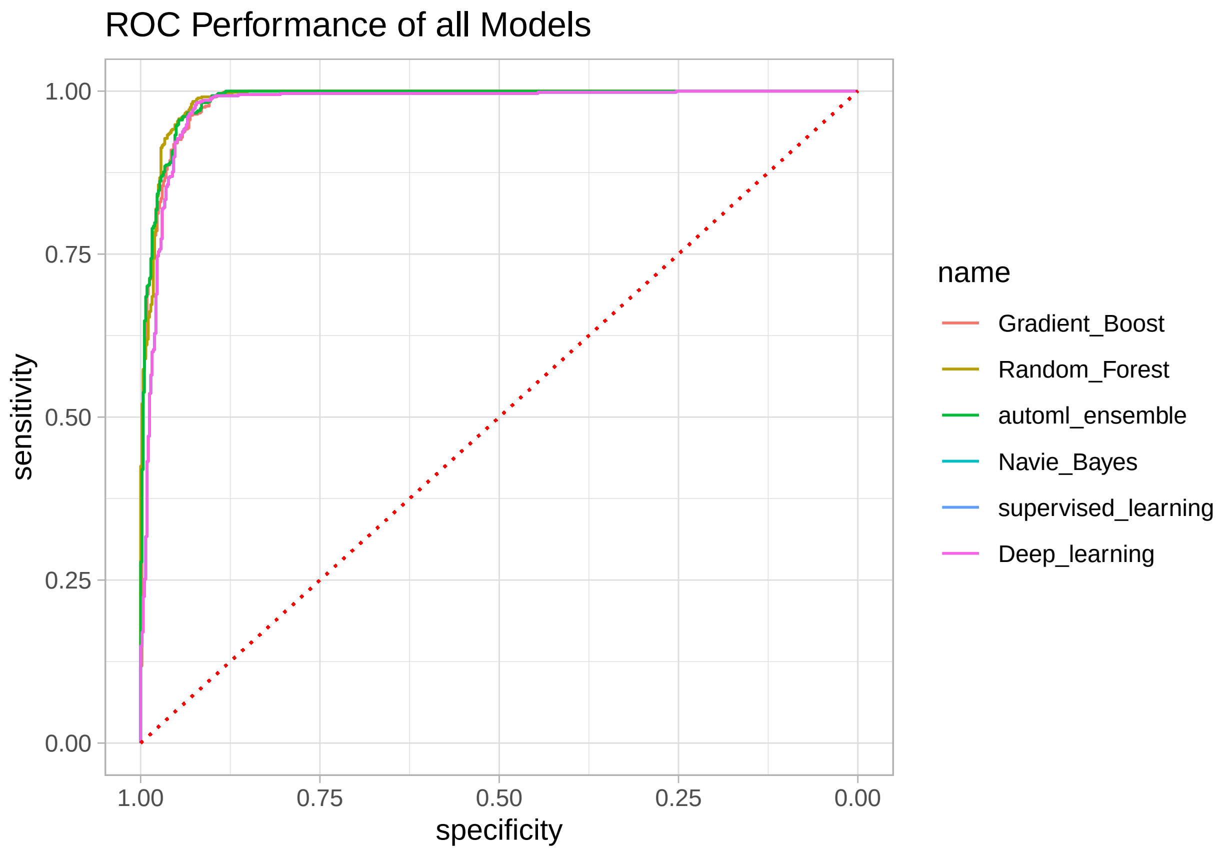
```r
svm.summary<-svm.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....svm.pred", N="N....svm.re

svm.auc<-roc(svm.summary$obs,Y)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
dl.summary<-dl.summary%>%rename(obs="obs....test_data.WFRI_R",pred="pred....dl.pred", N="N....dl.reclpre

dl.auc<-roc(dl.summary$obs,Y)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
rocs<-list(Gradient_Boost=gb.auc,Random_Forest=rf.auc,automl_ensemble=automl.auc,Navie_Bayes=nb.auc,supe
ggroc(rocs)+ggtitle("ROC Performance of all Models")+geom_segment(aes(x=1,y=0,xend=0,yend=1),linetype="
```



