```
# Group -02
## Group Members

   * **MD Shafiqul Islam (Leader) -> 211
   * Kazi Imon Hossain             -> 211
   * Ali Hyder                     -> 211
   * Al Muine                      -> 211
   * Sheratul Mostakim             -> 211

# Stroke Data Collection using Macing Lea
According to the World Health Organizatio
cause of death globally, responsible for

This dataset is used to predict whether a
on the input parameters like gender, age
Each row in the data provides relavant in

## Objectives
We will try to build a machine learning m
stroke rate is high by the value of varie

><font color=black>__Methods Used__</font

        -Correlation Matrix
        -Decision Tree
        -Data Analysis and Visualization
        -Confusion Matrix
        -Histograph

><font color=black>__Technologies/Librar

        1.Python 3
        2.Pandas
        3.NumPy
        4.Seaborn
        5.Scikit-learn
        6.Matplotlib
        7.Colab

><font color=black>__Dataset Name:__</for

        - stroke-data.csv

# Attribute Information

**1) id:** unique identifier

**2) gender:** "Male", "Female" or "Other

**3) age:** age of the patient

**4) hypertension:** 0 if the patient doe
```

Group -02

Group Members

- **MD Shafiqul Islam (Leader) -> 21190201181**
- Kazi Imon Hossain -> 21190201183
- Ali Hyder -> 21190201171
- Al Muine -> 21190201176
- Sheratul Mostakim -> 21190201146

Stroke Data Collection using Macing Learning

According to the World Health Organization (WHO) stroke is the 2nd leading cause of death globally, responsible for approximately 11% of total deaths.

This dataset is used to predict whether a patient is likely to get stroke based on the input parameters like gender, age, various diseases, and smoking status. Each row in the data provides relavant information about the patient.

Objectives

We will try to build a machine learning model to accurately predict whether stroke rate is high by the value of varius attribute calculations.

> **Methods Used**

```
-Correlation Matrix
-Decision Tree
-Data Analysis and Visualization
-Confusion Matrix
-Histograph
```

patient has hypertension

5) heart_disease: 0 if the patient do
the patient has a heart disease

6) ever_married: "No" or "Yes"

7) work_type: "children", "Govt_jov"
"Self-employed"

8) Residence_type: "Rural" or "Urban"

9) avg_glucose_level: average glucose

10) bmi: body mass index

11) smoking_status: "formerly smoked"
"Unknown"*

12) stroke: 1 if the patient had a st

Number of Observation Units: 5110

Variable Number: 11

GitHub Link: [Stroke Data-Machine-Le
Stroke-Data-Calculation-in-Machine-Learn

> **Technologies/Libraries Used**

1.Python 3
2.Pandas
3.NumPy
4.Seaborn
5.Scikit-learn
6.Matplotlib
7.Colab

> **Dataset Name:**

- stroke-data.csv

Attribute Information

1) id: unique identifier

2) gender: "Male", "Female" or "Other"

3) age: age of the patient

4) hypertension: 0 if the patient doesn't have hypertension, 1 if the patient has hypertension

5) heart_disease: 0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease

6) ever_married: "No" or "Yes"

7) work_type: "children", "Govt_jov", "Never_worked", "Private" or "Self-employed"

8) Residence_type: "Rural" or "Urban"

9) avg_glucose_level: average glucose level in blood

10) bmi: body mass index

11) smoking_status: "formerly smoked", "never smoked", "smokes" or "Unknown"*

12) stroke: 1 if the patient had a stroke or 0 if not

Number of Observation Units: 5110

Variable Number: 11

GitHub Link: [Stroke Data-Machine-Learning]

Import Libraries and Load Data set

```
#Installation of required libraries
import numpy as np
import pandas as pd
import statsmodels.api as sm
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import scale, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_scor
from sklearn.metrics import confusion_matrix, accuracy_score, mean_squared_error,
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from lightgbm import LGBMClassifier
from sklearn.model_selection import KFold
import warnings
warnings.simplefilter(action = "ignore")
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: Futu
  import pandas.util.testing as tm
```

Double-click (or enter) to edit

```
#Reading the dataset
df = pd.read_csv("/content/stroke.csv")
```

```
df
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Resic
0	Male	67.0	0	1	Yes	Private	
1	Female	61.0	0	0	Yes	Self-employed	
2	Male	80.0	0	1	Yes	Private	
3	Female	49.0	0	0	Yes	Private	

```
#Feature information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             5110 non-null   object 
 1   age                5110 non-null   float64
 2   hypertension       5110 non-null   int64  
 3   heart_disease      5110 non-null   int64  
 4   ever_married       5110 non-null   object 
 5   work_type          5110 non-null   object 
 6   Residence_type     5110 non-null   object 
 7   avg_glucose_level  5110 non-null   float64
 8   bmi                4909 non-null   float64
 9   smoking_status     5110 non-null   object 
 10  stroke             5110 non-null   int64  
dtypes: float64(3), int64(3), object(5)
memory usage: 439.3+ KB
```

