# YALE UNIVERSITY COMPUTATIONAL METHODS FOR INFORMATICS (BIS634)

Final Project Report

Stroke Prediction and Analysis

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# 1 Introduction

A stroke is a medical condition in which the blood supply to a part of the brain is disrupted, leading to brain cell death and possible long-term disability or death. Stroke is a leading cause of death and disability worldwide, with high rates of morbidity and mortality. It is worth paying attention to stroke because it can have a significant impact on an individual's quality of life and can also have a significant economic burden on society.

In order to better understand and ultimately prevent or treat stroke, it is important to analyze data on stroke incidents and outcomes. Choosing a dataset for stroke analysis can help researchers and healthcare professionals gain insights into the risk factors, causes, and consequences of stroke, as well as identify potential interventions or treatments that may be effective in reducing the incidence and severity of stroke. By analyzing data on stroke, we can improve our understanding of this important public health issue and work towards finding solutions to reduce the burden of stroke on individuals and society.

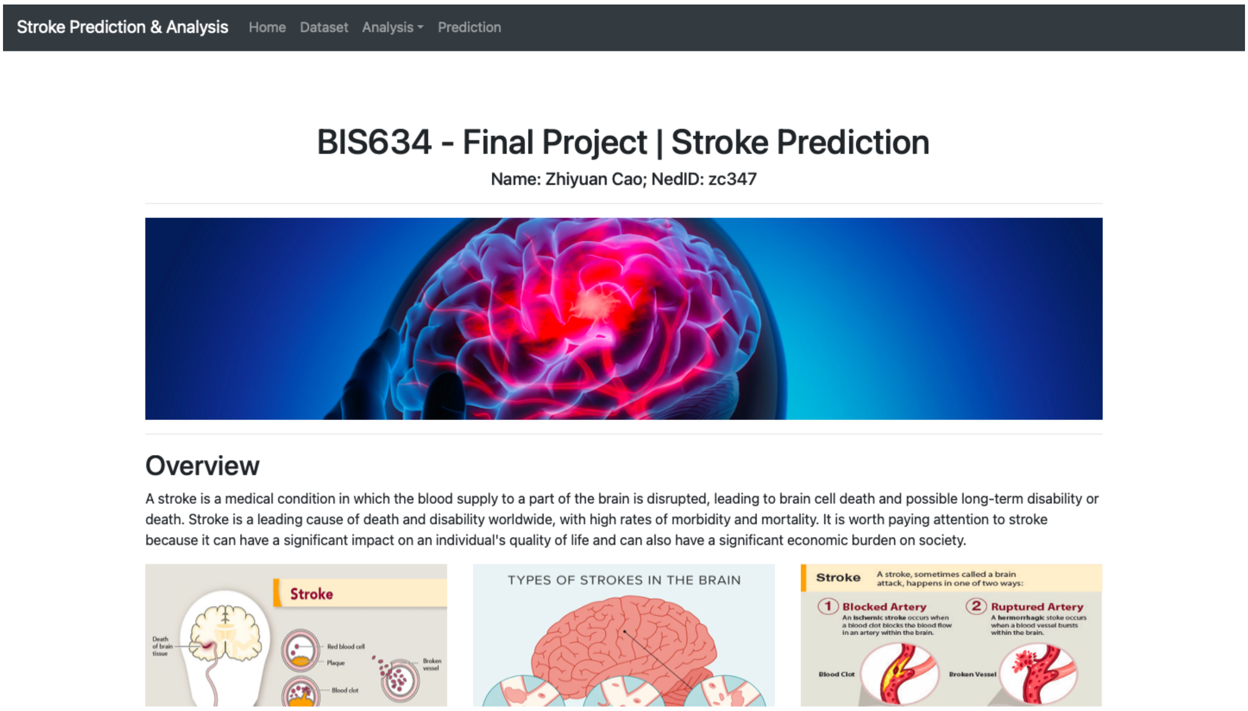



Figure 1: Webpage for Homepage

# 2 Dataset Description

## 2.1 About the Dataset

The dataset named "Stroke Prediction" is an open source dataset from Kaggle. It is under the healthcare-dataset-stroke-data.csv file. The data contains 5110 rows and 12 features in total. The metadata of this datset is also available on Kaggle.

Dataset citation: FEDESORIANO. Stroke Prediction Dataset. Retrieved December 17, 2022 from https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset?resource=download.

## 2.2 Features

- id: unique identifier of a patient
- 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
- smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*
- stroke: 1 if the patient had a stroke or 0 if not

## 2.3 Dateframe

| | id | gender | age | hypertension | heart_disease | ever_married | work_type | Residence_type | avg_glucose_level | bmi | smoking_status | stroke |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 9046 | Male | 67.0 | 0 | 1 | Yes | Private | Urban | 228.69 | 36.6 | formerly smoked | 1 |
| **1** | 51676 | Female | 61.0 | 0 | 0 | Yes | Self-employed | Rural | 202.21 | NaN | never smoked | 1 |
| **2** | 31112 | Male | 80.0 | 0 | 1 | Yes | Private | Rural | 105.92 | 32.5 | never smoked | 1 |
| **3** | 60182 | Female | 49.0 | 0 | 0 | Yes | Private | Urban | 171.23 | 34.4 | smokes | 1 |
| **4** | 1665 | Female | 79.0 | 1 | 0 | Yes | Self-employed | Rural | 174.12 | 24.0 | never smoked | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **5105** | 18234 | Female | 80.0 | 1 | 0 | Yes | Private | Urban | 83.75 | NaN | never smoked | 0 |
| **5106** | 44873 | Female | 81.0 | 0 | 0 | Yes | Self-employed | Urban | 125.20 | 40.0 | never smoked | 0 |
| **5107** | 19723 | Female | 35.0 | 0 | 0 | Yes | Self-employed | Rural | 82.99 | 30.6 | never smoked | 0 |
| **5108** | 37544 | Male | 51.0 | 0 | 0 | Yes | Private | Rural | 166.29 | 25.6 | formerly smoked | 0 |
| **5109** | 44679 | Female | 44.0 | 0 | 0 | Yes | Govt_job | Urban | 85.28 | 26.2 | Unknown | 0 |

5110 rows × 12 columns

Figure 2: Stroke Prediction Dataframe

## 2.4 Data Preprocessing

- Data Cleaning: I drop all the rows with missing value 'nan'. After doing so, the dataset contains 4909 rows. Except these missing values, the dataset is very clean and does not need further cleaning: The author has already performed necessary data cleaning.
- Data processing: I transform all the categorical data into dummy ones to enable machine learning models to process them.

