DS622-Stroke Prediction

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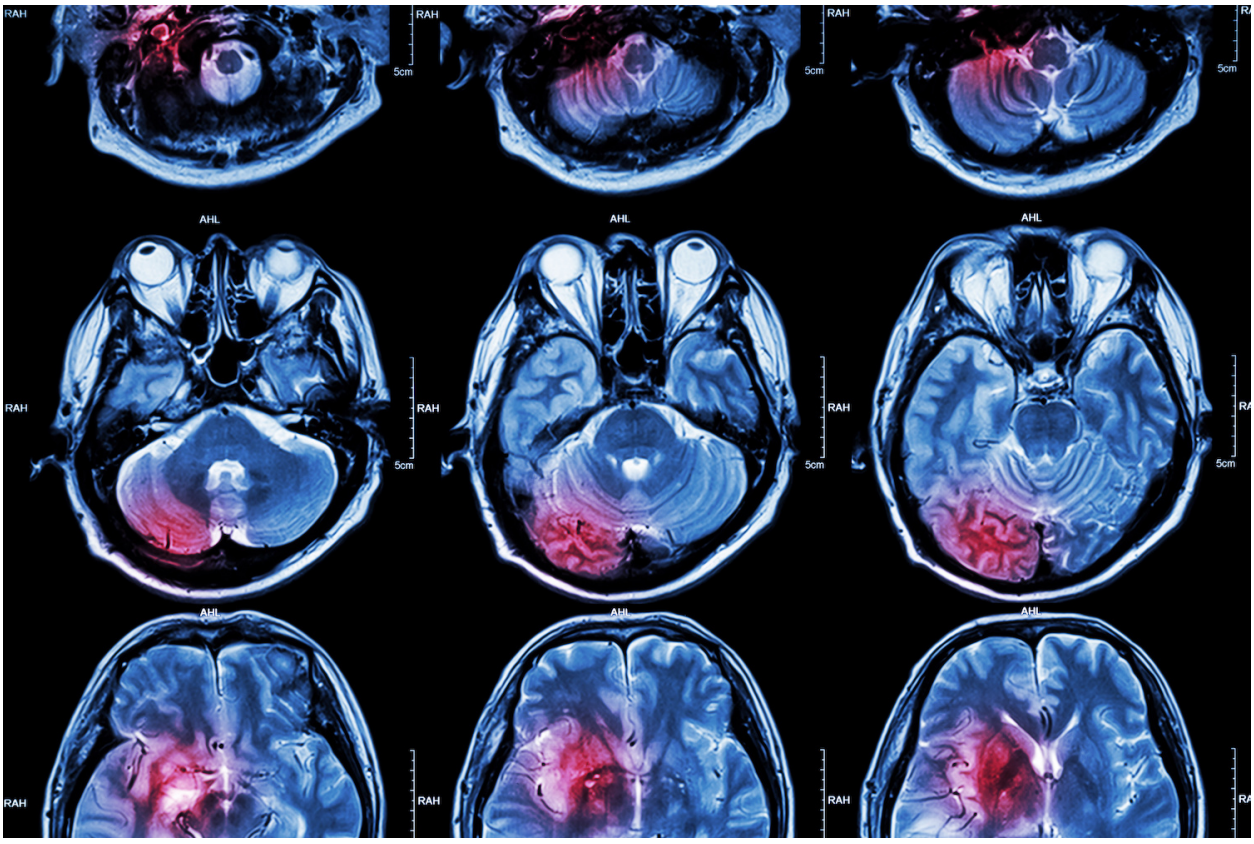
Abstract

According to [1](stroke.org) Stroke is the No. 5 cause of death and a leading cause of disability in the United States. This disease affects the arteries leading to and within the brain. A stroke occurs when a blood vessel that carries oxygen and nutrients to the brain is either blocked by a clot or bursts (or ruptures). When that happens, part of the brain cannot get the blood (and oxygen) it needs, so it and brain cells die.



[1]https://www.stroke.org/en

Contents

1 Overview

According to [2](stroke.org) Stroke is the No. 5 cause of death and a leading cause of disability in the United States. This disease affects the arteries leading to and within the brain. A stroke occurs when a blood vessel that carries oxygen and nutrients to the brain is either blocked by a clot or bursts (or ruptures). When that happens, part of the brain cannot get the blood (and oxygen) it needs, so it and brain cells die.

1.1 Learn more about the data [3]

Variable	Description
id	unique identifier
gender	"Male", "Female" or "Other"
age	age of the patient
hypertension	0 if the patient doesn't have hypertension, 1 if the patient has hypertension
heart_disease	0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease
ever_married	"No" or "Yes"
work_type	"children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
Residence_type	"Rural" or "Urban"
avg_glucose_level	average glucose level in blood
bmi	body mass index
smoking_status	"formerly smoked", "never smoked", "smokes" or "Unknown"*
stroke	1 if the patient had a stroke or 0 if not

*Note: "Unknown" in smoking_status means that the information is unavailable for this patient

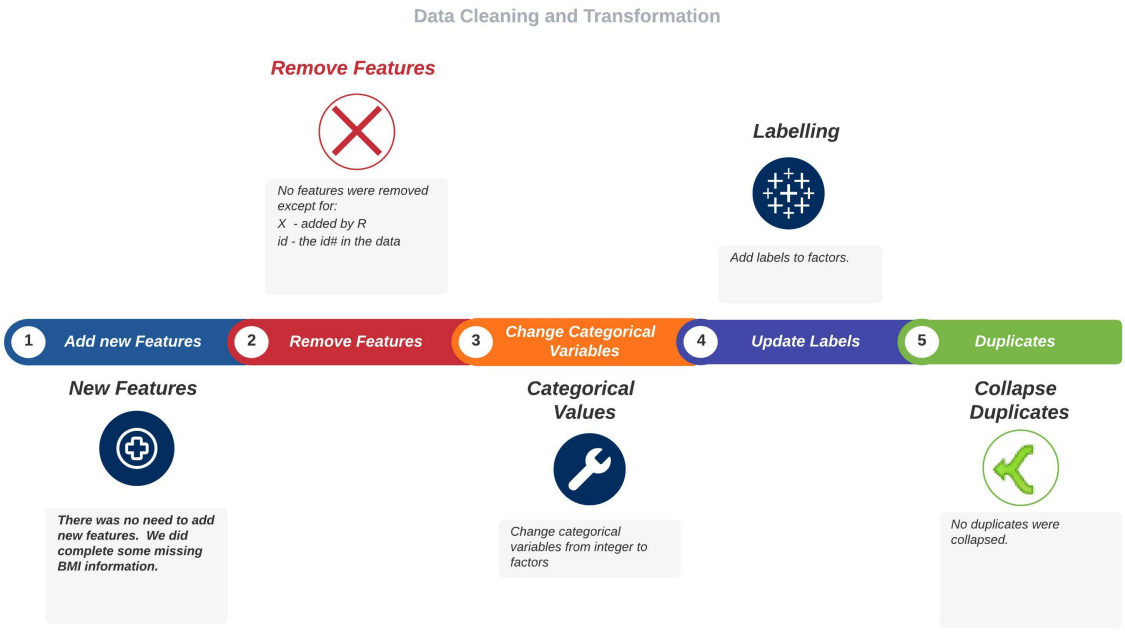
[2]https://www.stroke.org/en
[3]https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset

1.2 What to Predict?

Predictor (stroke)
Description: Predict based on the other variables, if the patient had a stroke or not. This will, in turn, allow us to predict the probability of a stroke on patients with similar profile

The values are determined in the following way:
- 0. No Stroke - 1. Patient had a stroke.

2 Data Cleaning and Transformation



2.1 EDA

2.1.1 Data Loading

We Load the data from `data/TestData/healthcare-dataset-stroke-data.csv` and look at it with `skim`.

```
## Warning: NAs introduced by coercion
```

id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
9046	Male	67	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
51676	Female	61	0	0	Yes	Self-employed	Rural	202.21	NA	never smoked	1

```
kable(skim(data), format="latex", booktabs=TRUE) %>%
  kable_styling(latex_options="scale_down")
```

skim_type	skim_variable	n_missing	complete_rate	character.min	character.max	character.empty	character.n_unique	character.whitespace	numeric.mean	numeric.sd	numeric.p0	numeric.p25	numeric.p50	numeric.p75	numeric.p100	numeric.hist
character	gender	0	1.0000000	4	6	0	3	0	NA	NA	NA	NA	NA	NA	NA	NA
character	ever_married	0	1.0000000	2	3	0	2	0	NA	NA	NA	NA	NA	NA	NA	NA
character	work_type	0	1.0000000	7	13	0	5	0	NA	NA	NA	NA	NA	NA	NA	NA
character	Residence_type	0	1.0000000	5	5	0	2	0	NA	NA	NA	NA	NA	NA	NA	NA
character	smoking_status	0	1.0000000	6	15	0	4	0	NA	NA	NA	NA	NA	NA	NA	NA
numeric	id	0	1.0000000	NA	NA	NA	NA	NA	3.651783e+04	2.116172e+04	67.00	17741.250	36932.000	54682.00	72940.00	<U+2587><U+2587><U+2587><U+2587><U+2587>
numeric	age	0	1.0000000	NA	NA	NA	NA	NA	4.322661e+01	2.261265e+01	0.08	25.000	45.000	61.00	82.00	<U+2585><U+2586><U+2587><U+2587><U+2586>
numeric	hypertension	0	1.0000000	NA	NA	NA	NA	NA	9.745600e-02	2.960067e-01	0.00	0.000	0.000	0.00	1.00	<U+2587><U+2581><U+2581><U+2581><U+2581>
numeric	heart_disease	0	1.0000000	NA	NA	NA	NA	NA	5.401170e-02	2.260630e-01	0.00	0.000	0.000	0.00	1.00	<U+2587><U+2581><U+2581><U+2581><U+2581>
numeric	avg_glucose_level	0	1.0000000	NA	NA	NA	NA	NA	1.061477e+02	4.528356e+01	55.12	77.245	91.885	114.09	271.74	<U+2587><U+2583><U+2581><U+2581><U+2581>
numeric	bmi	201	0.9606654	NA	NA	NA	NA	NA	2.889324e+01	7.854067e+00	10.30	23.500	28.100	33.10	97.60	<U+2587><U+2587><U+2581><U+2581><U+2581>
numeric	stroke	0	1.0000000	NA	NA	NA	NA	NA	4.872800e-02	2.153199e-01	0.00	0.000	0.000	0.00	1.00	<U+2587><U+2581><U+2581><U+2581><U+2581>

2.1.2 Missing Values Count

We noticed that bmi has some missing values:

```
map(data, ~sum(is.na(.))) %>% t()
```

```
##      id gender age hypertension heart_disease ever_married work_type
## [1,] 0  0      0   0            0             0            0
##      Residence_type avg_glucose_level bmi smoking_status stroke
## [1,] 0              0                 201 0              0
```

2.1.3 Populating missing values

We populate the missing bmi values by using the `mean` of the bmi:

```
# This will populate any missing value with its mean.
data <- data %>% mutate_all(~ifelse(is.na(.x), mean(.x, na.rm = TRUE), .x))
write.csv(data, './data/TrainingData/train_cleaned.csv')
```