```
df.shape
```

```
(5110, 11)
```

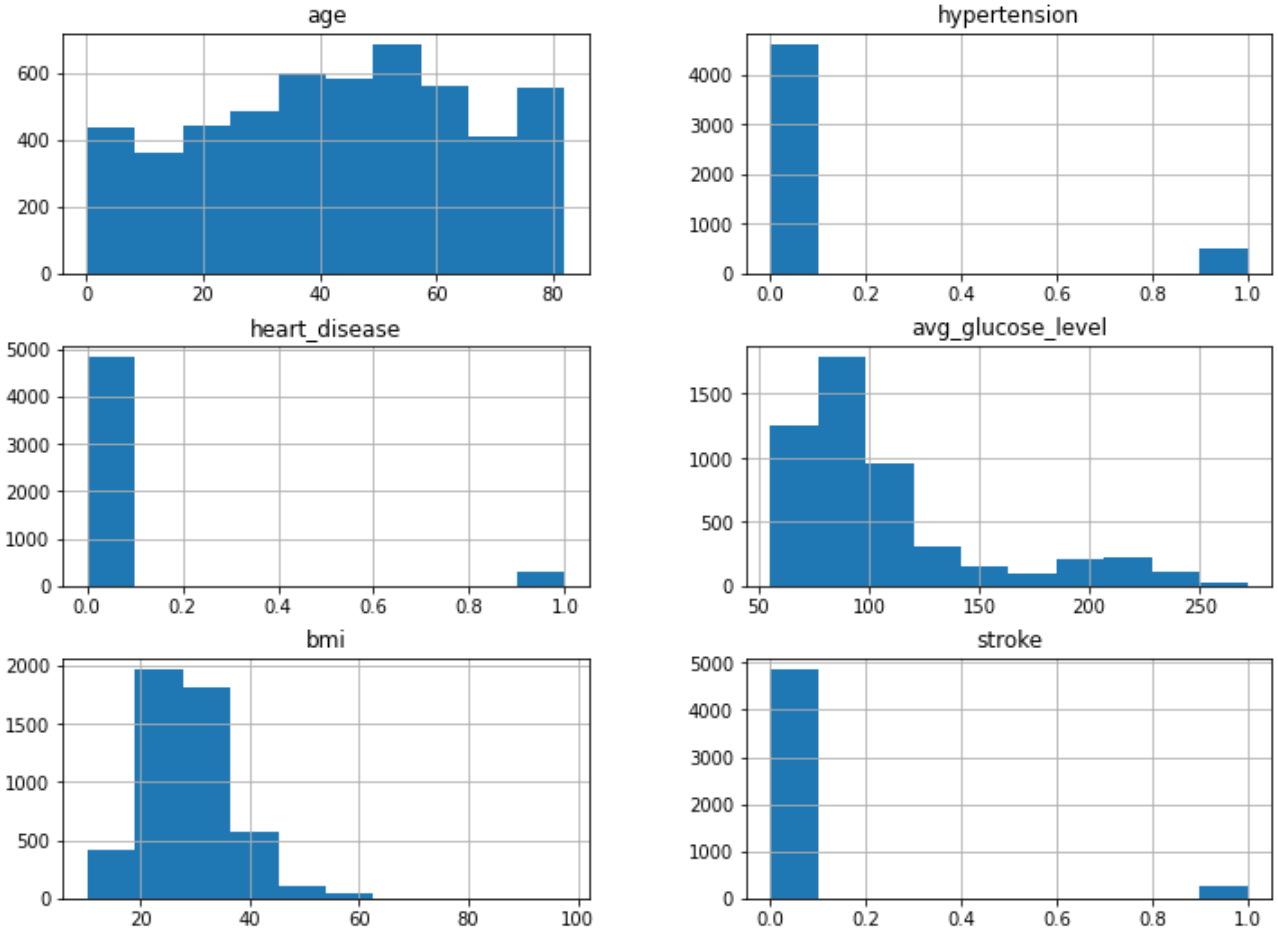
```
df.describe()
```

	age	hypertension	heart_disease	avg_glucose_level	bm
count	5110.000000	5110.000000	5110.000000	5110.000000	4909.00000
mean	43.226614	0.097456	0.054012	106.147677	28.89323
std	22.612647	0.296607	0.226063	45.283560	7.85406
min	0.080000	0.000000	0.000000	55.120000	10.30000
25%	25.000000	0.000000	0.000000	77.245000	23.50000
50%	45.000000	0.000000	0.000000	91.885000	28.10000
75%	61.000000	0.000000	0.000000	114.090000	33.10000
max	82.000000	1.000000	1.000000	271.740000	97.60000

Analysis data by using graph

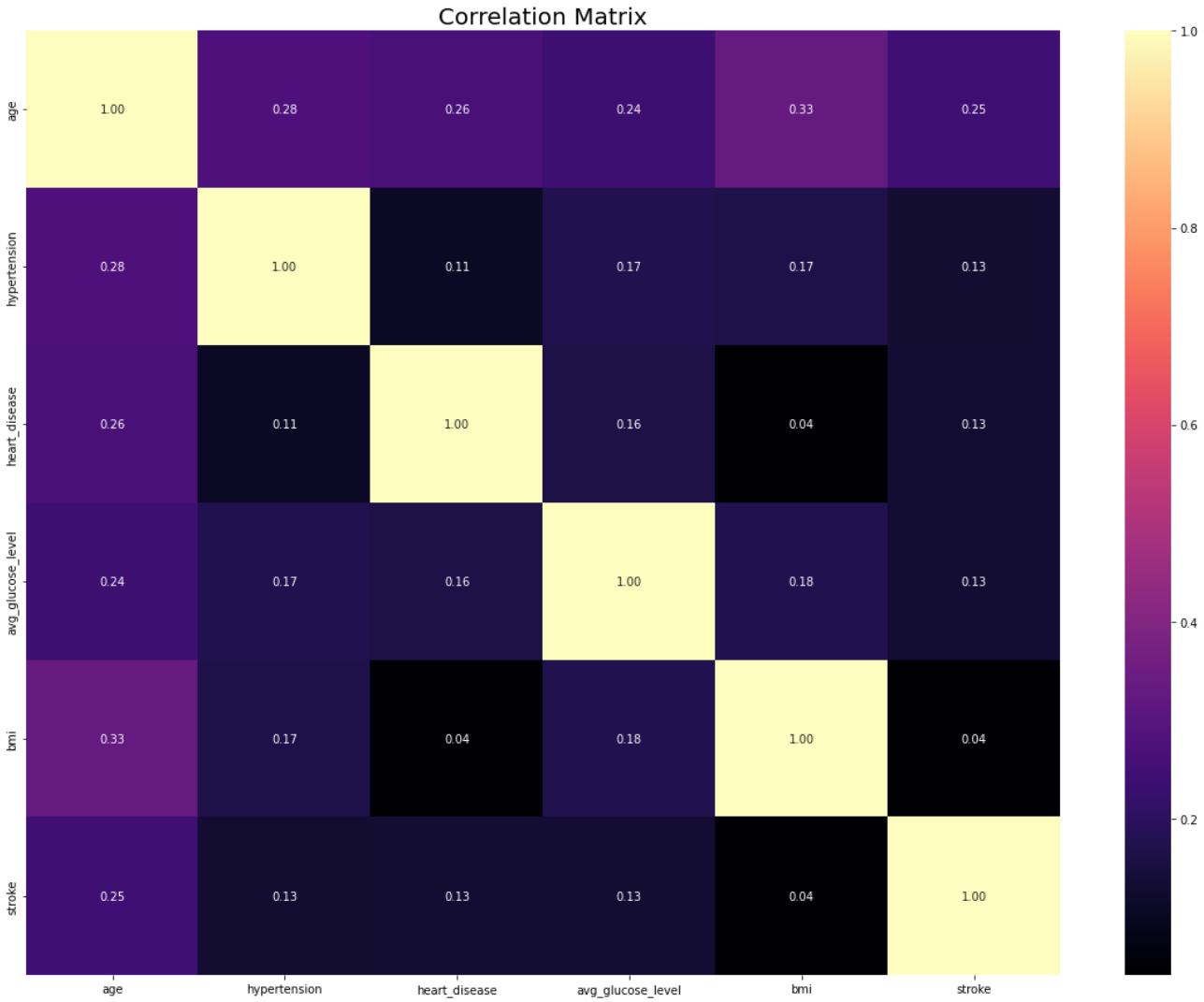
Histogram

