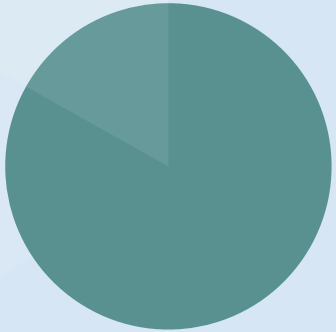
Stroke Prediction



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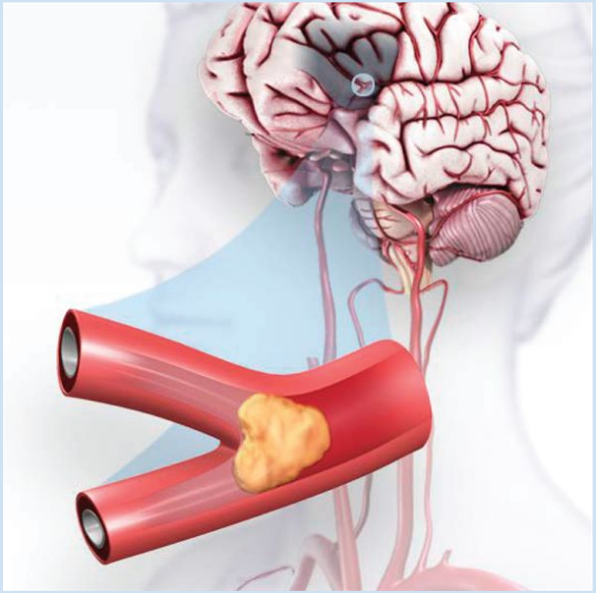
- **This project has been done as part of `Machine Learning' course, led by Prof. Lee-Ad Gottleib**

What is a Stroke?

Stroke is a **disease that affects the arteries leading to and within the brain**. It is the number 5 cause of death and a leading cause of disability in the United States. 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).

What are the effects of stroke?

The brain is an extremely complex organ that controls various body functions. If a stroke occurs and blood flow can't reach the region that controls a particular body function, that part of the body won't work as it should.



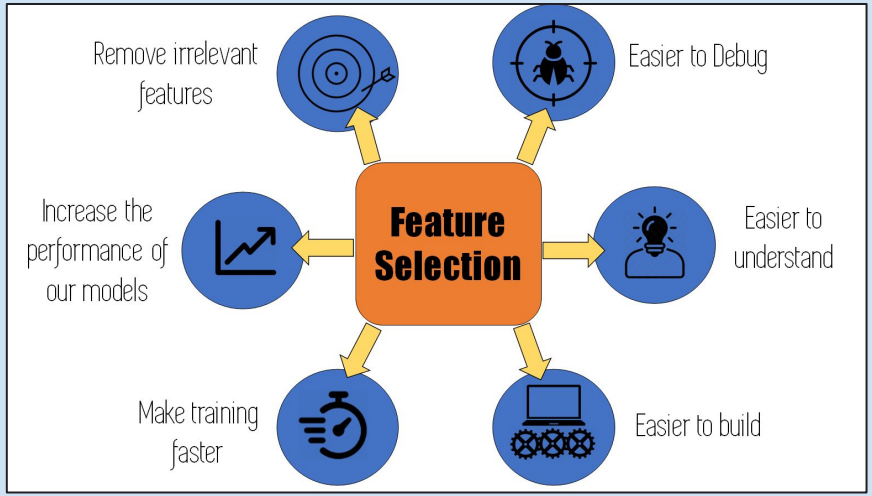
Project Target-

In order to try to reduce reduce stroke deaths, we will try to predict which people are more likely to have a stroke.

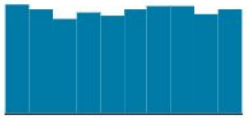
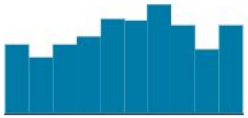
For this project we used Kaggle dataset, which includes 11 clinical features for predicting stroke events.

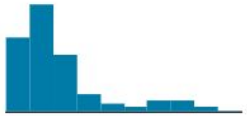
The Features-

1. Gender
2. Age
3. Hypertension binary feature
4. Heart disease binary feature
5. Has the patient ever been married?
6. Work type of the patient
7. Residence type of the patient
8. Average glucose level in blood
9. Body Mass Index
10. Smoking status of the patient
11. Stroke event



A Little Bit About Our Data..

id	gender	age	hypertension	heart_disease
Unique id	Gender	Age	Hypertension binary feature	Heart disease binary feature
 67 72.9k	Female 59% Male 41% Other (1) 0%	 0.08 82	 0 1	 0 1

ever_married	work_type	Residence_type	avg_glucose_level	bmi
Has the patient ever been married?	Work type of the patient	Residence type of the patient	Average glucose level in blood	Body Mass Index
 true 3353 66% false 1757 34%	Private 57% Self-employed 16% Other (1366) 27%	Urban 51% Rural 49%	 55.1 272	N/A 4% 28.7 1% Other (4868) 95%