## 2.5 Data FAIRness

- Findability: The stroke dataset is properly documented and has clear and accurate metadata. Hence, it is easy for others to discover and locate it.

- Accessibility: The stroke dataset is available in a format that is easy to use and that there are no barriers to accessing the data: It is totally free and liscensed by the author. Thus, the dataset can be easily accessible to those who need it.

- Interoperability: Using standardized formats and providing clear documentation about the data's structure and content, the dataset has a good interoperability, since it can be easily integrated with other datasets or tools.

- Reusability: The dataset provides clear documentation about the data's provenance, as well as any relevant ethical or legal considerations. Hence the dataset can be easily reused for multiple purposes.

## 2.6 Website Interface

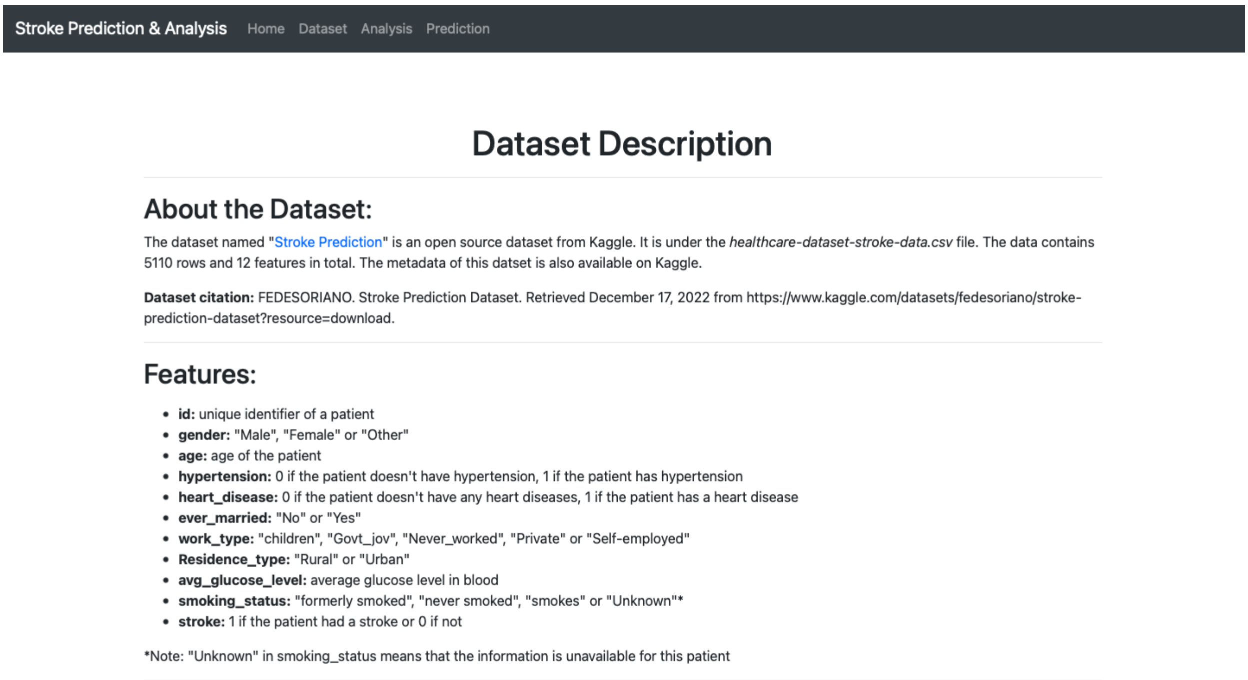



Figure 3: Webpage for Dataset Description

# 3 Exploratory Analysis

## 3.1 Summary Statistics

### 3.1.1 Statistical Analysis

| | age | hypertension | heart_disease | avg_glucose_level | bmi |
|---|---|---|---|---|---|
| **count** | 209.000000 | 209.000000 | 209.000000 | 209.000000 | 209.000000 |
| **mean** | 67.712919 | 0.287081 | 0.191388 | 134.571388 | 30.471292 |
| **std** | 12.402848 | 0.453486 | 0.394338 | 62.462047 | 6.329452 |
| **min** | 14.000000 | 0.000000 | 0.000000 | 56.110000 | 16.900000 |
| **25%** | 58.000000 | 0.000000 | 0.000000 | 80.430000 | 26.400000 |
| **50%** | 70.000000 | 0.000000 | 0.000000 | 106.580000 | 29.700000 |
| **75%** | 78.000000 | 1.000000 | 0.000000 | 196.920000 | 33.700000 |
| **max** | 82.000000 | 1.000000 | 1.000000 | 271.740000 | 56.600000 |

Figure 4: Summary statistics for patients with stroke

| | age | hypertension | heart_disease | avg_glucose_level | bmi |
|---|---|---|---|---|---|
| **count** | 4700.000000 | 4700.000000 | 4700.000000 | 4700.000000 | 4700.000000 |
| **mean** | 41.760451 | 0.083191 | 0.043191 | 104.003736 | 28.823064 |
| **std** | 22.268129 | 0.276201 | 0.203310 | 42.997798 | 7.908287 |
| **min** | 0.080000 | 0.000000 | 0.000000 | 55.120000 | 10.300000 |
| **25%** | 24.000000 | 0.000000 | 0.000000 | 76.887500 | 23.400000 |
| **50%** | 43.000000 | 0.000000 | 0.000000 | 91.210000 | 28.000000 |
| **75%** | 59.000000 | 0.000000 | 0.000000 | 112.432500 | 33.100000 |
| **max** | 82.000000 | 1.000000 | 1.000000 | 267.760000 | 97.600000 |

Figure 5: Summary statistics for patients without stroke

From the statistics, it is clear that:

- The mean age for people with stroke is much higher than those without stroke. Patients with stroke tends to be 26 years elder than the healthy on average.
- Patients with stroke have higher probability to have hypertension than healthy people.
- Patients with stroke have slightly higher probability to have heart disease than healthy people.
- Patients with stroke tends to have a higher average glucose level than healthy people.

In conclusion, elder people with other chronic diseases have a higher possiblility to have stroke.

### 3.1.2 Data Distribution and Outliers Analysis

In our dataset, there are three numberic features. The above figure are histogram and barplot, which shows the distribution of these data. From the figure:

- There is no outlier for age.
- There are a lot of outliers for avg glucose level and bmi. All the outlier are high values.