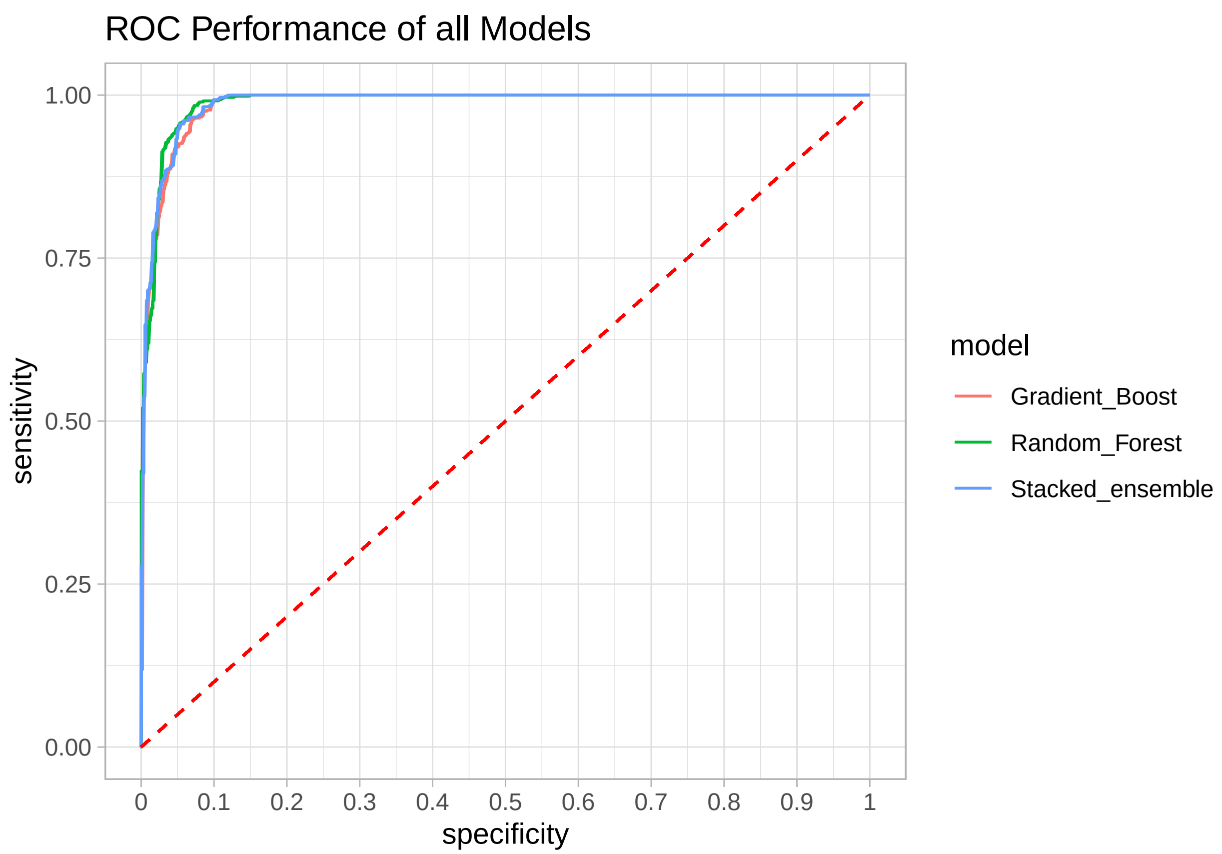

```r
#Updating test results for model performance for all remaining models
temp<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(nb.summary$pred)),y_true =as.numeric(as.character( nb
  t.mse<-MSE(as.numeric(as.character(nb.summary$pred)),as.numeric(as.character(nb.summary$obs))),
  t.RMSE<-RMSE(as.numeric(as.character(nb.summary$pred)),as.numeric(as.character(nb.summary$obs))),
  t.AUC<-nb.auc$auc,
  t.ClassError<-mean(nb.summary$pred!=nb.summary$obs)

)
temp<-temp%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.nb.summary.pred....",MSE="t.ms
,RMSE="t.RMSE....RMSE.as.numeric.as.character.nb.summary.pred....as.numeric.as.character.nb.summary.obs
,AUC="t.AUC....nb.auc.auc",classError="t.ClassError....mean.nb.summary.pred....nb.summary.obs.")

test.results[4,]<-c(R2=temp$R2,MSE=temp$MSE,RMSE=temp$RMSE,AUC=temp$AUC,classError=temp$classError)
```

```r
rownames(test.results)<-c("Random Forest","Gradient Boosting","automl- stack ensemble","Navie Bayes")

temp<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(svm.summary$pred)),y_true =as.numeric(as.character( sv
  t.mse<-MSE(as.numeric(as.character(svm.summary$pred)),as.numeric(as.character(svm.summary$obs))),
  t.RMSE<-RMSE(as.numeric(as.character(svm.summary$pred)),as.numeric(as.character(svm.summary$obs))),
  t.AUC<-svm.auc$auc,
  t.ClassError<-mean(svm.summary$pred!=svm.summary$obs)

)
temp<-temp%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.svm.summary.pred....",MSE="t.m
,RMSE="t.RMSE....RMSE.as.numeric.as.character.svm.summary.pred....as.numeric.as.character.svm.summary.ob
,AUC="t.AUC....svm.auc.auc",classError="t.ClassError....mean.svm.summary.pred....svm.summary.obs.")

test.results[5,]<-c(R2=temp$R2,MSE=temp$MSE,RMSE=temp$RMSE,AUC=temp$AUC,classError=temp$classError)
rownames(test.results)<-c("Random Forest","Gradient Boosting","automl- stack ensemble","Navie Bayes","Su

temp<-data.frame(
  t.R2<-R2_Score(y_pred = as.numeric(as.character(dl.summary$pred)),y_true =as.numeric(as.character( dl
  t.mse<-MSE(as.numeric(as.character(dl.summary$pred)),as.numeric(as.character(dl.summary$obs))),
  t.RMSE<-RMSE(as.numeric(as.character(dl.summary$pred)),as.numeric(as.character(dl.summary$obs))),
  t.AUC<-dl.auc$auc,
  t.ClassError<-mean(dl.summary$pred!=dl.summary$obs)

)
temp<-temp%>%rename(R2="t.R2....R2_Score.y_pred...as.numeric.as.character.dl.summary.pred....",MSE="t.ms
,RMSE="t.RMSE....RMSE.as.numeric.as.character.dl.summary.pred....as.numeric.as.character.dl.summary.obs
,AUC="t.AUC....dl.auc.auc",classError="t.ClassError....mean.dl.summary.pred....dl.summary.obs.")

test.results[6,]<-c(R2=temp$R2,MSE=temp$MSE,RMSE=temp$RMSE,AUC=temp$AUC,classError=temp$classError)
rownames(test.results)<-c("Random Forest","Gradient Boosting","automl- stack ensemble","Navie Bayes","Su
```

```r
# Assuming you have defined the rocs2 list with AUC values

rocs2 <- list(
  Gradient_Boost = roc(gb.summary$obs, gb.summary$Y),
  Random_Forest = roc(rf.summary$obs, rf.summary$Y),
  Stacked_ensemble = roc(automl.summary$obs, automl.summary$Y)

)
```

```
## Setting levels: control = 0, case = 1

## Setting direction: controls < cases

## Setting levels: control = 0, case = 1

## Setting direction: controls < cases

## Setting levels: control = 0, case = 1

## Setting direction: controls < cases
```

```
# Convert the list of ROC objects to a data frame
roc_data <- do.call(rbind, lapply(names(rocs2), function(model) {
  data.frame(
    model = model,
    sensitivity = rocs2[[model]]$sensitivities,
    specificity = 1 - rocs2[[model]]$specificities
  )
}))

# Create a ggplot object with reversed x-axis layout
ggplot(roc_data, aes(x = specificity, y = sensitivity, color = model)) +
  geom_line() +  # Use default line weight
  ggtitle("ROC Performance of all Models") +
  geom_segment(aes(x = 0, y = 0, xend = 1, yend = 1), linetype = "dashed", color = "red") +
  theme_light() +
  scale_x_continuous(
    breaks = seq(1, 0, by = -0.1),  # Reverse the breaks
    labels = seq(1, 0, by = -0.1),  # Reverse the labels
    limits = c(0, 1)  # Adjust the limits as needed
  )
```