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
data = pd.read_csv("/content/healthcare-dataset-stroke-data.csv")
data.head()
```

	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

Lets Explore Our Data-

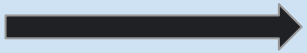
```
<bound method DataFrame.info of          id  gender   age  ...   bmi   smoking_status stroke
0      9046    Male  67.0  ...  36.6  formerly smoked      1
1     51676  Female  61.0  ...   NaN     never smoked      1
2     31112    Male  80.0  ...  32.5     never smoked      1
3     60182  Female  49.0  ...  34.4           smokes      1
4      1665  Female  79.0  ...  24.0     never smoked      1
...     ...     ...   ...  ...   ...              ...    ...
5105  18234  Female  80.0  ...   NaN     never smoked      0
5106  44873  Female  81.0  ...  40.0     never smoked      0
5107  19723  Female  35.0  ...  30.6     never smoked      0
5108  37544    Male  51.0  ...  25.6  formerly smoked      0
5109  44679  Female  44.0  ...  26.2          Unknown      0

[5110 rows x 12 columns]>
```

```
[34] data.isnull().sum()

id                     0
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
```

As we can see the 'bmi' column holds some missing values.

So we need to fill the null values:

```
data['bmi'].fillna(data['bmi'].mean(), inplace = True)
```



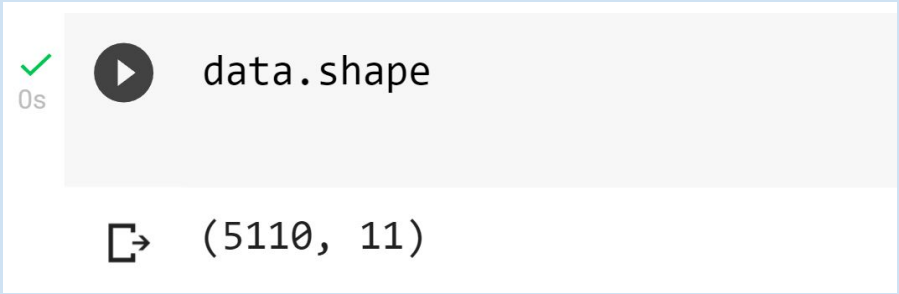
```
data.isnull().sum()

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

Removing an Unnecessary Column-

After we explored the data, we decided to remove one column- ‘id’,

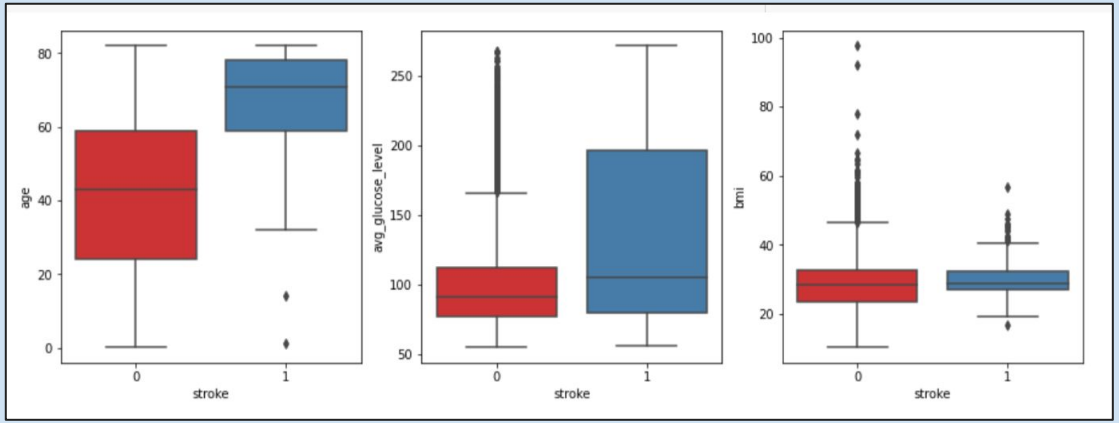
because the Id of the person is not a relevant information for our model.