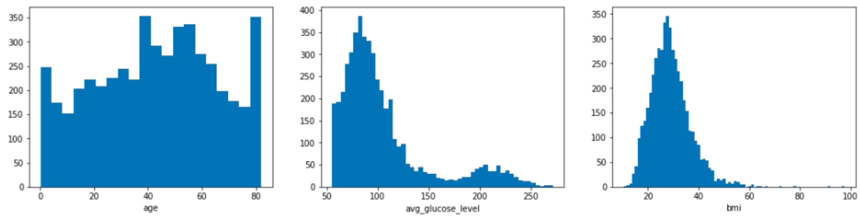



Figure 6: Histogram for features

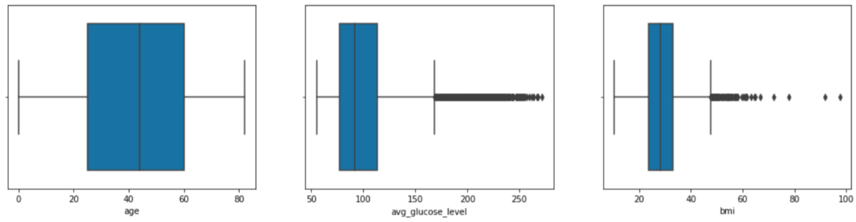
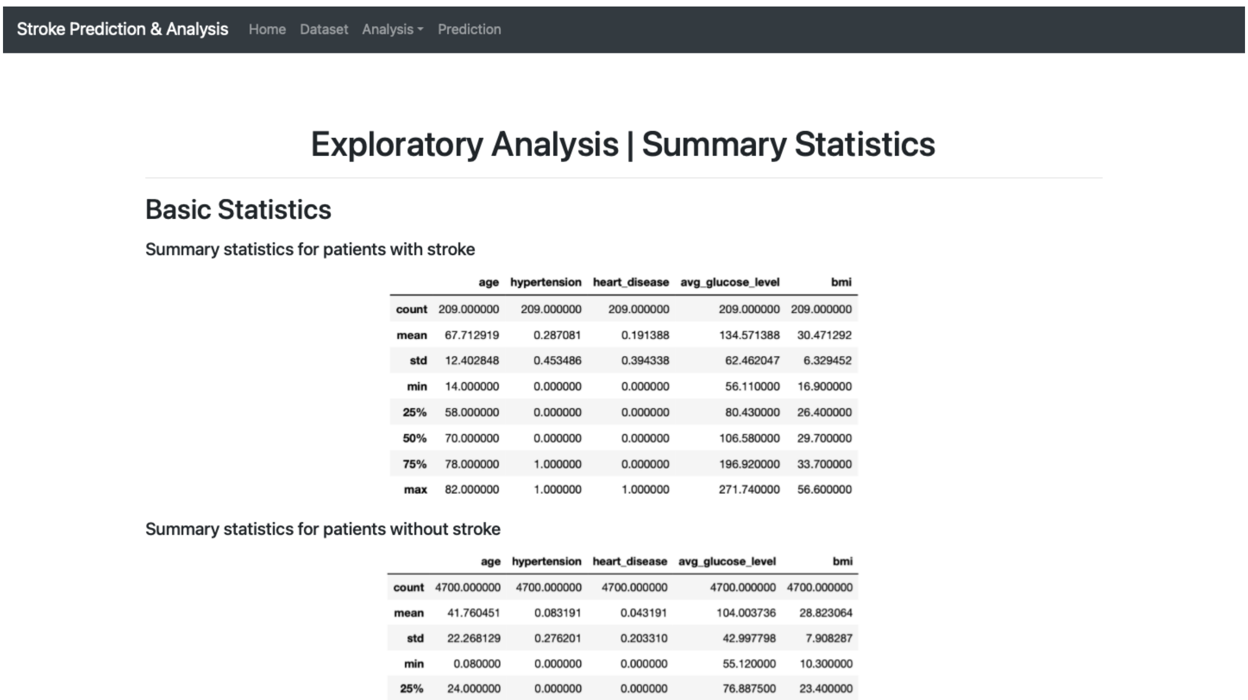



Figure 7: Bar plot for features

### 3.1.3 Website Interface




# Exploratory Analysis | Summary Statistics

## Basic Statistics

Summary statistics for patients with stroke

| | age | hypertension | heart_disease | avg_glucose_level | bmi |
|---|---|---|---|---|---|
| count | 209.000000 | 209.000000 | 209.000000 | 209.000000 | 209.000000 |
| mean | 67.712919 | 0.287081 | 0.191388 | 134.571388 | 30.471292 |
| std | 12.402848 | 0.453486 | 0.394338 | 62.462047 | 6.329452 |
| min | 14.000000 | 0.000000 | 0.000000 | 56.110000 | 16.900000 |
| 25% | 58.000000 | 0.000000 | 0.000000 | 80.430000 | 26.400000 |
| 50% | 70.000000 | 0.000000 | 0.000000 | 106.580000 | 29.700000 |
| 75% | 78.000000 | 1.000000 | 0.000000 | 196.920000 | 33.700000 |
| max | 82.000000 | 1.000000 | 1.000000 | 271.740000 | 56.600000 |

Summary statistics for patients without stroke

| | age | hypertension | heart_disease | avg_glucose_level | bmi |
|---|---|---|---|---|---|
| count | 4700.000000 | 4700.000000 | 4700.000000 | 4700.000000 | 4700.000000 |
| mean | 41.760451 | 0.083191 | 0.043191 | 104.003736 | 28.823064 |
| std | 22.268129 | 0.276201 | 0.203310 | 42.997798 | 7.908287 |
| min | 0.080000 | 0.000000 | 0.000000 | 55.120000 | 10.300000 |
| 25% | 24.000000 | 0.000000 | 0.000000 | 76.887500 | 23.400000 |

Figure 8: Webpage for Summary Statistics

## 3.2 Univariate Analysis

### 3.2.1 Analysis Questions

- Which age/gender has the highest probability to have stroke?
- How avg glucose level and bmi related to stroke?