Tables - Confusion Matrix

```r
names(nb_cm$byClass)
```

```r
names(nb_cm$overall)
```

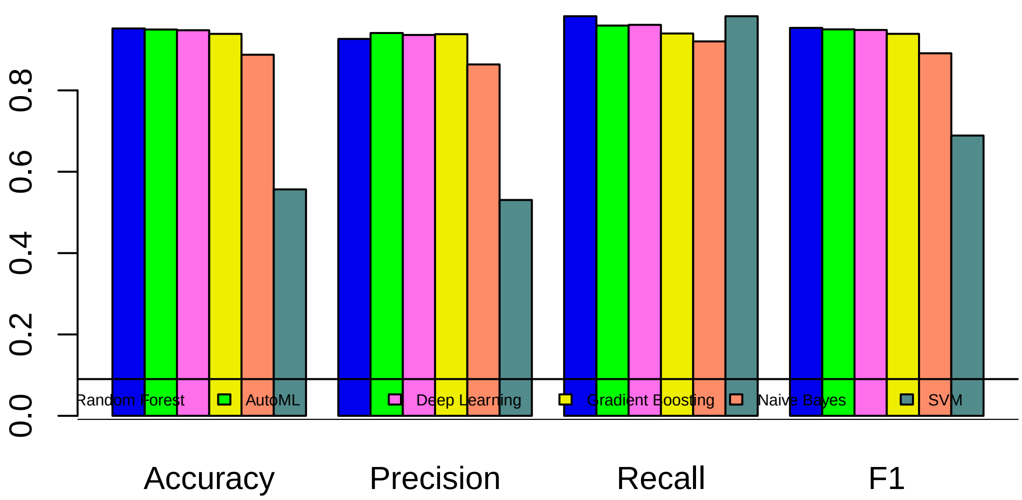
```
## [1] "Accuracy"       "Kappa"          "AccuracyLower"  "AccuracyUpper"
## [5] "AccuracyNull"   "AccuracyPValue" "McnemarPValue"
```

```r
metrics_drf <- c(rf.con$overall[1], rf.con$byClass[5], rf.con$byClass[6], rf.con$byClass[7])
metrics_aml <- c(aml_cm$overall[1], aml_cm$byClass[5], aml_cm$byClass[6], aml_cm$byClass[7])
metrics_dl <- c(dl_cm$overall[1], dl_cm$byClass[5], dl_cm$byClass[6], dl_cm$byClass[7])
metrics_gbm <- c(gb.con$overall[1], gb.con$byClass[5], gb.con$byClass[6], gb.con$byClass[7])
metrics_nb <- c(nb_cm$overall[1], nb_cm$byClass[5], nb_cm$byClass[6], nb_cm$byClass[7])
metrics_svm <- c(svm_cm$overall[1], svm_cm$byClass[5], svm_cm$byClass[6], svm_cm$byClass[7])

# Round the values to four decimals
metrics_drf <- round(metrics_drf, 4)
metrics_aml <- round(metrics_aml, 4)
metrics_dl <- round(metrics_dl, 4)
metrics_gbm <- round(metrics_gbm, 4)
metrics_nb <- round(metrics_nb, 4)
metrics_svm <- round(metrics_svm, 4)

tab_pref <- rbind(metrics_drf, metrics_aml, metrics_dl, metrics_gbm, metrics_nb, metrics_svm)
rownames(tab_pref) <- c("Distributed Random Forest",
                        "AutoML", "Deep Learning",
                        "Gradient Boosting Machine",
                        "Naive Bayes", "Support Vector Machine")


# Identify the column index of the accuracy values in your data frame
accuracy_column_index <- 1

# Order the rows of the data frame based on accuracy in descending order
tab_pref <- tab_pref[order(-tab_pref[, accuracy_column_index]), ]

# Create the data frame with the "Model" index name
(tab.pref <- data.frame( tab_pref))
```

```
##                           Accuracy Precision Recall     F1
## Deep Learning               0.9522    0.9265 0.9823 0.9536
## Distributed Random Forest   0.9496    0.9410 0.9593 0.9500
## AutoML                      0.9478    0.9362 0.9611 0.9485
## Gradient Boosting Machine   0.9389    0.9382 0.9398 0.9390
## Naive Bayes                 0.8876    0.8638 0.9204 0.8912
## Support Vector Machine      0.5566    0.5306 0.9823 0.6890
```