```
df.hist(figsize=(12,12), layout=(4,2),);
```



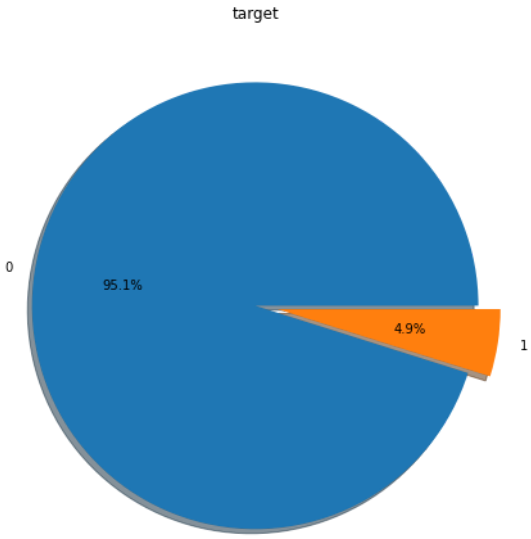
Correlation Matrix

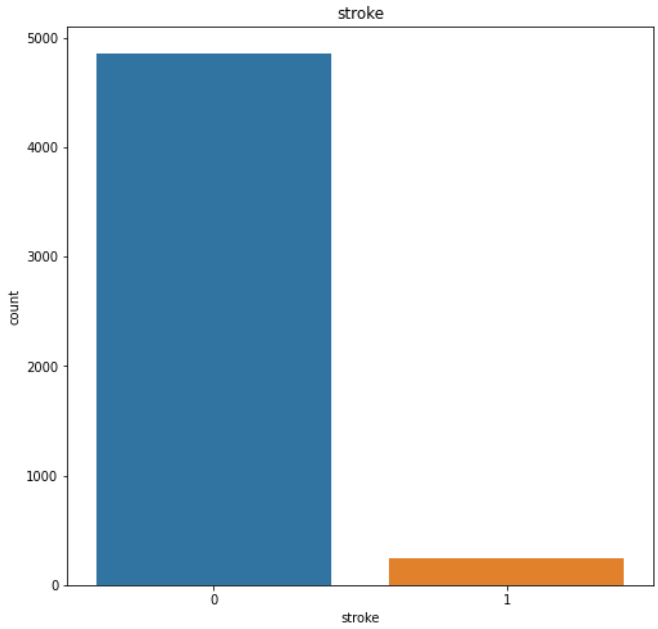
```
# Correlation matrix graph of the data set
f, ax = plt.subplots(figsize= [20,15])
sns.heatmap(df.corr(), annot=True, fmt=".2f", ax=ax, cmap = "magma" )
ax.set_title("Correlation Matrix", fontsize=20)
plt.show()
```



Piplot

```
# The distribution of the High income variable in the data examined and visualized
f,ax=plt.subplots(1,2,figsize=(18,8))
df['stroke'].value_counts().plot.pie(explode=[0,0.1],autopct='%1.1f%%',ax=ax[0],sh
ax[0].set_title('target')
ax[0].set_ylabel('')
sns.countplot(x='stroke',data=df,ax=ax[1])
ax[1].set_title('stroke')
plt.show()
```





Null Value remove

```
df.isnull().sum()
```

```
gender                0
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
Residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

```
df['bmi'] = df['bmi'].replace(0, df['bmi'].mean())
```

```
df.bmi.replace('', 0, inplace=False)
```

```
0       36.6
1        NaN
2       32.5
```

```
3       34.4
4       24.0
        ...
5105     NaN
5106    40.0
5107    30.6
5108    25.6
5109    26.2
Name: bmi, Length: 5110, dtype: float64
```

```
df.isnull().sum()
```

```
gender                0
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
Residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

```
df['bmi'].replace('N/A', 'Test',inplace=True)
```

```
df.isnull().sum()
```

```
gender                0
age                   0
hypertension          0
heart_disease         0
ever_married          0
work_type             0
Residence_type        0
avg_glucose_level     0
bmi                 201
smoking_status        0
stroke                0
dtype: int64
```

```
df['bmi']= df['bmi'].replace('nan', 'TEST')
```

```
df['bmi'].unique()
```

```
array([36.6,  nan, 32.5, 34.4, 24. , 29. , 27.4, 22.8, 24.2, 29.7, 36.8,
       27.3, 28.2, 30.9, 37.5, 25.8, 37.8, 22.4, 48.9, 26.6, 27.2, 23.5,
       28.3, 44.2, 25.4, 22.2, 30.5, 26.5, 33.7, 23.1, 32. , 29.9, 23.9,
       28.5, 26.4, 20.2, 33.6, 38.6, 39.2, 27.7, 31.4, 36.5, 33.2, 32.8,
       40.4, 25.3, 30.2, 47.5, 20.3, 30. , 28.9, 28.1, 31.1, 21.7, 27. ,
       24.1, 45.9, 44.1, 22.9, 29.1, 32.3, 41.1, 25.6, 29.8, 26.3, 26.2,
       29.4, 24.4, 28. , 28.8, 34.6, 19.4, 30.3, 41.5, 22.6, 56.6, 27.1,
       31.3, 31. , 31.7, 35.8, 28.4, 20.1, 26.7, 38.7, 34.9, 25. , 23.8,
       21.8, 27.5, 24.6, 32.9, 26.1, 31.9, 34.1, 36.9, 37.3, 45.7, 34.2,
```