### 3.2.2 Age Distribution

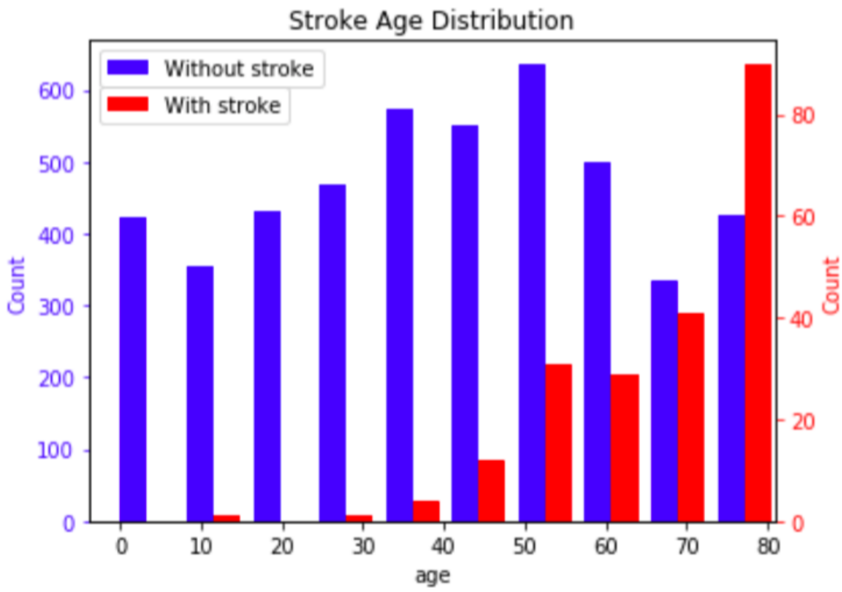



Figure 9: Histogram for age distribution

The larger the age is, the more possible a person have stroke.

### 3.2.3 Gender Distribution

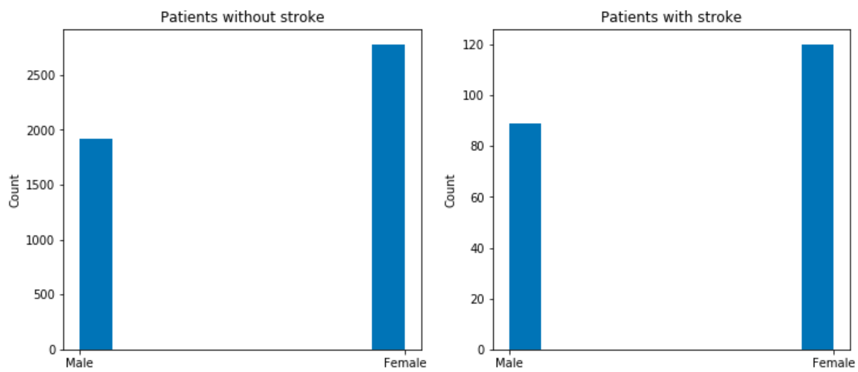



Figure 10: Histogram for gender distribution

The dataset contains more female patients than male ones. By comparing the proportion of gender within different groups, it can be concluded that there is no strong relationship between gender and stroke.

### 3.2.4 Glucose Distribution

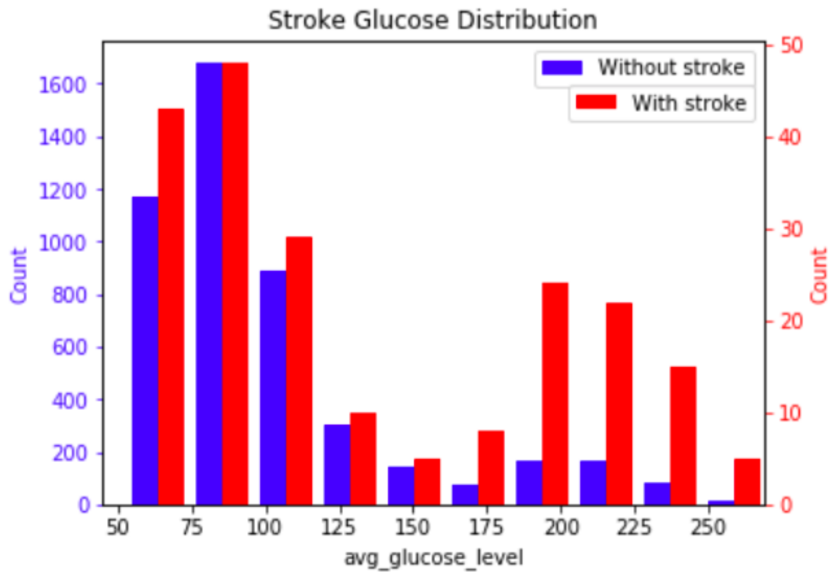



Figure 11: Histogram for glucose distribution

From the histogram, a higher glucose level do suggest a higher probability to have stroke. However, for patients with regular average glucose levels, the probability of having stroke won't decrease.

### 3.2.5 BMI Distribution

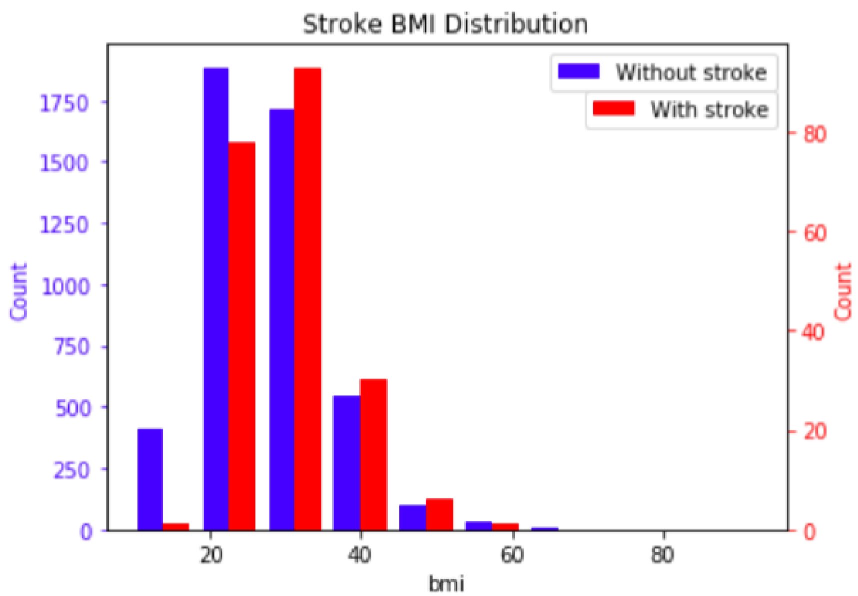



Figure 12: Histogram for BMI distribution

The histogram suggests that stroke patients tend to have a higher bmi. There exists a weak correlation between bmi and stroke.