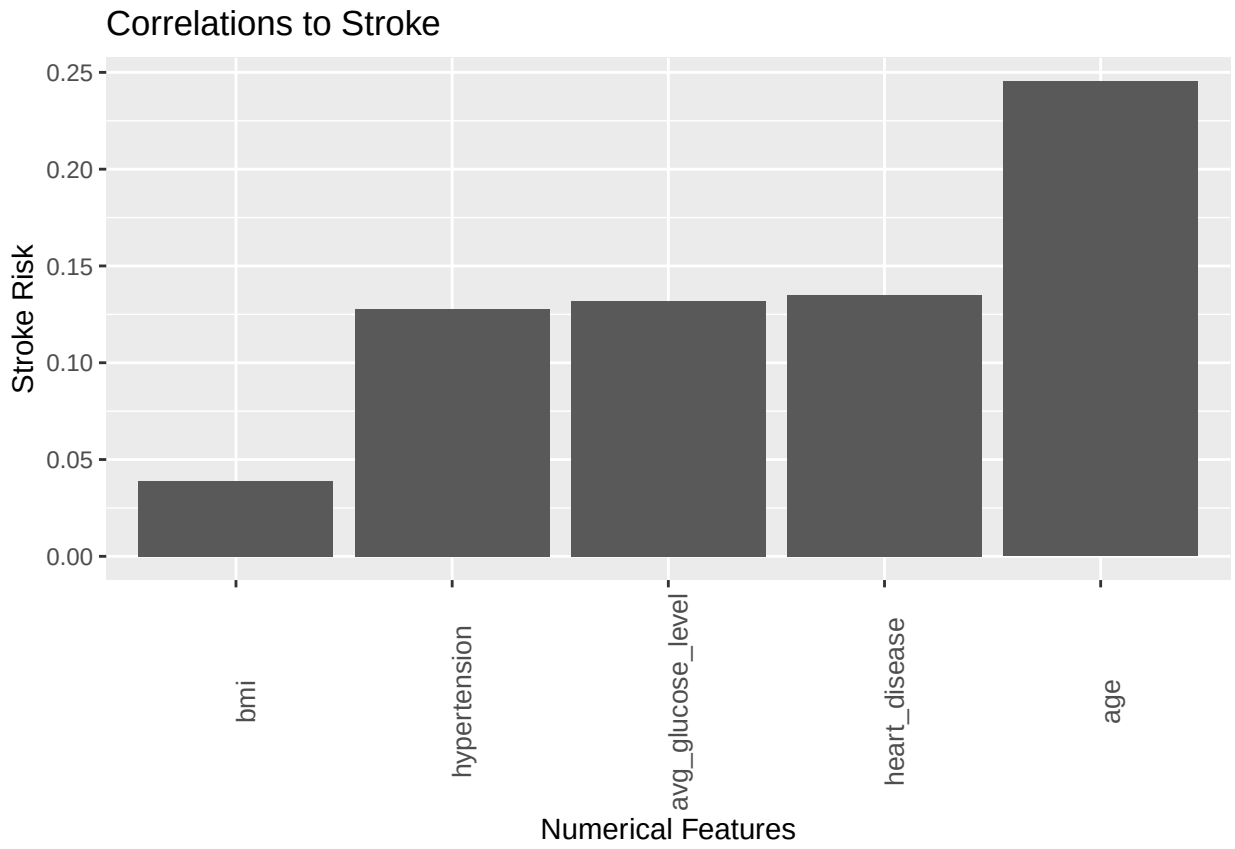
We performed some other data cleaning and transformation tasks like:
1. Change categorical variables from integer to factors.

3 Data Analysis and visualization

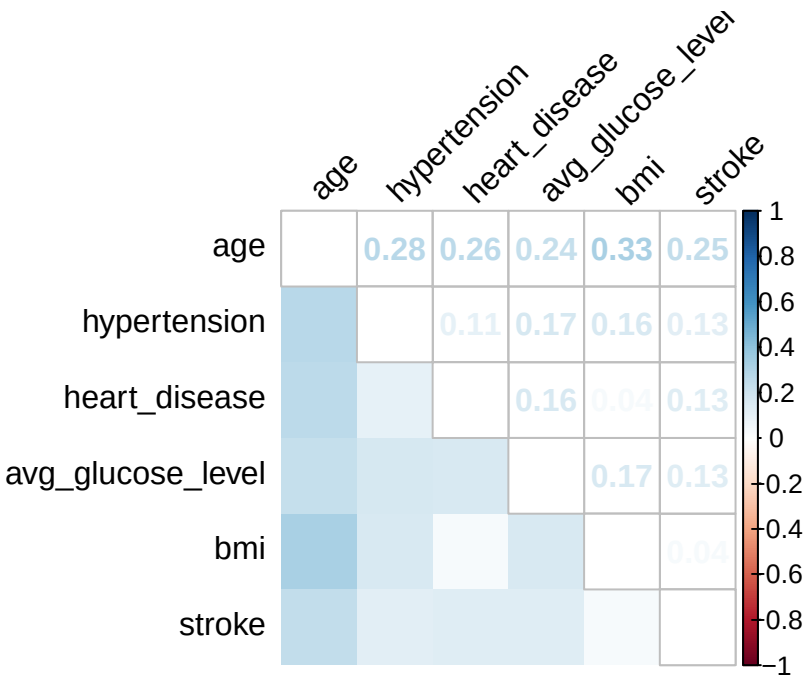
We explore our data to investigate, among other things, the correlation among variables in the data that could be used in our models.