```
       23.6, 22.3, 37.1, 45. , 25.5, 30.8, 37.4, 34.5, 27.9, 29.5, 46. ,
       42.5, 35.5, 26.9, 45.5, 31.5, 33. , 23.4, 30.7, 20.5, 21.5, 40. ,
       28.6, 42.2, 29.6, 35.4, 16.9, 26.8, 39.3, 32.6, 35.9, 21.2, 42.4,
       40.5, 36.7, 29.3, 19.6, 18. , 17.6, 19.1, 50.1, 17.7, 54.6, 35. ,
       22. , 39.4, 19.7, 22.5, 25.2, 41.8, 60.9, 23.7, 24.5, 31.2, 16. ,
       31.6, 25.1, 24.8, 18.3, 20. , 19.5, 36. , 35.3, 40.1, 43.1, 21.4,
       34.3, 27.6, 16.5, 24.3, 25.7, 21.9, 38.4, 25.9, 54.7, 18.6, 24.9,
       48.2, 20.7, 39.5, 23.3, 64.8, 35.1, 43.6, 21. , 47.3, 16.6, 21.6,
       15.5, 35.6, 16.7, 41.9, 16.4, 17.1, 29.2, 37.9, 44.6, 39.6, 40.3,
       41.6, 39. , 23.2, 18.9, 36.1, 36.3, 46.5, 16.8, 46.6, 35.2, 20.9,
       13.8, 31.8, 15.3, 38.2, 45.2, 17. , 49.8, 27.8, 60.2, 23. , 22.1,
       26. , 44.3, 51. , 39.7, 34.7, 21.3, 41.2, 34.8, 19.2, 35.7, 40.8,
       24.7, 19. , 32.4, 34. , 28.7, 32.1, 51.5, 20.4, 30.6, 71.9, 19.3,
       40.9, 17.2, 16.1, 16.2, 40.6, 18.4, 21.1, 42.3, 32.2, 50.2, 17.5,
       18.7, 42.1, 47.8, 20.8, 30.1, 17.3, 36.4, 12. , 36.2, 55.7, 14.4,
       43. , 41.7, 33.8, 43.9, 22.7, 57.5, 37. , 38.5, 16.3, 44. , 32.7,
       54.2, 40.2, 33.3, 17.4, 41.3, 52.3, 14.6, 17.8, 46.1, 33.1, 18.1,
       43.8, 50.3, 38.9, 43.7, 39.9, 15.9, 19.8, 12.3, 78. , 38.3, 41. ,
       42.6, 43.4, 15.1, 20.6, 33.5, 43.2, 30.4, 38. , 33.4, 44.9, 44.7,
       37.6, 39.8, 53.4, 55.2, 42. , 37.2, 42.8, 18.8, 42.9, 14.3, 37.7,
       48.4, 50.6, 46.2, 49.5, 43.3, 33.9, 18.5, 44.5, 45.4, 55. , 54.8,
       19.9, 17.9, 15.6, 52.8, 15.2, 66.8, 55.1, 18.2, 48.5, 55.9, 57.3,
       10.3, 14.1, 15.7, 56. , 44.8, 13.4, 51.8, 38.1, 57.7, 44.4, 38.8,
       49.3, 39.1, 54. , 56.1, 97.6, 53.9, 13.7, 11.5, 41.4, 14.2, 49.4,
       15.4, 45.1, 49.2, 48.7, 53.8, 42.7, 48.8, 52.7, 53.5, 50.5, 15.8,
       45.3, 14.8, 51.9, 63.3, 40.7, 61.2, 48. , 46.8, 48.3, 58.1, 50.4,
       11.3, 12.8, 13.5, 14.5, 15. , 59.7, 47.4, 52.5, 13.2, 52.9, 61.6,
       49.9, 54.3, 47.9, 13. , 13.9, 50.9, 57.2, 64.4, 92. , 50.8, 57.9,
       45.8, 47.6, 14. , 46.4, 46.9, 47.1, 13.3, 48.1, 51.7, 46.3, 54.1,
       14.9])
```

```
#nullvalue removal
df = df.dropna()
```

```
df.isnull().sum()
```

```
gender              0
age                 0
hypertension        0
heart_disease       0
ever_married        0
work_type           0
Residence_type      0
avg_glucose_level   0
bmi                 0
smoking_status      0
stroke              0
dtype: int64
```

```
df.bmi
```

```
0       36.6
2       32.5
3       34.4
4       24.0
5       29.0
        ...
```

```
5104    18.6
5106    40.0
5107    30.6
5108    25.6
5109    26.2
Name: bmi, Length: 4909, dtype: float64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4909 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             4909 non-null   object 
 1   age                4909 non-null   float64
 2   hypertension       4909 non-null   int64  
 3   heart_disease      4909 non-null   int64  
 4   ever_married       4909 non-null   object 
 5   work_type          4909 non-null   object 
 6   Residence_type     4909 non-null   object 
 7   avg_glucose_level  4909 non-null   float64
 8   bmi                4909 non-null   int8   
 9   smoking_status     4909 non-null   object 
 10  stroke             4909 non-null   int64  
dtypes: float64(2), int64(3), int8(1), object(5)
memory usage: 426.7+ KB
```

```
df.nunique()
```

```
gender                 3
age                  104
hypertension           2
heart_disease          2
ever_married           2
work_type              5
Residence_type         2
avg_glucose_level    3852
bmi                    6
smoking_status         4
stroke                 2
dtype: int64
```

```
df.smoking_status.value_counts()
```

```
never smoked       1852
Unknown            1483
formerly smoked     837
smokes              737
Name: smoking_status, dtype: int64
```

```
df.smoking_status.replace('Unknown', 'never smoked', inplace=True)
```

```
df.smoking_status.value_counts()
```

```
never smoked       3335
formerly smoked     837
smokes              737
Name: smoking_status, dtype: int64
```

```
df.ever_married.replace('No',0,inplace=True)
df.ever_married.replace('Yes',1,inplace=True)
```