### 3.2.6 Website Interface

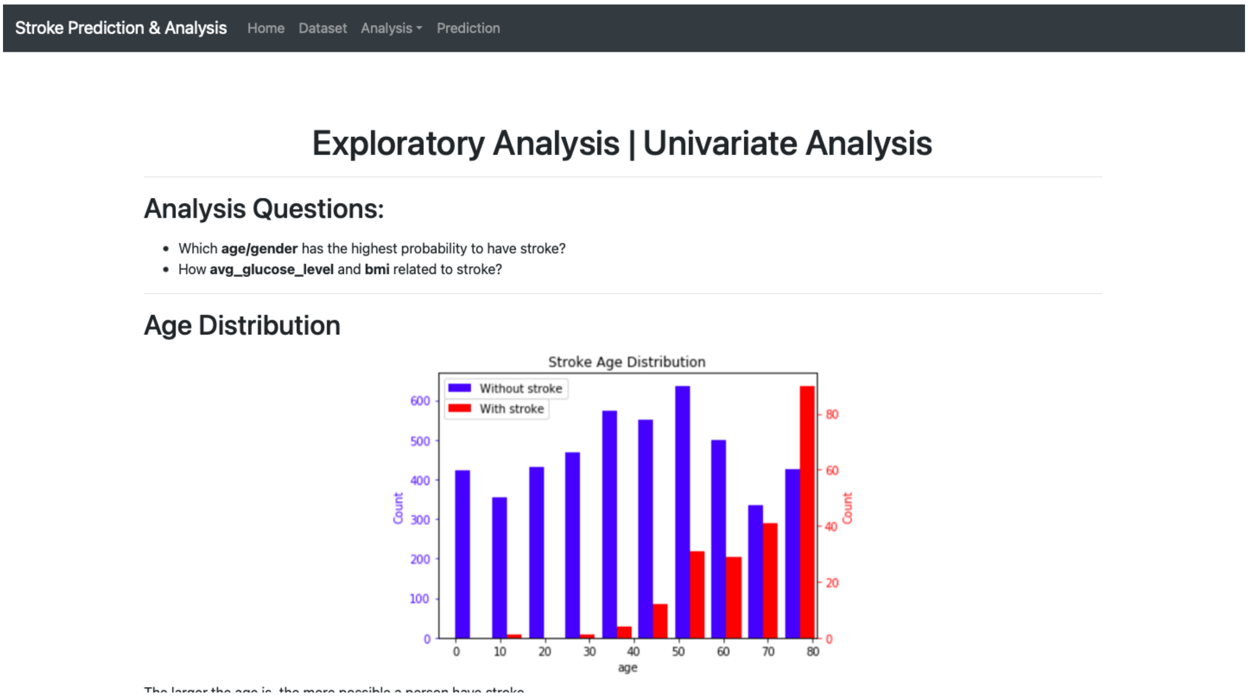



Figure 13: Webpage for Summary Statistics

## 3.3 Bivariate Analysis

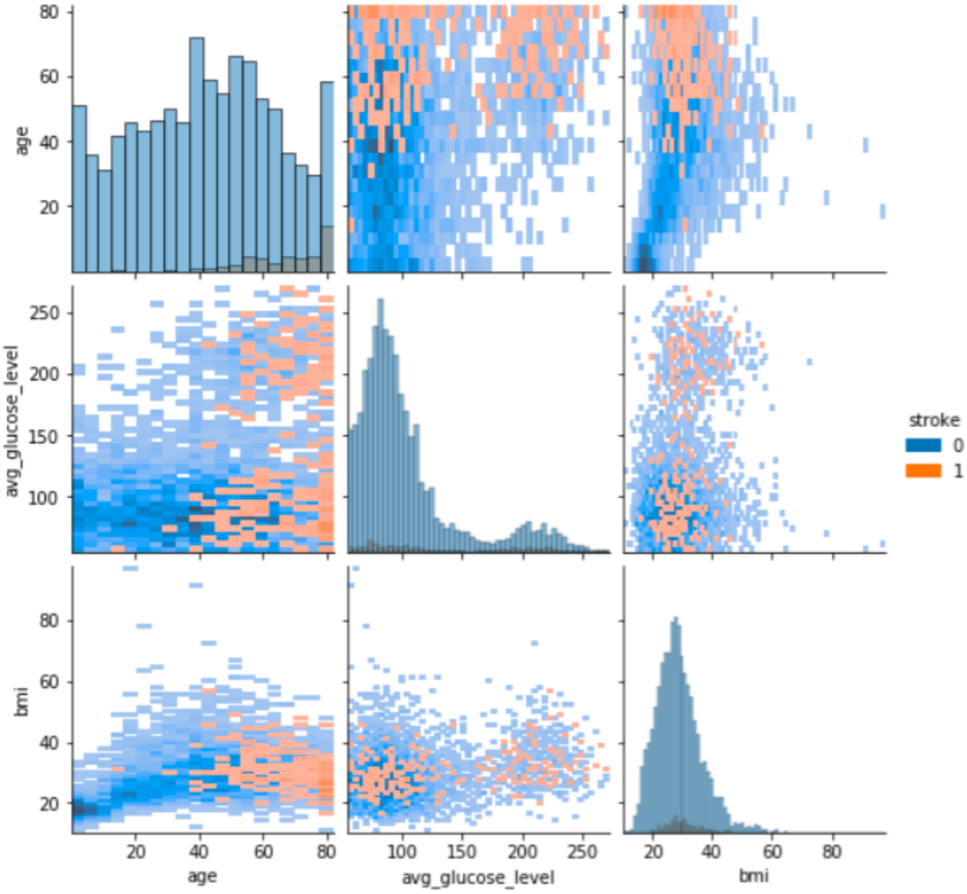



Figure 14: Summary plot for features

The above figure is the pairplot of three numeric features: age, avg glucose level and bmi. Patients with higher age are more likely to have stroke. A higher average glucose level and a larger bmi are more likely to result in stroke.