Visualization

```r
# Increase bottom margin
par(mar = c(6, 4, 6, 4))

# Your existing barplot code
bp <- barplot(tab_pref,
              col = c("#0000EE", "#00FF00", "#FF6EEB", "#EEEE00", "#FF8C69", "#528B8B"),
              beside = TRUE)

# Legend at the bottom
legend(x = "bottom",
       y = -0.4,
       legend = c("Random Forest", "AutoML", "Deep Learning", "Gradient Boosting", "Naive Bayes", "SVM"
       fill = c("#0000EE", "#00FF00", "#FF6EEB", "#EEEE00", "#FF8C69", "#528B8B"),
       cex = 0.53,
       ncol = 6)
```



Model Accuracy and Unique Hyperparameters

```r
# Create a data frame with the information
model_data <- data.frame(
  Model = c("Distributed Random Forest (DRF)",
            "AutoML (Automatic Machine Learning)",
            "Deep Learning",
```

```r
            "Gradient Boosting Machine (GBM)",
            "Naïve-Bayes (NB)",
            "Support Vector Machine (SVM)"
  ),
  Accuracy = round(c(rf.con$overall[1], aml_cm$overall[1], dl_cm$overall[1],
             gb.con$overall[1], nb_cm$overall[1], svm_cm$overall[1]), 4),
  Unique_Hyperparameters = c("balance_classes = FALSE",
                             "max_models = 5",
                             "Hidden = c(1), activation = 'Tanh', epochs = 1000",
                             "learn_rate = 0.1, ntrees = 1000",
                             "",
                             "Gamma = 0.01, rank_ratio = 0.1"
  )
)

# Order the values in descending order based on the "Model" column
model_df2 <- model_data[order(model_data$Model, decreasing = FALSE), ]

# Print the table
(model.df2 <- data.frame(model_df2))
```