```
df.ever_married.value_counts()
```

```
1    3204
0    1705
Name: ever_married, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4909 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             4909 non-null   object 
 1   age                4909 non-null   float64
 2   hypertension       4909 non-null   int64  
 3   heart_disease      4909 non-null   int64  
 4   ever_married       4909 non-null   int64  
 5   work_type          4909 non-null   object 
 6   Residence_type     4909 non-null   object 
 7   avg_glucose_level  4909 non-null   float64
 8   bmi                4909 non-null   int8   
 9   smoking_status     4909 non-null   object 
 10  stroke             4909 non-null   int64  
dtypes: float64(2), int64(4), int8(1), object(4)
memory usage: 426.7+ KB
```

```
df["gender"] = df["gender"].astype('category')
df["work_type"] = df["work_type"].astype('category')
df["Residence_type"] = df["Residence_type"].astype('category')
df["smoking_status"] = df["smoking_status"].astype('category')
print(df.dtypes)
```

```
gender              category
age                  float64
hypertension           int64
heart_disease          int64
ever_married           int64
work_type           category
Residence_type      category
avg_glucose_level    float64
bmi                     int8
smoking_status      category
stroke                 int64
dtype: object
```

Encoding

```
#df["gender"] = df["gender"].cat.codes
df["work_type"] = df["work_type"].cat.codes
df["Residence_type"] = df["Residence_type"].cat.codes
df["smoking_status"] = df["smoking_status"].cat.codes
```

```
df.head(5)
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	Male	67.0	0	1	1	2	
2	Male	80.0	0	1	1	2	
3	Female	49.0	0	0	1	2	
4	Female	79.0	1	0	1	3	
5	Male	81.0	0	0	1	2	

Normalization

```
li = df["bmi"].to_list()
```

```
li = df["bmi"].to_list()
for i in range(0,len(li)):
    if li[i]<=18.5:
        li[i] = "Underweight"
    elif li[i] > 18.5 and li[i] <=24.9:
        li[i]= "Normal"
    elif li[i] > 24.9 and li[i] <=29.9:
        li[i]= "Overweight"
    elif li[i] > 29.9 and li[i] <=34.9:
        li[i]= "Obesity 1"
    elif li[i] > 34.9 and li[i] <=39.9:
        li[i]= "Obesity 2"
    elif li[i] > 39.9:
        li[i]= "Obesity 3"
df["bmi"]=li
```

```
df.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	Male	67.0	0	1	Yes	Private	

```
df["bmi"] = df["bmi"].astype('category')
df["bmi"] = df["bmi"].cat.codes
```

```
df["gender"] = df["gender"].astype('category')
df["gender"] = df["gender"].cat.codes
```

```
df.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	1	67.0	0	1	1	2	
2	1	80.0	0	1	1	2	
3	0	49.0	0	0	1	2	
4	0	79.0	1	0	1	3	
5	1	81.0	0	0	1	2	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4909 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   gender             4909 non-null   int8   
 1   age                4909 non-null   float64
 2   hypertension       4909 non-null   int64  
 3   heart_disease      4909 non-null   int64  
 4   ever_married       4909 non-null   int64  
 5   work_type          4909 non-null   int8   
 6   Residence_type     4909 non-null   int8   
 7   avg_glucose_level  4909 non-null   float64
 8   bmi                4909 non-null   int8   
 9   smoking_status     4909 non-null   int8   
 10  stroke             4909 non-null   int64  
dtypes: float64(2), int64(4), int8(5)
memory usage: 292.4 KB
```

```
y = df["stroke"]
X = df.drop(["stroke"], axis = 1)
cols = X.columns
index = X.index
```

```
X.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residen
0	1	67.0	0	1	1	2	
2	1	80.0	0	1	1	2	
3	0	49.0	0	0	1	2	
4	0	79.0	1	0	1	3	
5	1	81.0	0	0	1	2	

```
y.head()
```

```
0    1
2    1
3    1
4    1
5    1
Name: stroke, dtype: int64
```

```
X.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residen
0	1	67.0	0	1	1	2	
2	1	80.0	0	1	1	2	
3	0	49.0	0	0	1	2	
4	0	79.0	1	0	1	3	
5	1	81.0	0	0	1	2	

```
y.head()
```

```
0    1
2    1
3    1
4    1
5    1
Name: stroke, dtype: int64
```

Spliting 70/30

```
y_train = y.iloc[0:3436]
y_test = y.iloc[3436:]
X_train = X.iloc[0:3436]
X_test = X.iloc[3436:]
```

Model Creation

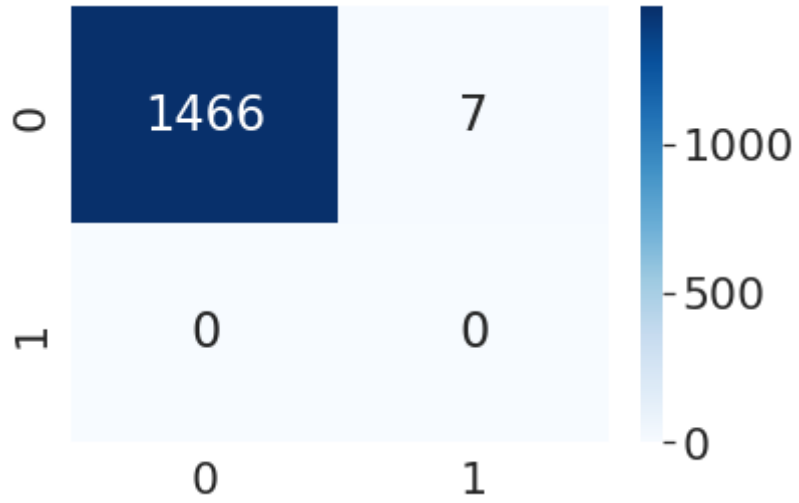
```
#import all models library
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
import keras
import sklearn
from matplotlib import pyplot as plt
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
import numpy as np
import h5py
import os
import json
import pickle
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np


import sklearn
model = sklearn.ensemble.RandomForestClassifier()
model.fit(X_train, y_train)
```