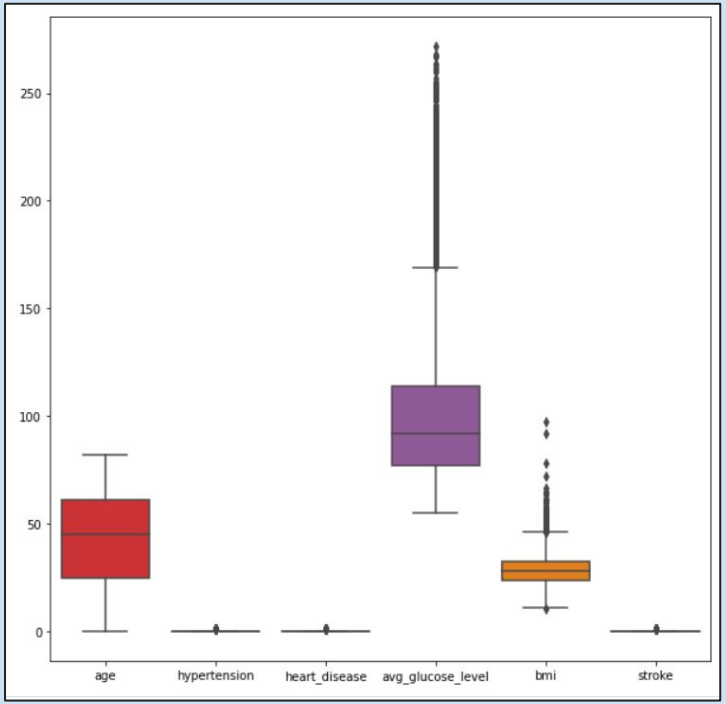
So now we have 11 attributes.



Outliers-

We used subplot function to find the outliers in our data.





Algorithms-

We want to know, based on the 11 features, what are the chances to of having a stroke.

We will use the following techniques:

- Logistic Regression
- SVM
- Decision Trees
- K- nearest neighbour

Train and Test-

We split our data into train and test,

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 0)
```

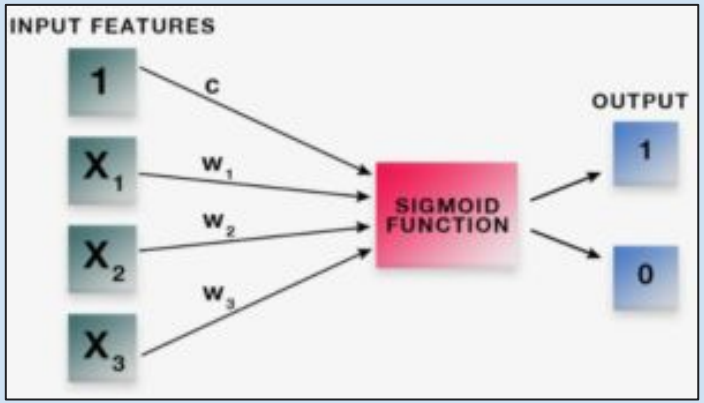
In order to scale the train and test features ,we used StandardScaler -

StandardScaler **removes the mean and scales each feature/variable to unit variance**. This operation is performed feature-wise in an independent way. StandardScaler can be influenced by outliers (if they exist in the dataset) since it involves the estimation of the empirical mean and standard deviation of each feature.

After that, we used fit_transform() on the x_train variable and transform on the x_test variable.

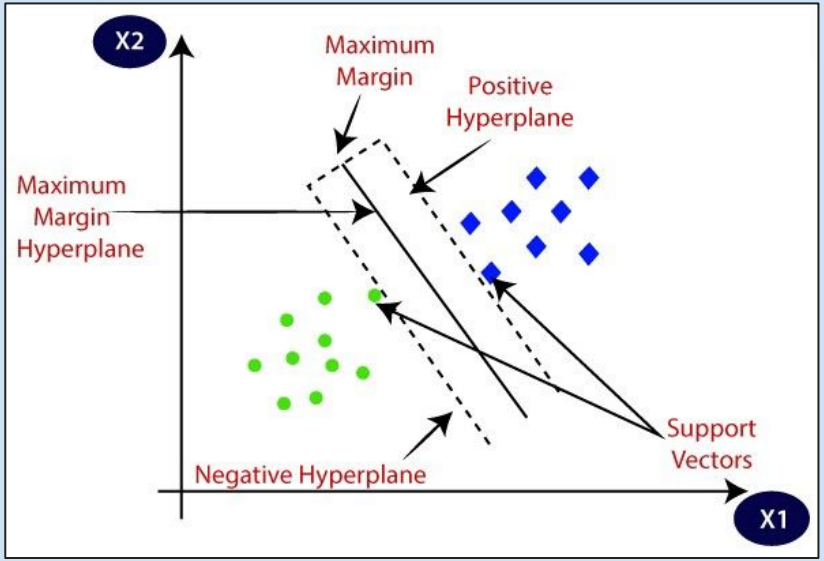
Logistic Regression-

```
[382] #Logistic regression-


      from sklearn.linear_model import LogisticRegression
      from sklearn.metrics import accuracy_score

      logistic_reg = LogisticRegression()

      logistic_reg.fit(x_train_std, y_train)

      y_pred_logistic_reg = logistic_reg.predict(x_test_std)

      accuracy_logistic_reg = accuracy_score(y_test, y_pred_logistic_reg)
      print("Logistic Regression accuracy = " +  str(accuracy_logistic_reg*100) + "%")