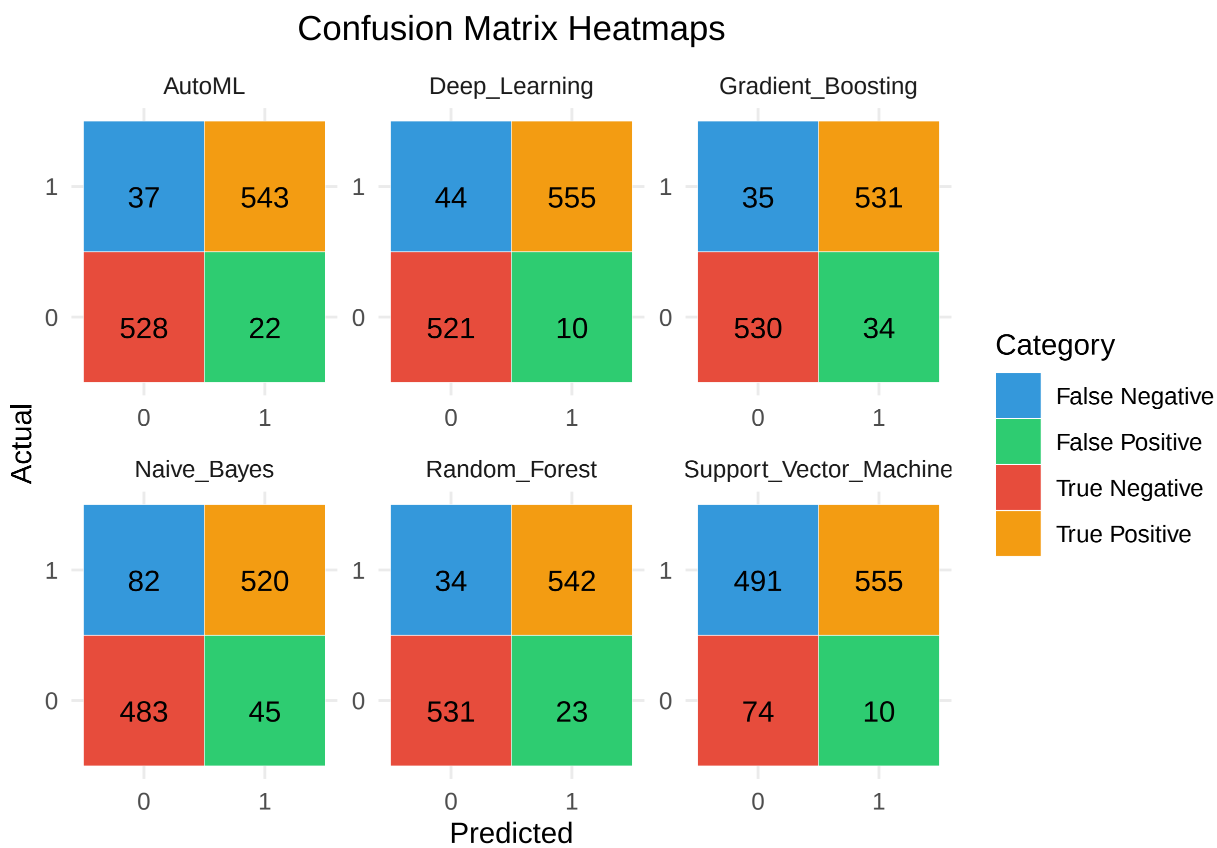
```
##                                  Model Accuracy
## 2 AutoML (Automatic Machine Learning)   0.9478
## 3                       Deep Learning   0.9522
## 1     Distributed Random Forest (DRF)   0.9496
## 4     Gradient Boosting Machine (GBM)   0.9389
## 5                    Naïve-Bayes (NB)   0.8876
## 6        Support Vector Machine (SVM)   0.5566
##                               Unique_Hyperparameters
## 2                                     max_models = 5
## 3 Hidden = c(1), activation = 'Tanh', epochs = 1000
## 1                            balance_classes = FALSE
## 4                    learn_rate = 0.1, ntrees = 1000
## 5
## 6                     Gamma = 0.01, rank_ratio = 0.1
```

Confusion Matrix Model Heatmaps

```r
#install.packages("dplyr")
library(dplyr)
```

```r
# Function to create a custom confusion matrix plot
create_confusion_matrix_plot <- function(cm, title) {
  # Convert confusion matrix to a data frame
  cm_data <- as.data.frame(cm$table)

  # Create a custom confusion matrix plot with different colors for each category
  ggplot(cm_data, aes(x = Reference, y = Prediction, fill = as.factor(Category), label = Freq)) +
    geom_tile(color = "white") +
    geom_text(vjust = 1, hjust = 0.5) +  # Center text
    scale_fill_manual(values = c("#3498db", "#2ecc71", "#e74c3c", "#f39c12"), name = "Category") +  # A
```

```r
    labs(title = title,
         x = "Predicted",
         y = "Actual") +
    theme_minimal() +
    theme(plot.title = element_text(hjust = 0.5))  # Center the title
}

# List of confusion matrices with categories
confusion_matrices <- list(
  Random_Forest = rf.con,
  AutoML = aml_cm,
  Deep_Learning = dl_cm,
  Gradient_Boosting = gb.con,
  Naive_Bayes = nb_cm,
  Support_Vector_Machine = svm_cm
)

# Add a 'Category' column to the data frames representing the four categories
all_cm_data <- do.call(rbind, lapply(names(confusion_matrices), function(name) {
  cm <- confusion_matrices[[name]]
  cm_data <- as.data.frame(cm$table)
  cm_data$Category <- factor(rep(c("True Negative", "False Negative", "False Positive", "True Positive"
  cm_data$Model <- name
  return(cm_data)
}))

# Create and display a facet_wrap confusion matrix plot with different colors for each category
ggplot(all_cm_data, aes(x = Reference, y = Prediction, fill = as.factor(Category), label = Freq)) +
  geom_tile(color = "white") +
  geom_text(vjust = 1, hjust = 0.5) +  # Center text
  scale_fill_manual(values = c("#3498db", "#2ecc71", "#e74c3c", "#f39c12"), name = "Category") +  # Ass
  labs(title = "Confusion Matrix Heatmaps",
       x = "Predicted",
       y = "Actual") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5)) +  # Center the title
  facet_wrap(~Model, scales = "free")  # Create a separate panel for each model
```