### 3.3.1 Website Interface

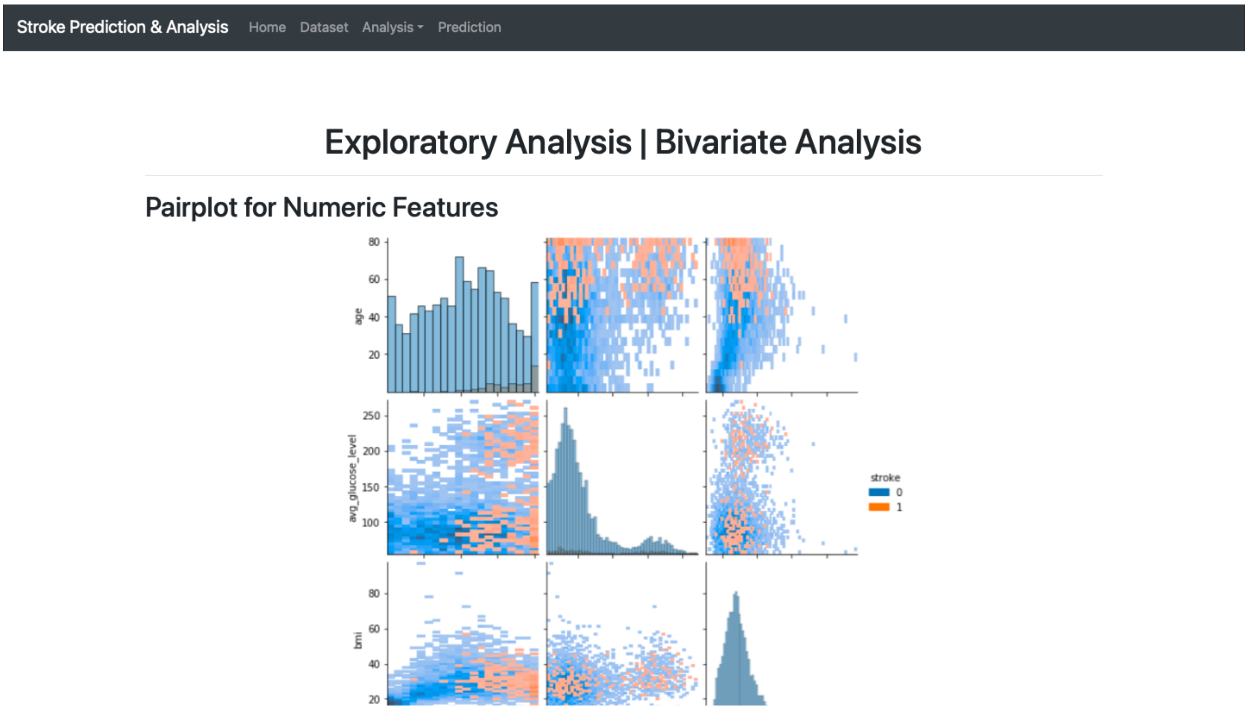



Figure 15: Webpage for Bivariate Analysis

## 3.4 Feature Correlation

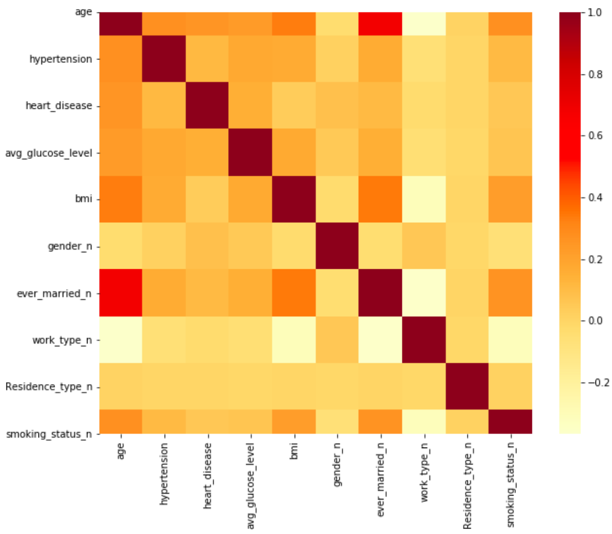



Figure 16: Correlation matrix for all features

First, I transform all the categorical features into numeric ones.

Then I plot the correlation matrix of the 10 features. The heatmap shows the Pearson correlation coefficients between the features in my dataset. The relationships between the features can then be identified and how they may affect the target variable be understood.

The Pearson correlation coefficient is a measure of the linear relationship between two variables. It ranges from -1 to 1, where -1 indicates a strong negative relationship, 0 indicates no relationship, and 1 indicates a strong positive relationship. A correlation matrix can help identify which features are highly correlated with each other and which are not.

If two features are highly correlated, it may be beneficial to remove one of them from the model to avoid overfitting and improve the model's performance. From the result, it is shown that there does not exist two features that are highly correlated. Thus I keep all the 10 features to train the models.

### 3.4.1 Any surprise

The feature correlation are small, so I keep all these features.