3.1 Feature Correlation

3.1.1 Correlation of each feature to Stroke

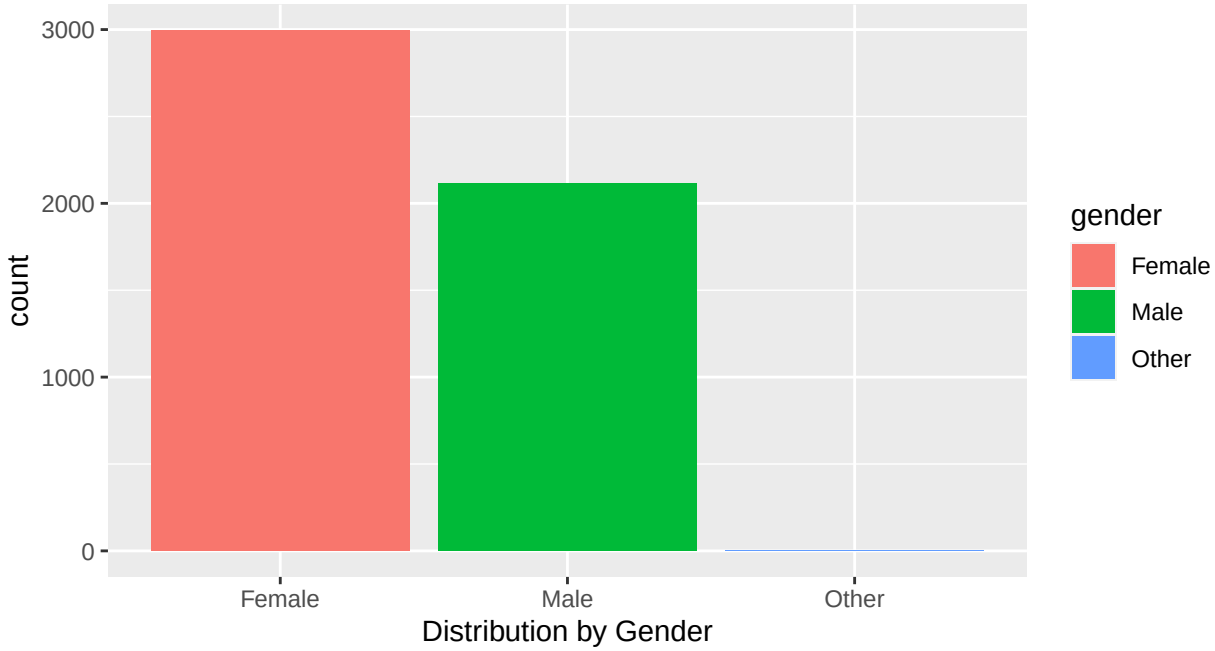


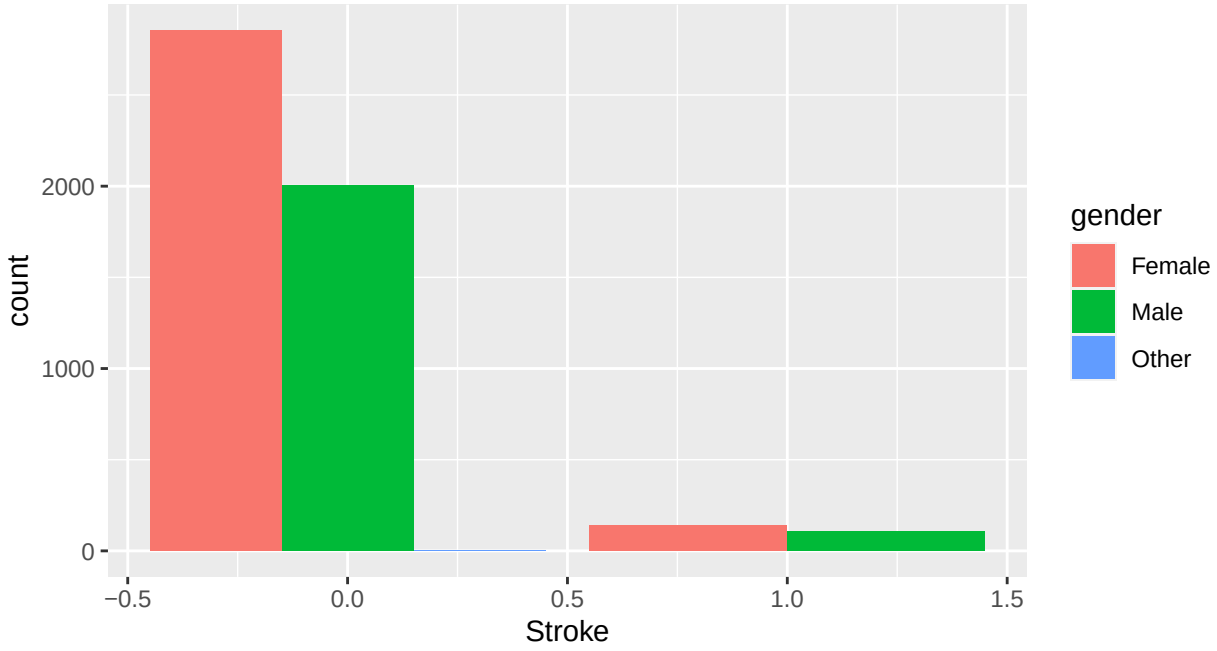
3.1.2 Visual Correlation between features



3.1.3 Gender

One of the first questions we asked, does `gender` affect the chances of having a stroke?

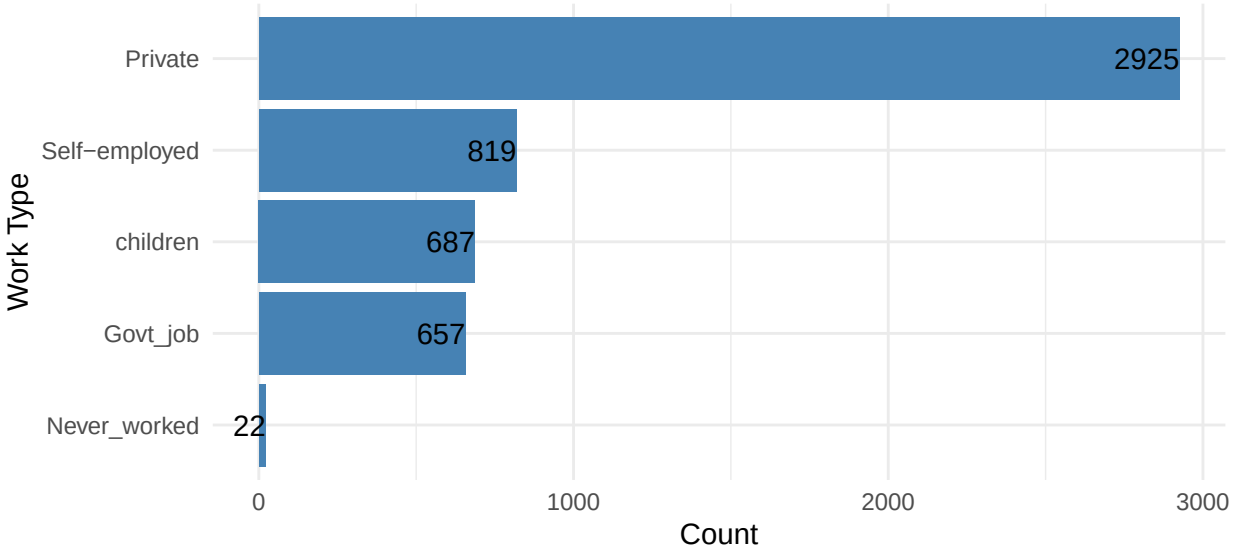




We can see there are more women than men in our study, but the gender seems to have some implication in the incidence of stroke.