Confusion Matrix Tables for Models

```r
# Create an empty list to store dataframes
confusion_matrix_dataframes <- list()

for (name in names(confusion_matrices)) {
  cm <- confusion_matrices[[name]]

  # Accessing individual values from the confusion matrix
  TP <- cm$table[2, 2]  # second row and second column
  TN <- cm$table[1, 1]  # first row and first column
  FP <- cm$table[1, 2]  # first row and second column
  FN <- cm$table[2, 1]  # second row and first column

  # Create a dataframe for each model
  model_dataframe <- data.frame(
    Model = name,
    True_Positive = TP,
    True_Negative = TN,
    False_Positive = FP,
    False_Negative = FN
  )

  # Append the dataframe to the list
```

```
  confusion_matrix_dataframes[[name]] <- model_dataframe
}

# Combine all dataframes into a single dataframe without row names
all_confusion_matrices_df <- bind_rows(confusion_matrix_dataframes)

# Combine all dataframes into a single dataframe without row names
all_confusion_matrices_df <- bind_rows(confusion_matrix_dataframes)

# Arrange the dataframe in descending order based on the "True_Positive" column
all_confusion_matrices_df <- arrange(all_confusion_matrices_df, desc(True_Positive))

# Print the resulting dataframe
print(all_confusion_matrices_df)
```

```
##                    Model True_Positive True_Negative False_Positive
## 1          Deep_Learning           555           521             10
## 2 Support_Vector_Machine           555            74             10
## 3                 AutoML           543           528             22
## 4          Random_Forest           542           531             23
## 5      Gradient_Boosting           531           530             34
## 6            Naive_Bayes           520           483             45
##   False_Negative
## 1             44
## 2            491
## 3             37
## 4             34
## 5             35
## 6             82
```

True Positive Rate vs False Positive Rate

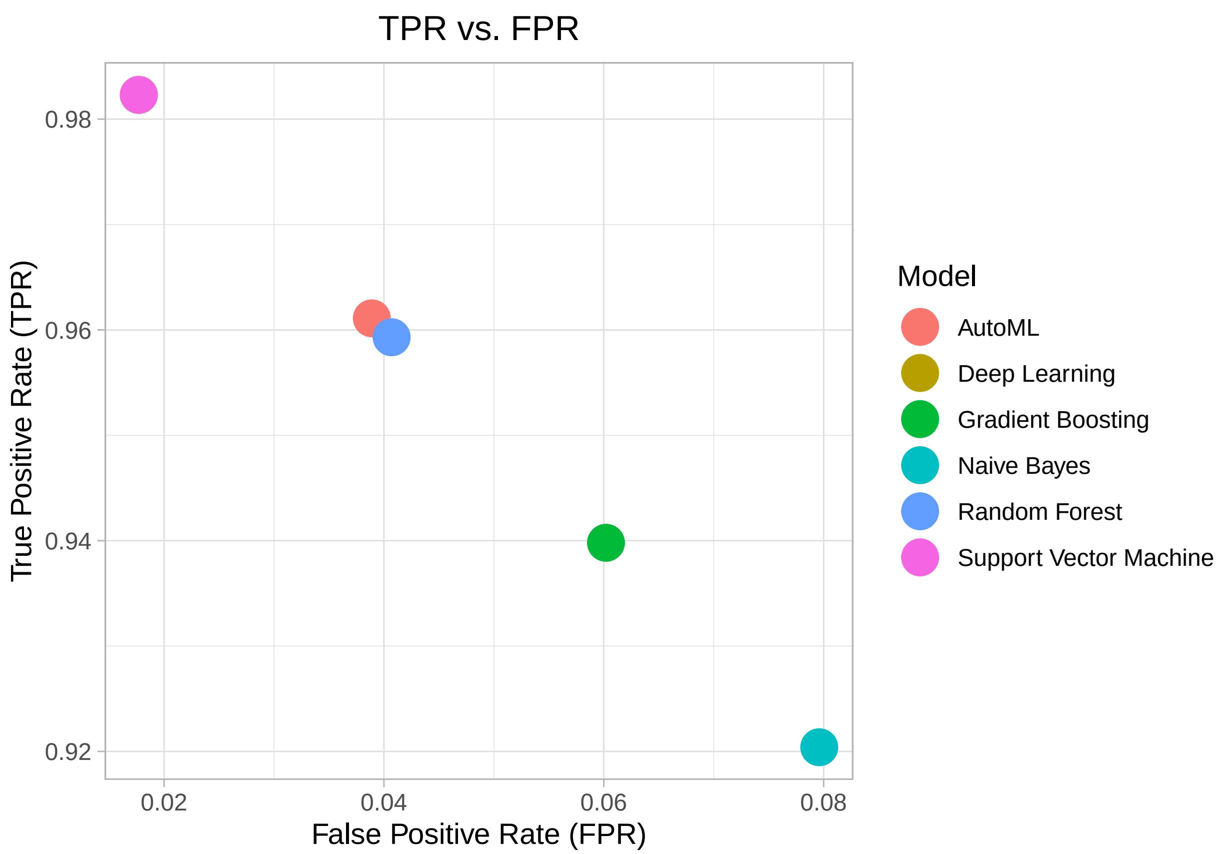
```
# Extract True Positive Rate or Sensitivity values
sens_drf <- round(rf.con$byClass[1], 4)
sens_aml <- round(aml_cm$byClass[1], 4)
sens_dl <- round(dl_cm$byClass[1], 4)
sens_gbm <- round(gb.con$byClass[1], 4)
sens_nb <- round(nb_cm$byClass[1], 4)
sens_svm <- round(svm_cm$byClass[1], 4)

# Calculate False Positive Rate (FPR)
fpr_drf <- round(1 - sens_drf, 4)
fpr_aml <- round(1 - sens_aml, 4)
fpr_dl <- round(1 - sens_dl, 4)
fpr_gbm <- round(1 - sens_gbm, 4)
fpr_nb <- round(1 - sens_nb, 4)
fpr_svm <- round(1 - sens_svm, 4)

# Create a data frame to store the results
results <- data.frame(
  Model = c("Random Forest", "AutoML", "Deep Learning", "Gradient Boosting", "Naive Bayes", "Support Ve
```

```r
  TPR = c(sens_drf, sens_aml, sens_dl, sens_gbm, sens_nb, sens_svm),
  FPR = c(fpr_drf, fpr_aml, fpr_dl, fpr_gbm, fpr_nb, fpr_svm)
)

# Arrange in descending order
results <- results[order(-results$TPR), ]

# Multiply values by 100
#results$TPR <- results$TPR * 100
#results$FPR <- results$FPR * 100

# Print the results
print(results)
```

```
##                    Model    TPR    FPR
## 3          Deep Learning 0.9823 0.0177
## 6 Support Vector Machine 0.9823 0.0177
## 2                 AutoML 0.9611 0.0389
## 1          Random Forest 0.9593 0.0407
## 4      Gradient Boosting 0.9398 0.0602
## 5            Naive Bayes 0.9204 0.0796
```