### 3.4.2 Website Interface

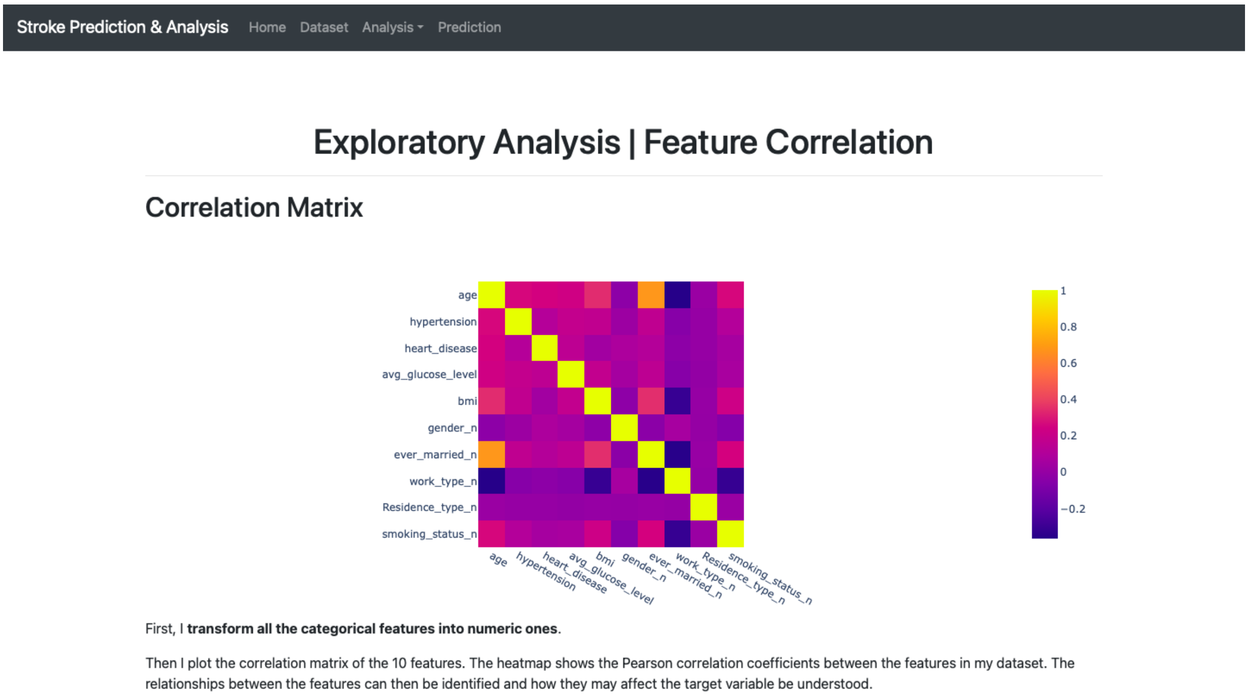



Figure 17: Webpage for Feature Correlation

# 4 Prediction

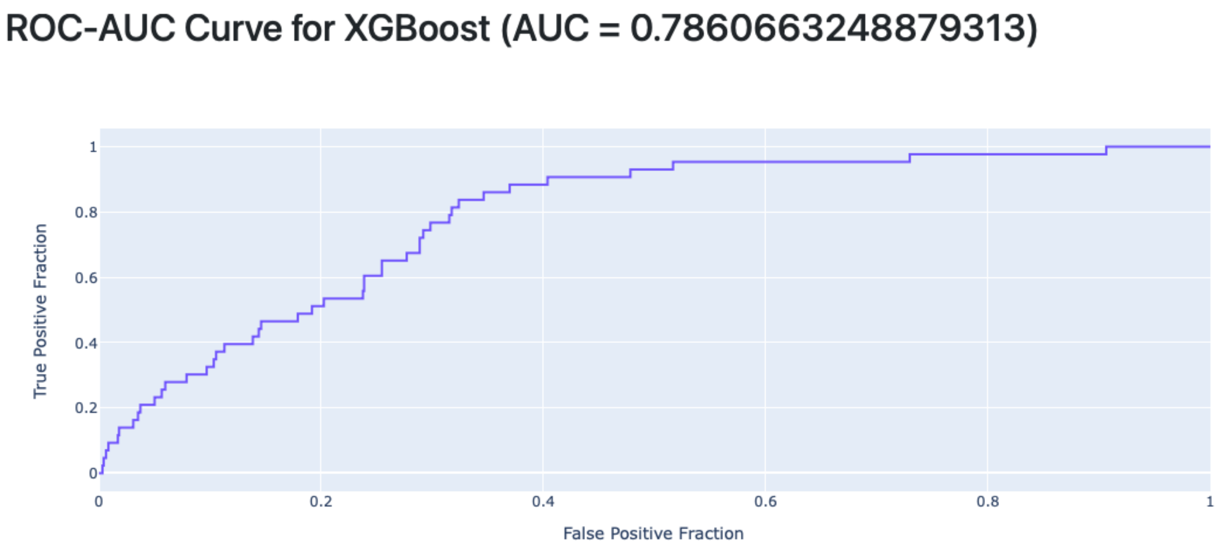
I choose two model for prediction. One is XGBoost.

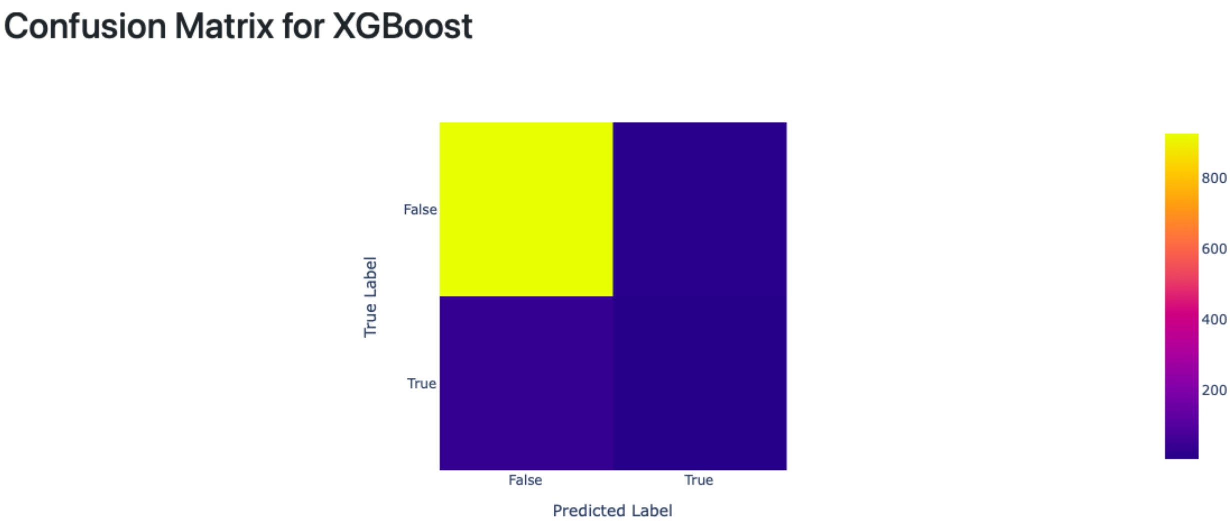
## 4.1 Performance of XGBoost

XGBoost (eXtreme Gradient Boosting) is a popular and efficient open-source implementation of the gradient boosting algorithm for machine learning.

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. The main idea behind gradient boosting is to train weak models sequentially, each trying to correct the mistakes of the previous model.

Overall, XGBoost is a powerful and flexible tool for implementing gradient boosting and is well-suited for a wide range of machine learning tasks.