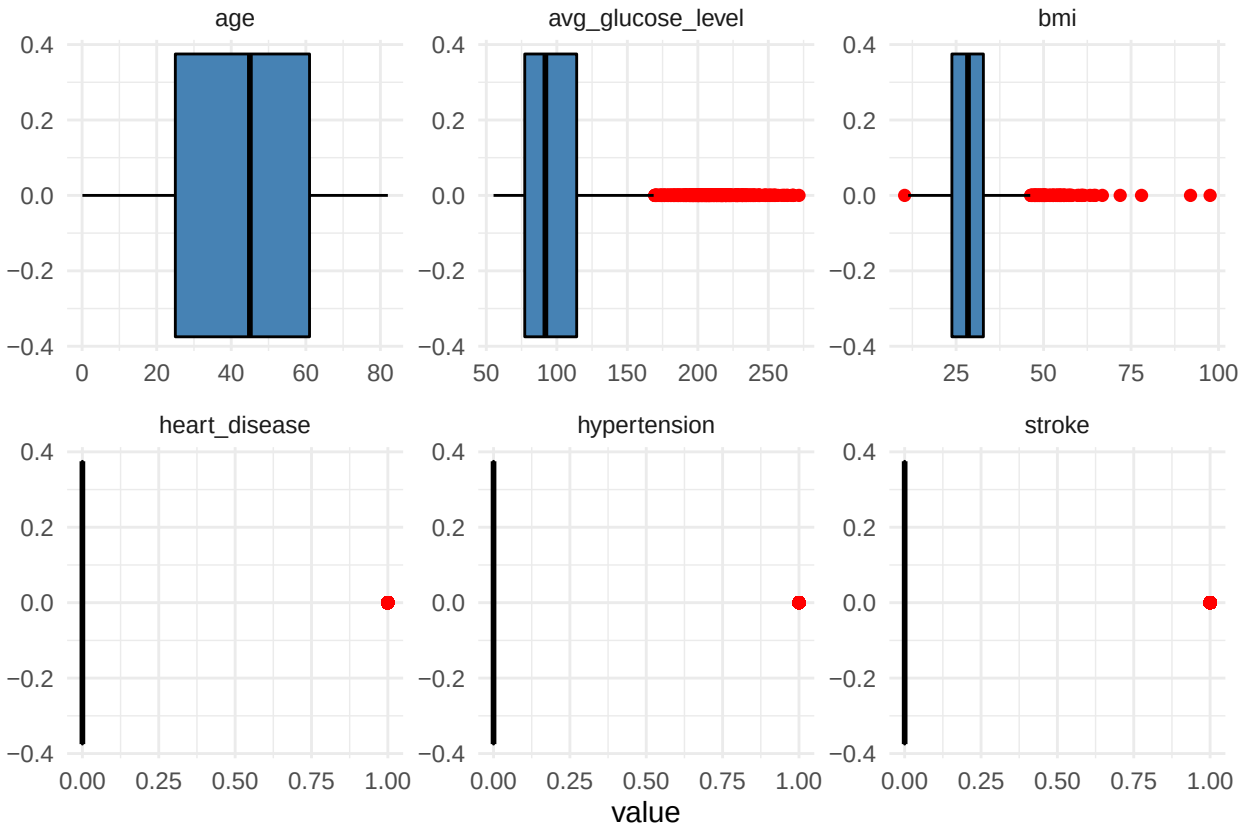
3.2 Bar plots

As part of exploring the data, below we look into our response variable and see which level of `Stroke` has the most occurrences.



3.3 Distributions of Numeric Variables

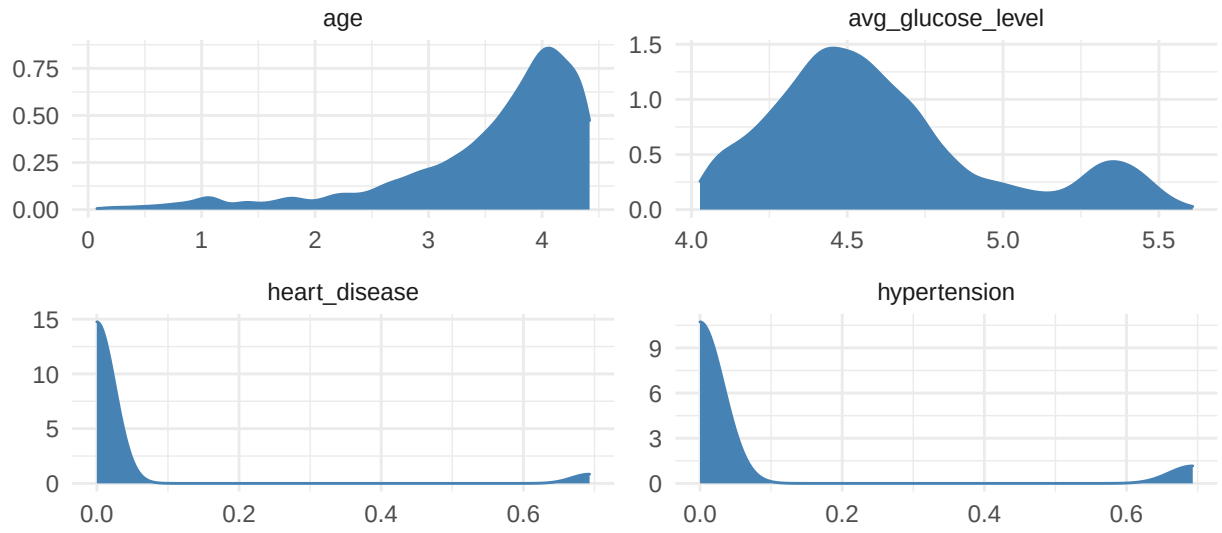
We subset our numeric predictor variables to check their distributions.



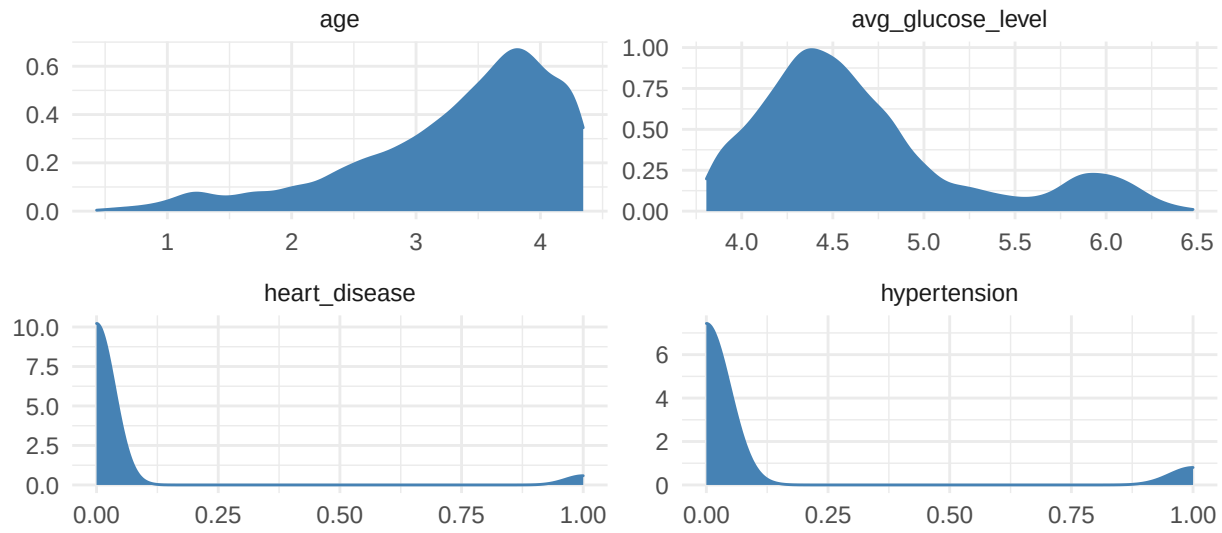
3.4 Transformations of numeric variables