```
    RandomForestClassifier()
```

```
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
y_pred=model.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(y_test,y_pred)
accuracy=accuracy_score(y_test,y_pred)
print(classification_report(y_test, y_pred, digits=5))
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
print(cm)
print('Legitimate Transactions Detected (True Negatives): ', cm[0][0])
print('Legitimate Transactions Incorrectly Detected (False Positives): ', cm[0][1]
```

```
print('Fraudulent Transactions Missed (False Negatives): ', cm[1][0])
print('Fraudulent Transactions Detected (True Positives): ', cm[1][1])
print('Total Fraudulent Transactions: ', np.sum(cm[1]))
print('Sensitivy: ',cm[1][1]/(cm[1][1]+cm[1][0]))
print('Specificity: ',cm[0][0]/(cm[0][0]+cm[0][1]))
print('P0: ',cm[0][0]/(cm[0][0]+cm[1][0]))
print('P1: ',cm[1][1]/(cm[1][1]+cm[0][1]))
y_true = ["0","1"]
#y_true=['Angry', 'Fear', 'Happy','Neutral','Sad']
data = cm
df_cm = pd.DataFrame(data, columns=np.unique(y_true), index = np.unique(y_true))
#df_cm.index.name = 'Actual'
#df_cm.columns.name = 'Predicted'
sn.set(font_scale=2)#for label size
sn.heatmap(df_cm, cmap="Blues", annot=True,annot_kws={"size": 24}, fmt="d")
plt.savefig('Cm.pdf', format='pdf', dpi=300)
plt.savefig('Cm.png', format='png', dpi=300)
```

```
                   precision    recall  f1-score   support

                0    1.00000   0.99525   0.99762      1473
                1    0.00000   0.00000   0.00000         0

         accuracy                        0.99525      1473
        macro avg    0.50000   0.49762   0.49881      1473
     weighted avg    1.00000   0.99525   0.99762      1473

     0.9952477936184657
     [[1466    7]
      [   0    0]]
     Legitimate Transactions Detected (True Negatives):  1466
     Legitimate Transactions Incorrectly Detected (False Positives):  7
     Fraudulent Transactions Missed (False Negatives):  0
     Fraudulent Transactions Detected (True Positives):  0
     Total Fraudulent Transactions:  0
     Sensitivy:  nan
     Specificity:  0.9952477936184657
     P0:  1.0
     P1:  0.0
```




```
import sklearn
```

```
model =  sklearn.tree.DecisionTreeClassifier(criterion='entropy')
model.fit(X_train, y_train)
```

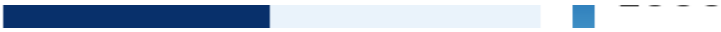
```
    DecisionTreeClassifier(criterion='entropy')
```

```
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
y_pred=model.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(y_test,y_pred)
accuracy=accuracy_score(y_test,y_pred)
print(classification_report(y_test, y_pred, digits=5))
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
print(cm)
print('Legitimate Transactions Detected (True Negatives): ', cm[0][0])
print('Legitimate Transactions Incorrectly Detected (False Positives): ', cm[0][1]
print('Fraudulent Transactions Missed (False Negatives): ', cm[1][0])
print('Fraudulent Transactions Detected (True Positives): ', cm[1][1])
print('Total Fraudulent Transactions: ', np.sum(cm[1]))
print('Sensitivy: ',cm[1][1]/(cm[1][1]+cm[1][0]))
print('Specificity: ',cm[0][0]/(cm[0][0]+cm[0][1]))
print('P0: ',cm[0][0]/(cm[0][0]+cm[1][0]))
print('P1: ',cm[1][1]/(cm[1][1]+cm[0][1]))
y_true = ["0","1"]
#y_true=['Angry', 'Fear', 'Happy','Neutral','Sad']
data = cm
df_cm = pd.DataFrame(data, columns=np.unique(y_true), index = np.unique(y_true))
#df_cm.index.name = 'Actual'
#df_cm.columns.name = 'Predicted'
sn.set(font_scale=2)#for label size
sn.heatmap(df_cm, cmap="Blues", annot=True,annot_kws={"size": 24}, fmt="d")
plt.savefig('Cm.pdf', format='pdf', dpi=300)
plt.savefig('Cm.png', format='png', dpi=300)
```

```
                   precision    recall  f1-score   support

                0    1.00000   0.94026   0.96921      1473
                1    0.00000   0.00000   0.00000         0

         accuracy                        0.94026      1473
        macro avg    0.50000   0.47013   0.48460      1473
     weighted avg    1.00000   0.94026   0.96921      1473

     0.9402579769178547
     [[1385   88]
      [   0    0]]
     Legitimate Transactions Detected (True Negatives):  1385
     Legitimate Transactions Incorrectly Detected (False Positives):  88
     Fraudulent Transactions Missed (False Negatives):  0
     Fraudulent Transactions Detected (True Positives):  0
     Total Fraudulent Transactions:  0
     Sensitivy:  nan
     Specificity:  0.9402579769178547
```

```
import sklearn
model =  sklearn.naive_bayes.GaussianNB()
model.fit(X_train, y_train)
```

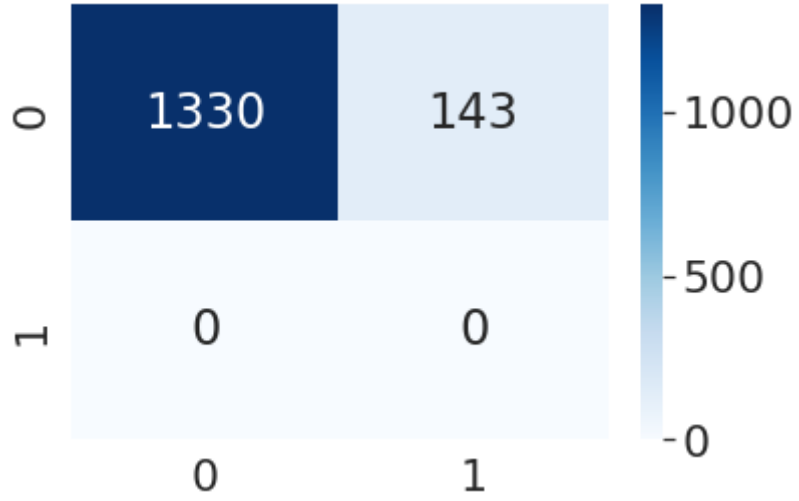
```
     GaussianNB()
```