Visualization of TPR vs FPR

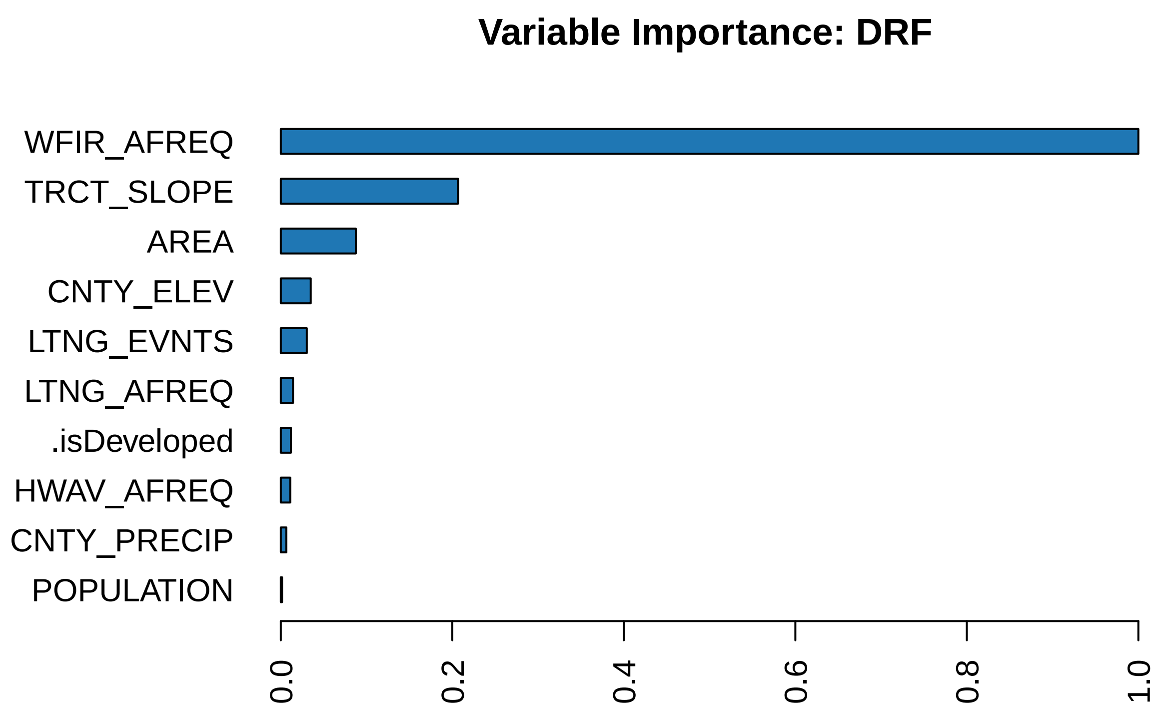
```r
# Arrange in descending order by TPR
results <- results[order(-results$TPR), ]

# Create a scatter plot for each model
ggplot(results, aes(x = FPR, y = TPR, group = Model, color = Model)) +
  geom_point(size = 6) +
  labs(title = "TPR vs. FPR",
       x = "False Positive Rate (FPR)",
       y = "True Positive Rate (TPR)") +
  theme_light() +
  theme(plot.title = element_text(hjust = 0.5))
```