Next we will take transformations of the variables reviewed above to see if the transformed variables are worth looking into and using for our model.

3.5 Log Transformations



3.6 Cube root transformations



The transformations of the numerical variables did not give us any meaningful changes.

4 Data Modeling

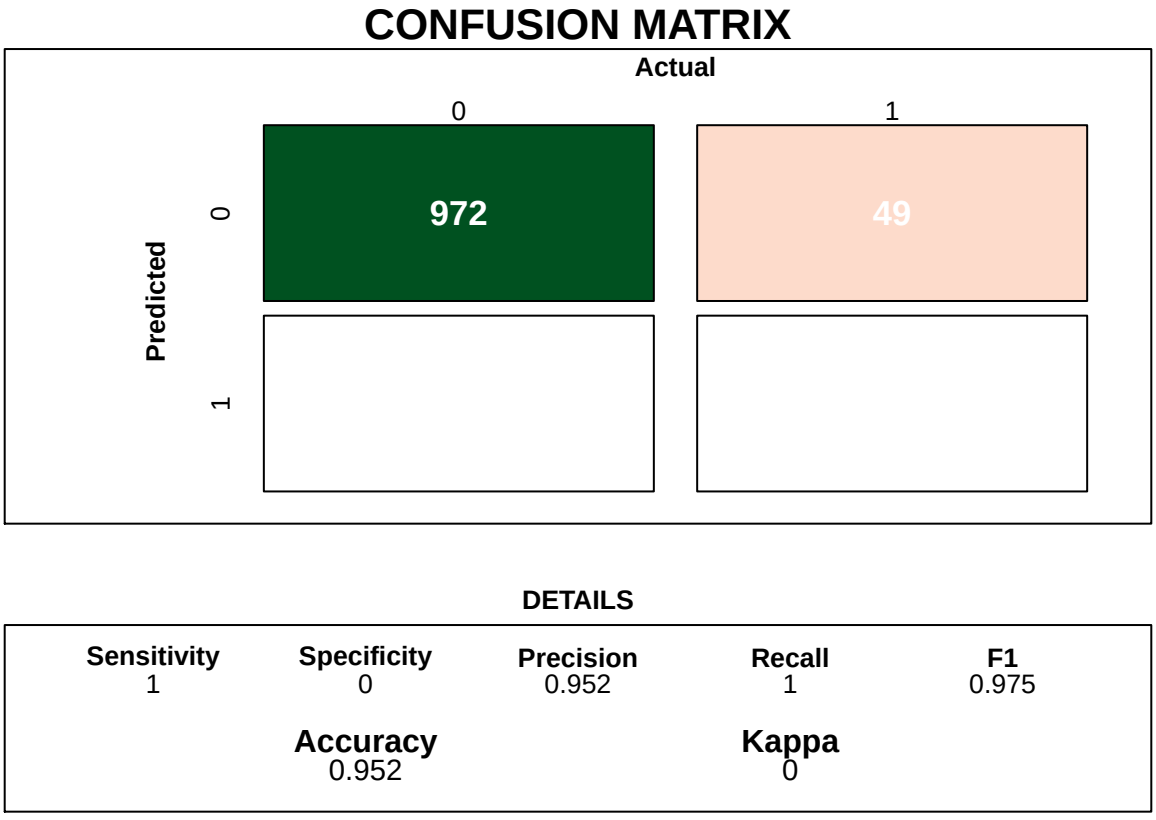
4.1 Random Forest

Helpful article from TowardsDataScience

We explored a few Random Forest models.

We first created a Random Forest model obviating the Categorical variables more prone to cause us issue.

```
rf_model2 <- randomForest(as.factor(stroke) ~.,
                                    data = subset(data_train, select=-c(X,id, age, avg_g
rf_pred2 <- predict(rf_model2, data_test)
c_matrix2 <- confusionMatrix(rf_pred2, as.factor(data_test$stroke))
draw_confusion_matrix(c_matrix2)
```



This model Accuracy is 95% with the sample data. Pretty good.