```
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
y_pred=model.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(y_test,y_pred)
accuracy=accuracy_score(y_test,y_pred)
print(classification_report(y_test, y_pred, digits=5))
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
print(cm)
print('Legitimate Transactions Detected (True Negatives): ', cm[0][0])
print('Legitimate Transactions Incorrectly Detected (False Positives): ', cm[0][1]
print('Fraudulent Transactions Missed (False Negatives): ', cm[1][0])
print('Fraudulent Transactions Detected (True Positives): ', cm[1][1])
print('Total Fraudulent Transactions: ', np.sum(cm[1]))
print('Sensitivy: ',cm[1][1]/(cm[1][1]+cm[1][0]))
print('Specificity: ',cm[0][0]/(cm[0][0]+cm[0][1]))
print('P0: ',cm[0][0]/(cm[0][0]+cm[1][0]))
print('P1: ',cm[1][1]/(cm[1][1]+cm[0][1]))
y_true = ["0","1"]
#y_true=['Angry', 'Fear', 'Happy','Neutral','Sad']
data = cm
df_cm = pd.DataFrame(data, columns=np.unique(y_true), index = np.unique(y_true))
#df_cm.index.name = 'Actual'
#df_cm.columns.name = 'Predicted'
sn.set(font_scale=2)#for label size
```

```
sn.heatmap(df_cm, cmap="Blues", annot=True,annot_kws={"size": 24}, fmt="d")
plt.savefig('Cm.pdf', format='pdf', dpi=300)
plt.savefig('Cm.png', format='png', dpi=300)
```

```
                   precision    recall  f1-score   support

               0    1.00000   0.90292   0.94898      1473
               1    0.00000   0.00000   0.00000         0

        accuracy                        0.90292      1473
       macro avg    0.50000   0.45146   0.47449      1473
    weighted avg    1.00000   0.90292   0.94898      1473

    0.902919212491514
    [[1330  143]
     [   0    0]]
    Legitimate Transactions Detected (True Negatives):  1330
    Legitimate Transactions Incorrectly Detected (False Positives):  143
    Fraudulent Transactions Missed (False Negatives):  0
    Fraudulent Transactions Detected (True Positives):  0
    Total Fraudulent Transactions:  0
    Sensitivy:  nan
    Specificity:  0.902919212491514
    P0:  1.0
    P1:  0.0
```




```
import sklearn
model =  sklearn.tree.DecisionTreeClassifier(criterion='gini')
model.fit(X_train, y_train)
```

```
    DecisionTreeClassifier()
```

```
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
y_pred=model.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(y_test,y_pred)
```

```
accuracy=accuracy_score(y_test,y_pred)
print(classification_report(y_test, y_pred, digits=5))
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
print(cm)
print('Legitimate Transactions Detected (True Negatives): ', cm[0][0])
print('Legitimate Transactions Incorrectly Detected (False Positives): ', cm[0][1]
print('Fraudulent Transactions Missed (False Negatives): ', cm[1][0])
print('Fraudulent Transactions Detected (True Positives): ', cm[1][1])
print('Total Fraudulent Transactions: ', np.sum(cm[1]))
print('Sensitivy: ',cm[1][1]/(cm[1][1]+cm[1][0]))
print('Specificity: ',cm[0][0]/(cm[0][0]+cm[0][1]))
print('P0: ',cm[0][0]/(cm[0][0]+cm[1][0]))
print('P1: ',cm[1][1]/(cm[1][1]+cm[0][1]))
y_true = ["0","1"]
#y_true=['Angry', 'Fear', 'Happy','Neutral','Sad']
data = cm
df_cm = pd.DataFrame(data, columns=np.unique(y_true), index = np.unique(y_true))
#df_cm.index.name = 'Actual'
#df_cm.columns.name = 'Predicted'
sn.set(font_scale=2)#for label size
sn.heatmap(df_cm, cmap="Blues", annot=True,annot_kws={"size": 24}, fmt="d")
plt.savefig('Cm.pdf', format='pdf', dpi=300)
plt.savefig('Cm.png', format='png', dpi=300)
```

```
                   precision    recall  f1-score   support

                0    1.00000   0.94026   0.96921      1473
                1    0.00000   0.00000   0.00000         0
```

```
import sklearn
model =  sklearn.tree.DecisionTreeClassifier(splitter='best')
model.fit(X_train, y_train)
```

```
    DecisionTreeClassifier()
```

```
     [   0    0]]
```

```
from sklearn.metrics import confusion_matrix
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
y_pred=model.predict(X_test)
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(y_test,y_pred)
accuracy=accuracy_score(y_test,y_pred)
print(classification_report(y_test, y_pred, digits=5))
accuracy=accuracy_score(y_test,y_pred)
print(accuracy)
print(cm)
print('Legitimate Transactions Detected (True Negatives): ', cm[0][0])
print('Legitimate Transactions Incorrectly Detected (False Positives): ', cm[0][1]
print('Fraudulent Transactions Missed (False Negatives): ', cm[1][0])
print('Fraudulent Transactions Detected (True Positives): ', cm[1][1])
print('Total Fraudulent Transactions: ', np.sum(cm[1]))
print('Sensitivy: ',cm[1][1]/(cm[1][1]+cm[1][0]))
print('Specificity: ',cm[0][0]/(cm[0][0]+cm[0][1]))
print('P0: ',cm[0][0]/(cm[0][0]+cm[1][0]))
print('P1: ',cm[1][1]/(cm[1][1]+cm[0][1]))
y_true = ["0","1"]
#y_true=['Angry', 'Fear', 'Happy','Neutral','Sad']
data = cm
df_cm = pd.DataFrame(data, columns=np.unique(y_true), index = np.unique(y_true))
#df_cm.index.name = 'Actual'
#df_cm.columns.name = 'Predicted'
sn.set(font_scale=2)#for label size
sn.heatmap(df_cm, cmap="Blues", annot=True,annot_kws={"size": 24}, fmt="d")
plt.savefig('Cm.pdf', format='pdf', dpi=300)

plt.savefig('Cm.png', format='png', dpi=300)
```

```
                  precision    recall  f1-score   support

               0    1.00000   0.94229   0.97029      1473
               1    0.00000   0.00000   0.00000         0

        accuracy                        0.94229      1473
       macro avg    0.50000   0.47115   0.48515      1473
    weighted avg    1.00000   0.94229   0.97029      1473