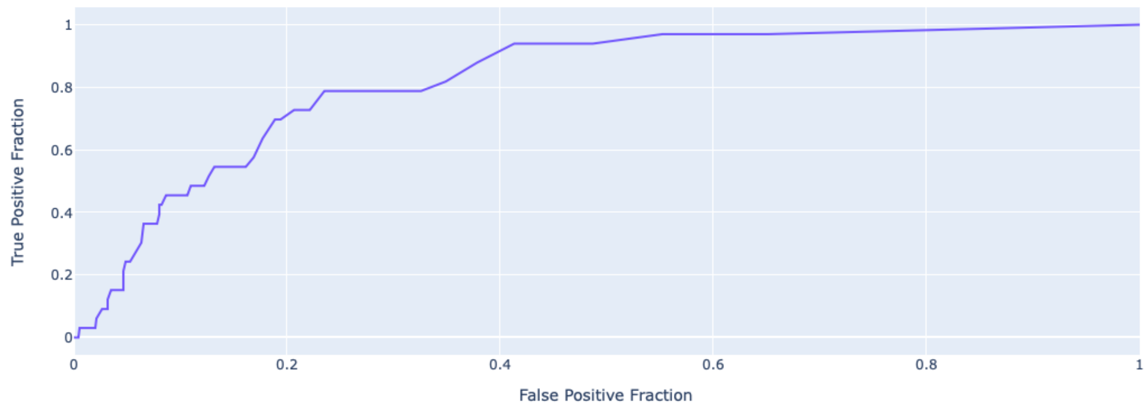

## 4.2 Performance of Random Forest

Random Forest is a popular and powerful ensemble machine learning algorithm that is used for classification and regression tasks.

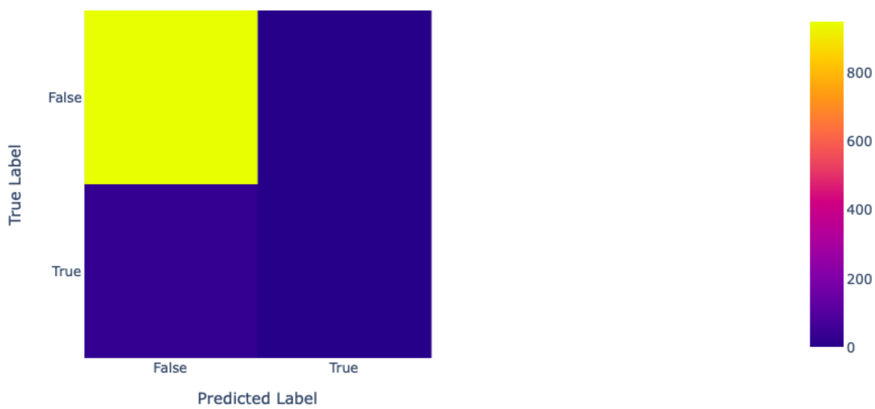
Random Forest is a flexible and easy-to-use algorithm that can handle a large number of input features and can deal with missing values and categorical variables automatically. It is also relatively resistant to overfitting, due to the way it combines multiple decision trees.

Overall, random forest is a widely used and robust machine learning algorithm that is well-suited for many applications.

# ROC-AUC Curve for Random Forest (AUC = 0.8231312066928504)




# Confusion Matrix for Random Forest



### 4.2.1 Website Interface

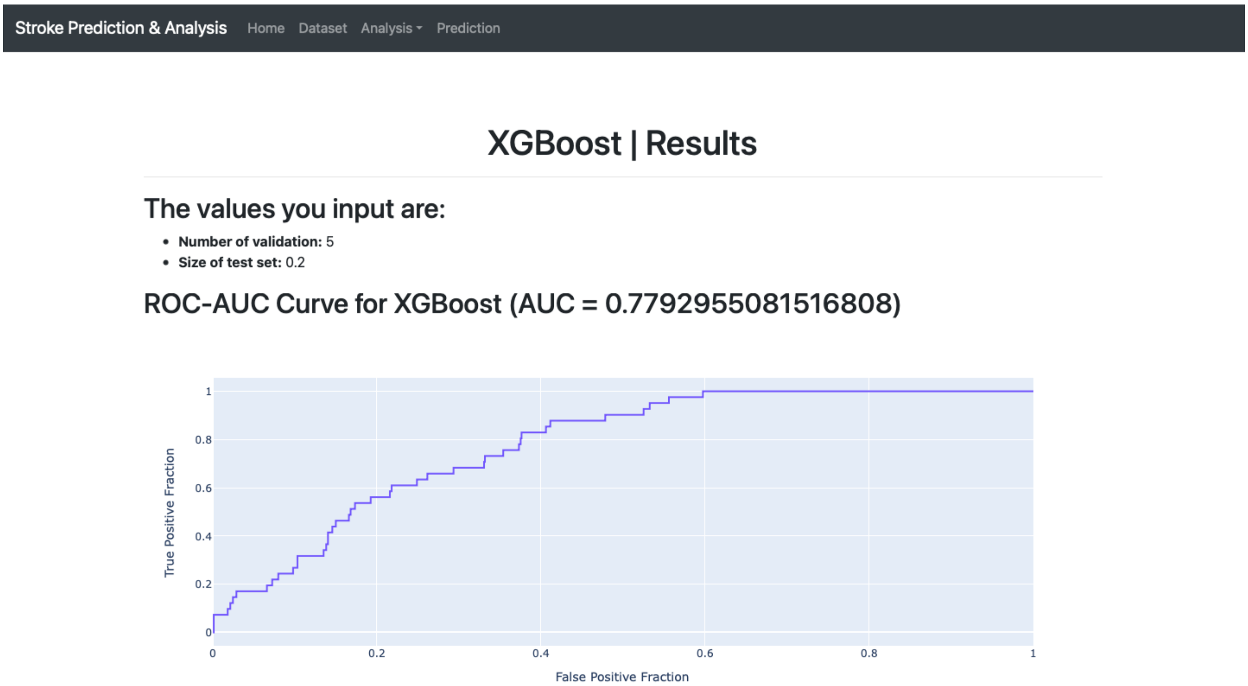



Figure 18: Webpage for Feature Correlation

# 5 Findings and Limitations

The findings of my final project includes:

- Patients with higher age are more likely to have stroke.
- A higher glucose level do suggest a higher probability to have stroke.
- Stroke patients tend to have a higher bmi.
- Both XGboost and Random Forest have satisfactory performance for predicting stroke. Among them, Random Forest is better and have higher AUC.

The limitations of my final project includes:

- Too many healthy patients compared with the number of stroke patients, making the false positive rate high.
- The dataset contains 5110 patients. The size of dataset may not be large enough.

# 6 Conclusion

In conclusion, in this final project, I analyze stroke prediction dataset and use XGBoost and Random Forest to make prediction. The results are satisfactory. I also made a website which have all the information on it.