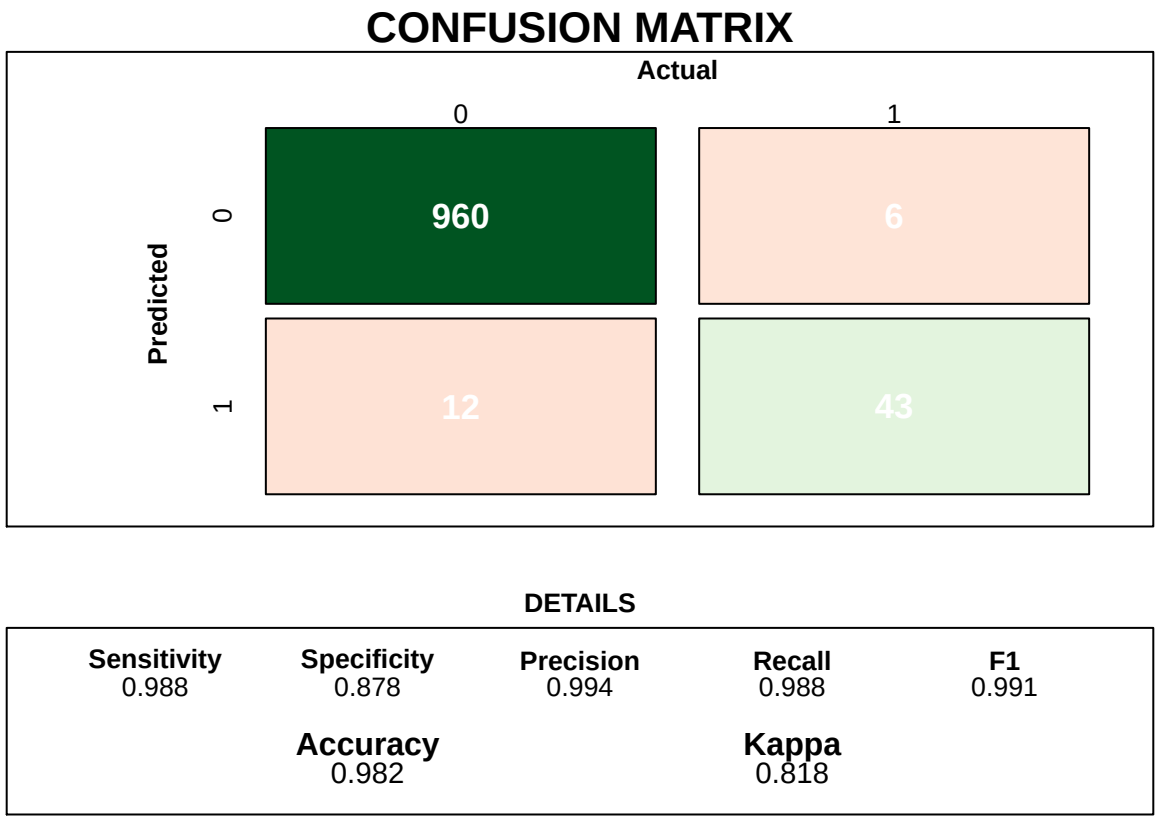
4.2 SVM Model

Drawing from past experience, I only used `e1071::svm` model this time:

```
library(e1071)
svm_model <- svm(stroke ~ .,
                 data = data_train,
                 type = 'C-classification',
                 kernel = "linear")

test_pred <- predict(svm_model, newdata = data_test)

c_matrix <- confusionMatrix(table(test_pred, data_test$stroke))
draw_confusion_matrix(c_matrix)
```



Our SVM model gave us a greater accuracy 98!!! than our RandomForest Model. This is probably due to the use of certain predictors that we excluded from our RF Model.

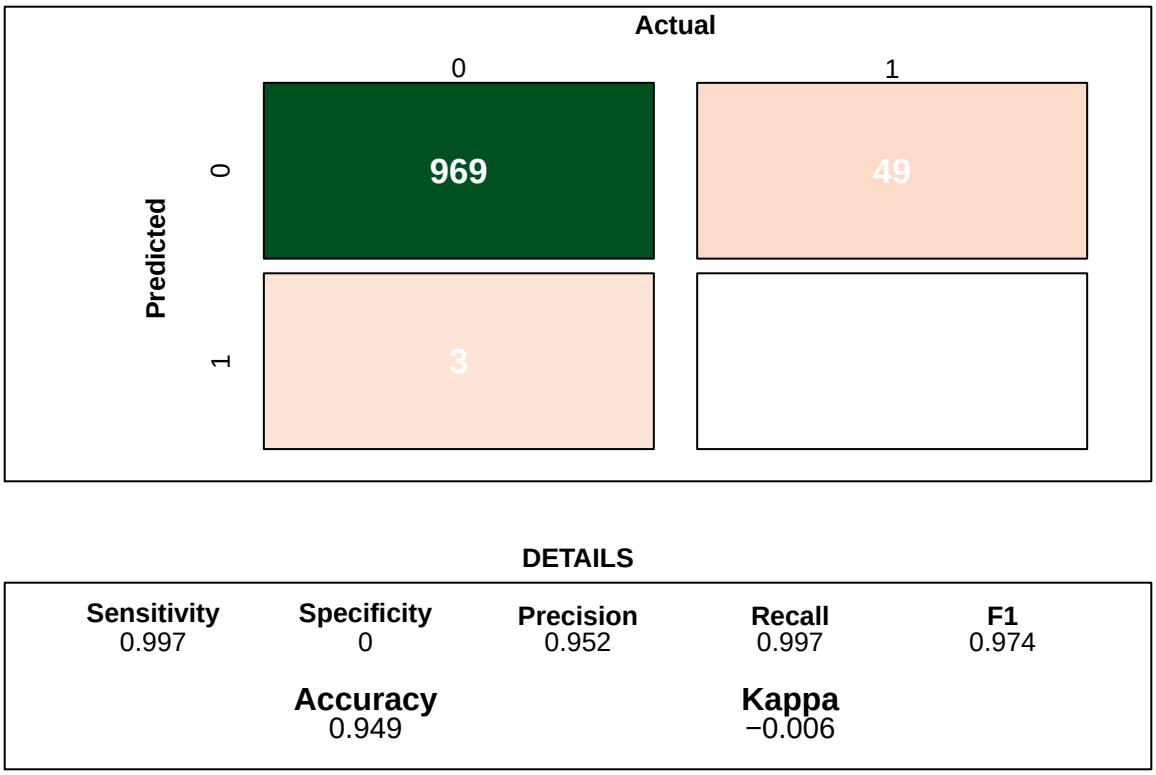
4.3 XGBoost Model

```
library(xgboost)
#train, test data for XG model 1
data_train <- subset(data_train, select=-c(X, id))
data_test <- subset(data_test, select=-c(X,id))

xg_train = as.matrix(data_train)
xg_test = as.matrix(data_test)
#separate out the target variable
stroke_train = xg_train[ , ncol(xg_train)]
stroke_test = xg_test[ , ncol(xg_test)]
#drop stroke from train and test
xg_train = subset(xg_train, select=-c(ncol(xg_train)))
xg_test = subset(xg_test, select=-c(ncol(xg_test)))
#XGBoost requires a dgc matrix
xg_train=as(xg_train, "dgCMatrix")
xg_test=as(xg_test, "dgCMatrix")

#Create the model
xg <- xgboost(data = xg_train, label = stroke_train, nrounds = 300, verbose=0)

#Predict
xg_pred <- predict(xg, xg_test)
#Create a confusion matrix for XG model 1
xg_pred = factor(as.integer(xg_pred))
stroke_test = factor(as.integer(stroke_test))
xg_confusion_matrix = confusionMatrix(xg_pred, stroke_test)
draw_confusion_matrix(xg_confusion_matrix)
```



95% Accuracy, not bad.