    0.9422946367956552
    [[1388   85]
     [   0    0]]
    Legitimate Transactions Detected (True Negatives):  1388
    Legitimate Transactions Incorrectly Detected (False Positives):  85
    Fraudulent Transactions Missed (False Negatives):  0
    Fraudulent Transactions Detected (True Positives):  0
    Total Fraudulent Transactions:  0
    Sensitivy:  nan
    Specificity:  0.9422946367956552
    P0:  1.0
    P1:  0.0
```

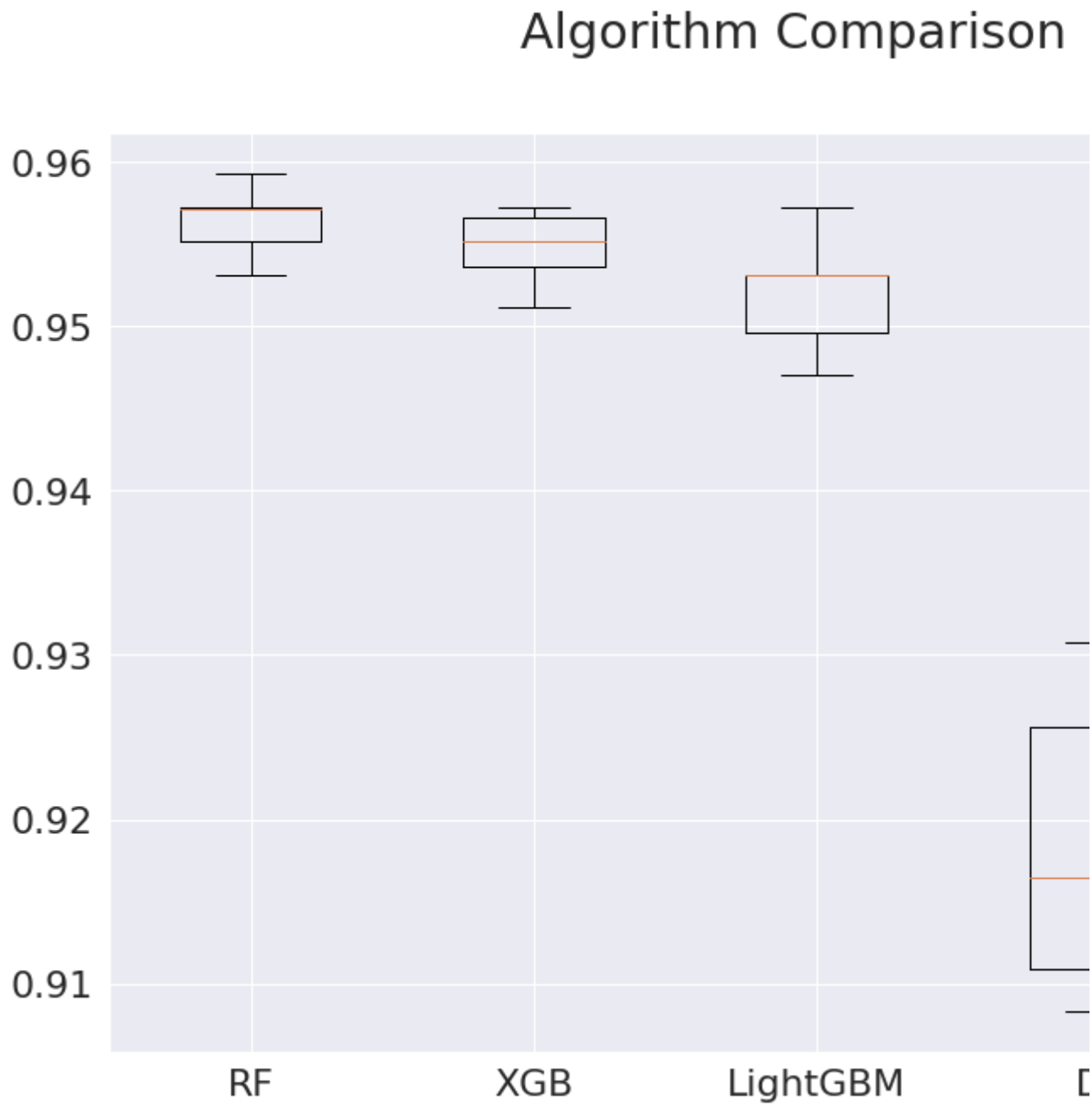

```
import sklearn
models = []

models.append(('RF', sklearn.ensemble.RandomForestClassifier()))
models.append(('XGB', GradientBoostingClassifier()))
models.append(("LightGBM", LGBMClassifier()))
models.append(("DT",sklearn.tree.DecisionTreeClassifier()))
models.append(("LR",sklearn.linear_model.LogisticRegression()))
# evaluate each model in turn
results = []
names = []
```

Comparison Boxchart for all models accuracy

```
for name, model in models:

        kfold = KFold(n_splits = 10)
        cv_results = cross_val_score(model, X, y, cv = 10, scoring= "accuracy")
        results.append(cv_results)
        names.append(name)
        msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
        print(msg)

# boxplot algorithm comparison
fig = plt.figure(figsize=(15,10))
fig.suptitle('Algorithm Comparison')
```

```
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```

```
RF: 0.956407 (0.002074)
XGB: 0.954981 (0.001911)
LightGBM: 0.951924 (0.002774)
DT: 0.918108 (0.008098)
LR: 0.957425 (0.001083)
```



Reports

So in this mini-project, we saw some of the factors that might result in strokes. Where Age was highly correlated followed by hypertension, heart disease, avg glucose level, and ever married.

RandomForestClassifier was a knight who performed well. There are outliers in some variable, reason behind why I kept it as it is because these things are either depends on other factors and

there are possibilities of having such kind of records. For example, BMI can be high and still no stroke as a person is young or he does not have any heart disease. **Accuracy(0.99)**