      Logistic Regression accuracy = 94.71624266144813%
```



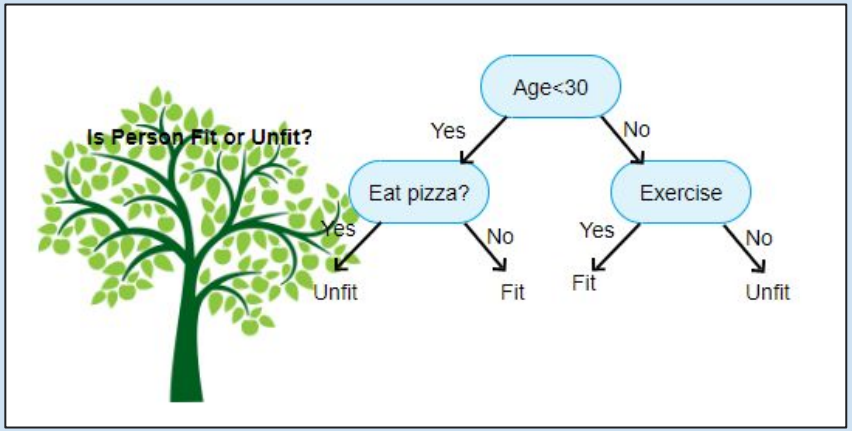
SVM-

```
[383] #SVM-

      from sklearn.svm import SVC
      svc = SVC()

      svc.fit(x_train_std, y_train)

      y_pred_svc = svc.predict(x_test_std)

      ac_svc = accuracy_score(y_test, y_pred_svc)
      print("SVM accuracy = " +  str(ac_svc*100) + "%")

      SVM accuracy = 94.71624266144813%
```



Decision Tree-

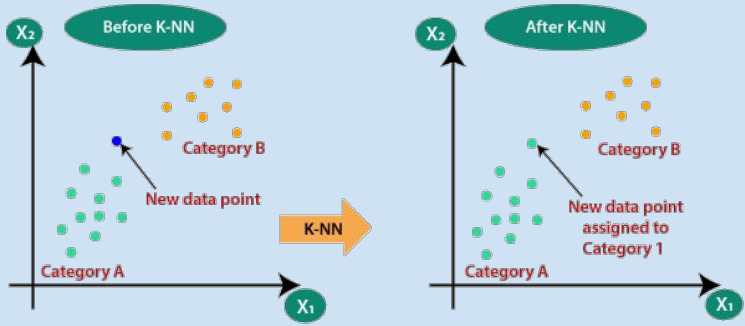
```
[390] #Decision tree-

      from sklearn.tree import DecisionTreeClassifier
      decision_tree = DecisionTreeClassifier()

      decision_tree.fit(x_train_std, y_train)

      decision_tree.feature_importances_

      array([0.04505728, 0.20077799, 0.03420359, 0.02100343, 0.00581771,
             0.03533076, 0.02881657, 0.29332933, 0.26733965, 0.06832369])

[386] x_train.columns


      Index(['gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
             'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
             'smoking_status'],
            dtype='object')

[387] from sklearn.metrics import accuracy_score

      y_pred_decision_tree = decision_tree.predict(x_test_std)

      accuracy_decision_tree = accuracy_score(y_test, y_pred_decision_tree)
      print("decision tree accuracy = " +  str(accuracy_decision_tree*100) + "%")

      decision tree accuracy = 91.6829745596869%
```



K- Nearest Neighbour-

```
#K-Nearest-Neighbour

from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()

knn.fit(x_train_std, y_train)

y_pred_knn = knn.predict(x_test_std)

accuracy_knn = accuracy_score(y_test, y_pred_knn)
print("K-nearest neighbour accuracy = " +  str(accuracy_knn*100) + "%")
```

```
K-nearest neighbour accuracy = 94.71624266144813%
```



Results-

Algorithms-	Logistic regression	SVM	Decision Tree	K- Nearest Neighbour
Accuracy-	**94.71624266144813%**	**94.71624266144813%**	91.6829745596869%	94.7162426144813%

Could We Use Other Algorithms?

Of course.

We could use other algorithms and make the necessary adjustments, and then choose the algorithm with the best accuracy to predict the chances of having a stroke.

Sources and reference materials-

- https://www.kaggle.com/fedesoriano/stroke-prediction-dataset
- https://towardsdatascience.com/scale-standardize-or-normalize-with-scikit-learn-6ccc7d176a02
- https://github.com/riddhi-jain
- https://machinelearningmastery.com/how-to-use-statistics-to-identify-outliers-in-data