5 Conclusions

We tried several models:
- Random Forest
- XGBoost
- SVM

With the data provided, our best fitted models was the **SVM** which gave us a 98% accuracy. Due to the nature and presentation of the data, we did not need to work more on cleaning or preparing it to use in other models. I would love to use clustering and grouping the categorical variables in ranges so we could use them to fit other RandomForest models.

Accurately predicting Strokes will potentially save millions of lives. Therefore, the application of this analysis is extremely valuable.

** Next Steps** As mentioned, I would like to apply clustering and unsupervised learning to this dataset. Regardless of this being a classification exercise, there is much more to learn about these accidents and their prevention. If we're able to accurately identify the warning signs (we know them but applying this information as part of some Medical Information System) would potentially allow us to take some measures in their prevention.

6 References

Kaggle - About the data. "https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset". Dec, 2021.
TowardsDataScience - Random Forest in R. "https://towardsdatascience.com/random-forest-in-r-f66adf80ec9". May 2024.

7 Appendix A.

7.1 Notable Code.

```
### Function to Create Confusion Matrix

create_rf_confusion_matrix <- function(pred, test){

  #Creates vectors having data points
  stroke_test = as.numeric(unlist(test$stroke))
  expected_value <- factor(c(stroke_test))

  predicted_value <- factor(c(pred))

  #Creating confusion matrix
  rf_confusion_matrix <- confusionMatrix(data=predicted_value,
                                         reference = expected_value,
                                         positive='1')

  #Results
  return(rf_confusion_matrix)
}

### Function to draw confusion matrix
### Credit: https://stackoverflow.com/questions/23891140/r-how-to-visualize-confusion-
draw_confusion_matrix <- function(cm) {

  total <- sum(cm$table)
  res <- as.numeric(cm$table)

  # Generate color gradients. Palettes come from RColorBrewer.
  greenPalette <- c("#F7FCF5",
                    "#E5F5E0",
                    "#C7E9C0",
                    "#A1D99B","#74C476",
                    "#41AB5D","#238B45",
                    "#006D2C","#00441B")
  redPalette <- c("#FFF5F0","#FEE0D2",
                  "#FCBBA1","#FC9272",
                  "#FB6A4A","#EF3B2C",
                  "#CB181D","#A50F15",
                  "#67000D")
  getColor <- function (greenOrRed = "green", amount = 0) {
```

```
  if (amount == 0)
    return("#FFFFFF")
  palette <- greenPalette
  if (greenOrRed == "red")
    palette <- redPalette
  colorRampPalette(palette)(100)[10 + ceiling(90 * amount / total)]
}

# set the basic layout
layout(matrix(c(1,1,2)))
par(mar=c(2,2,2,2))
plot(c(100, 345), c(300, 450), type = "n",
     xlab="", ylab="", xaxt='n', yaxt='n')
title('CONFUSION MATRIX', cex.main=2)

# create the matrix
classes = colnames(cm$table)
rect(150, 430, 240, 370, col=getColor("green", res[1]))
text(195, 435, classes[1], cex=1.2)
rect(250, 430, 340, 370, col=getColor("red", res[3]))
text(295, 435, classes[2], cex=1.2)
text(125, 370, 'Predicted', cex=1.3, srt=90, font=2)
text(245, 450, 'Actual', cex=1.3, font=2)
rect(150, 305, 240, 365, col=getColor("red", res[2]))
rect(250, 305, 340, 365, col=getColor("green", res[4]))
text(140, 400, classes[1], cex=1.2, srt=90)
text(140, 335, classes[2], cex=1.2, srt=90)

# add in the cm results
text(195, 400, res[1], cex=1.6, font=2, col='white')
text(195, 335, res[2], cex=1.6, font=2, col='white')
text(295, 400, res[3], cex=1.6, font=2, col='white')
text(295, 335, res[4], cex=1.6, font=2, col='white')

# add in the specifics
plot(c(100, 0), c(100, 0), type = "n", xlab="",
     ylab="", main = "DETAILS", xaxt='n', yaxt='n')
text(10, 85, names(cm$byClass[1]), cex=1.2, font=2)
text(10, 70, round(as.numeric(cm$byClass[1]), 3), cex=1.2)
text(30, 85, names(cm$byClass[2]), cex=1.2, font=2)
text(30, 70, round(as.numeric(cm$byClass[2]), 3), cex=1.2)
text(50, 85, names(cm$byClass[5]), cex=1.2, font=2)
text(50, 70, round(as.numeric(cm$byClass[5]), 3), cex=1.2)
text(70, 85, names(cm$byClass[6]), cex=1.2, font=2)
```

```
  text(70, 70, round(as.numeric(cm$byClass[6]), 3), cex=1.2)
  text(90, 85, names(cm$byClass[7]), cex=1.2, font=2)
  text(90, 70, round(as.numeric(cm$byClass[7]), 3), cex=1.2)

  # add in the accuracy information
  text(30, 35, names(cm$overall[1]), cex=1.5, font=2)
  text(30, 20, round(as.numeric(cm$overall[1]), 3), cex=1.4)
  text(70, 35, names(cm$overall[2]), cex=1.5, font=2)
  text(70, 20, round(as.numeric(cm$overall[2]), 3), cex=1.4)
}

#### Function to create train and test

partition_data <- function(data, isTest) {
  sample <- sample.split(data$stroke,
                         SplitRatio = .75)
  train <- subset(data,
                  sample == isTest)

  return(train)
}

#Create train data
create_train_data  <- function(data) {

  new_data <- partition_data(data, TRUE)

  return(new_data)
}

#Create test data
create_test_data  <- function(data) {

  new_data <- partition_data(data, FALSE)

  return(new_data)
}


rf_model_func <- function(data) {
  #train, test data for RF model 1
  rf_train = create_train_data(data)
  rf_test = create_test_data(data)
```

```
  #create RF model 1
  rf <- randomForest(
    stroke ~ .,
    data=rf_train
  )

  #Predict stroke with RF model 1
  rf_pred = predict(rf, newdata=rf_test)

  #Create a confusion matrix for RF model 1
  rf_confusion_matrix = create_rf_confusion_matrix(rf_pred, rf_test)
  return(rf_confusion_matrix)
}
```

...