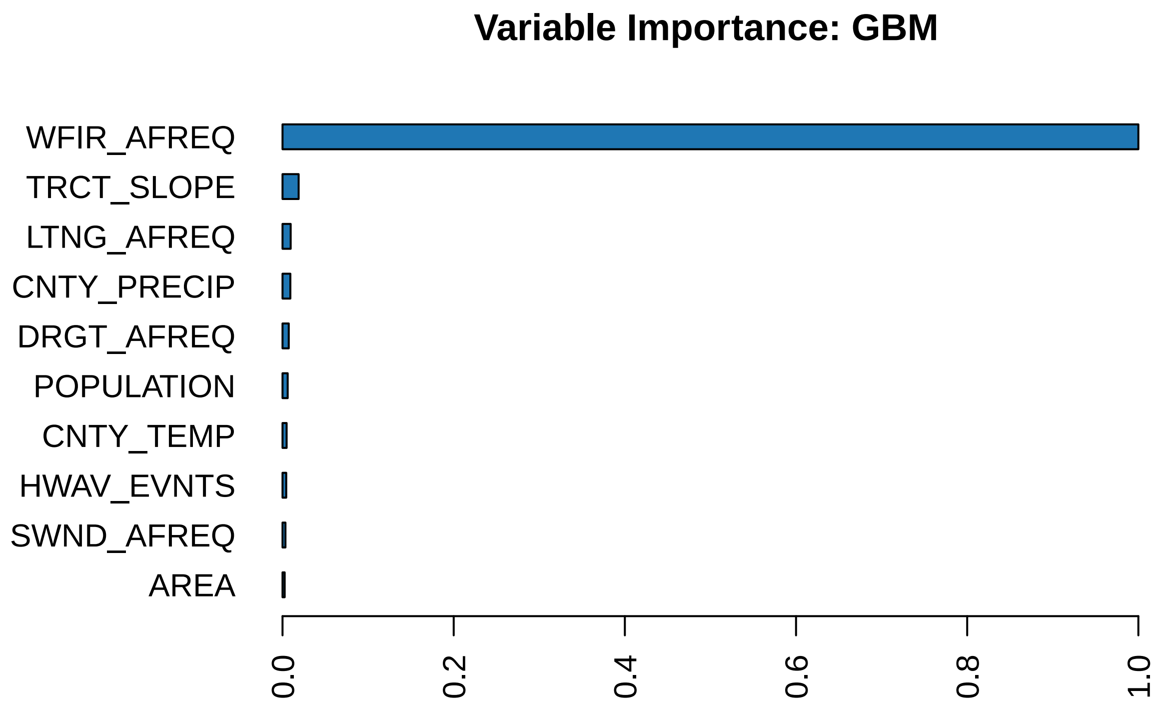
##Variance Importance Plot

These model doesn't have variable importances: `aml`, `pros_nb`, and `svm_model`

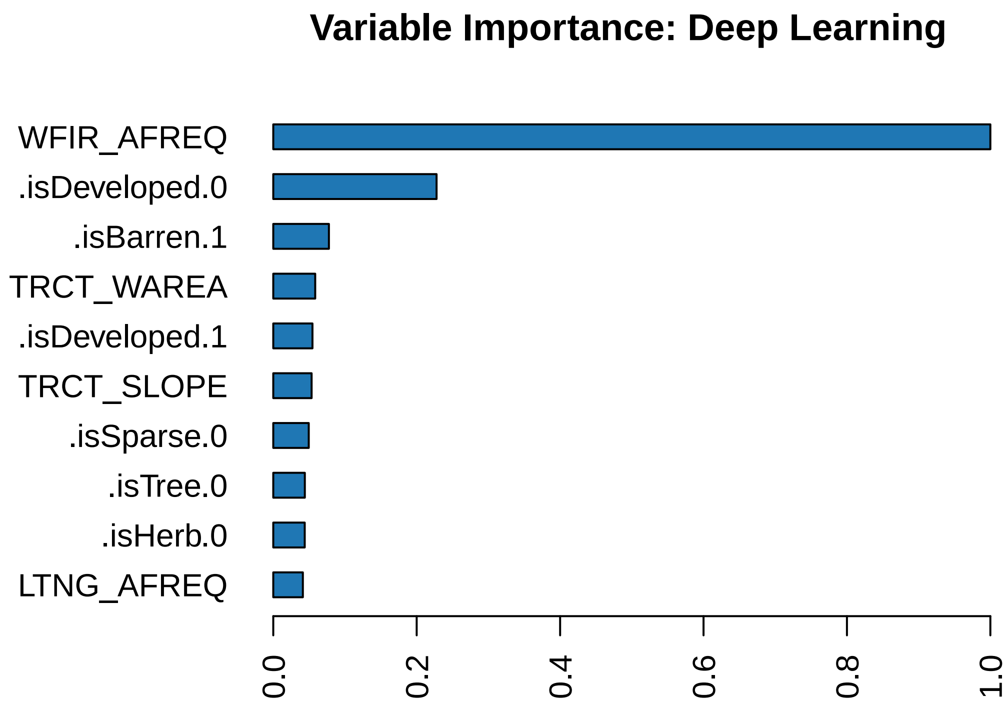
```
h2o.varimp_plot(rf.v2)
```




```r
h2o.varimp_plot(gb_v2)
```




```
h2o.varimp_plot(dl)
```




```
h2o.shutdown()
```