### **IMPORTING LIBRARIES**

```
import pandas as pd
import numpy as np
import xgboost
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report
from tensorflow.keras import models
from tensorflow.keras import layers
from tensorflow.keras import optimizers
from tensorflow.keras.callbacks import EarlyStopping
import seaborn as sns
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt
```

#### LOADING THE DATASET

stroke\_dataset = pd.read\_csv("healthcare-dataset-stroke-data.csv")

stroke\_dataset

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Resi
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self- employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self- employed	
5105	18234	Female	80.0	1	0	Yes	Private	
5106	44873	Female	81.0	0	0	Yes	Self- employed	
5107	19723	Female	35.0	0	0	Yes	Self- employed	
5108	37544	Male	51.0	0	0	Yes	Private	
5109	44679	Female	44.0	0	0	Yes	Govt_job	
		_						

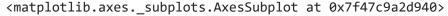
5110 rows × 12 columns

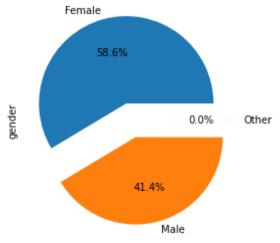
### CONVERTING POSSIBLE VALUES TO CATEGORICAL VARIABLES

```
for col in stroke_dataset.columns:
    if stroke_dataset[col].dtype == 'object' or (stroke_dataset[col].dtype == 'int64' and
        print(col,"->", stroke_dataset[col].unique())

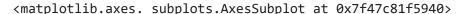
    gender -> ['Male' 'Female' 'Other']
    hypertension -> [0 1]
    heart_disease -> [1 0]
    ever_married -> ['Yes' 'No']
    work_type -> ['Private' 'Self-employed' 'Govt_job' 'children' 'Never_worked']
    Residence_type -> ['Urban' 'Rural']
    smoking_status -> ['formerly smoked' 'never smoked' 'smokes' 'Unknown']
    stroke -> [1 0]
```

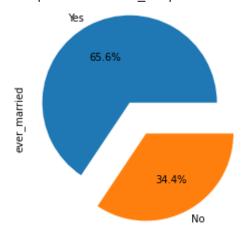
stroke\_dataset['gender'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2, 0.2, 0.2





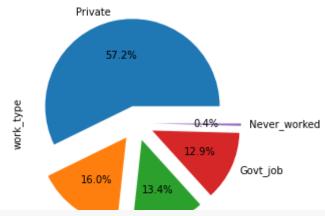
stroke\_dataset['ever\_married'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2, 0.





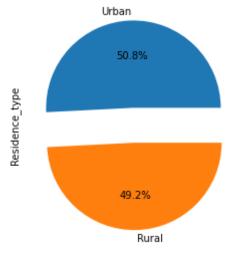
stroke\_dataset['work\_type'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2, 0.2,

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f47c81aea90>



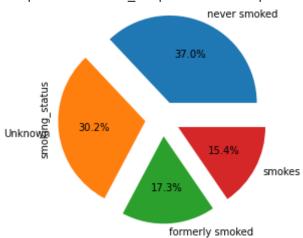
stroke\_dataset['Residence\_type'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2,

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f47c817c670>



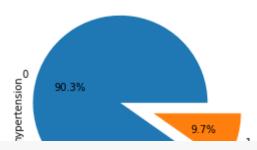
stroke\_dataset['smoking\_status'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2,

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f47c80c0790>



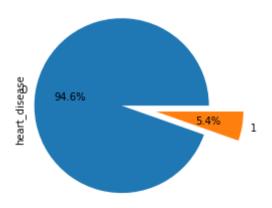
stroke\_dataset['hypertension'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2, 0.

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f47c9a0fac0>



stroke\_dataset['heart\_disease'].value\_counts().plot.pie(autopct='%1.1f%%', explode=[0.2, 0

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f47c8044dc0>



#### **IDENTIFYING THE NULL VALUES**

```
stroke_dataset.isna().sum()
```

id	0
gender	0
age	0
hypertension	0
heart_disease	0
ever_married	0
work_type	0
Residence_type	0
<pre>avg_glucose_level</pre>	0
bmi	201
smoking_status	0
stroke	0
dtype: int64	

### **DATA PREPROCESSING**

```
# Exclude id column
stroke_dataset.pop('id')
# exclude the rows containing Other and Never_worked
stroke_dataset = stroke_dataset[stroke_dataset.gender != 'Other']
stroke_dataset = stroke_dataset[stroke_dataset.work_type != 'Never_worked']
```

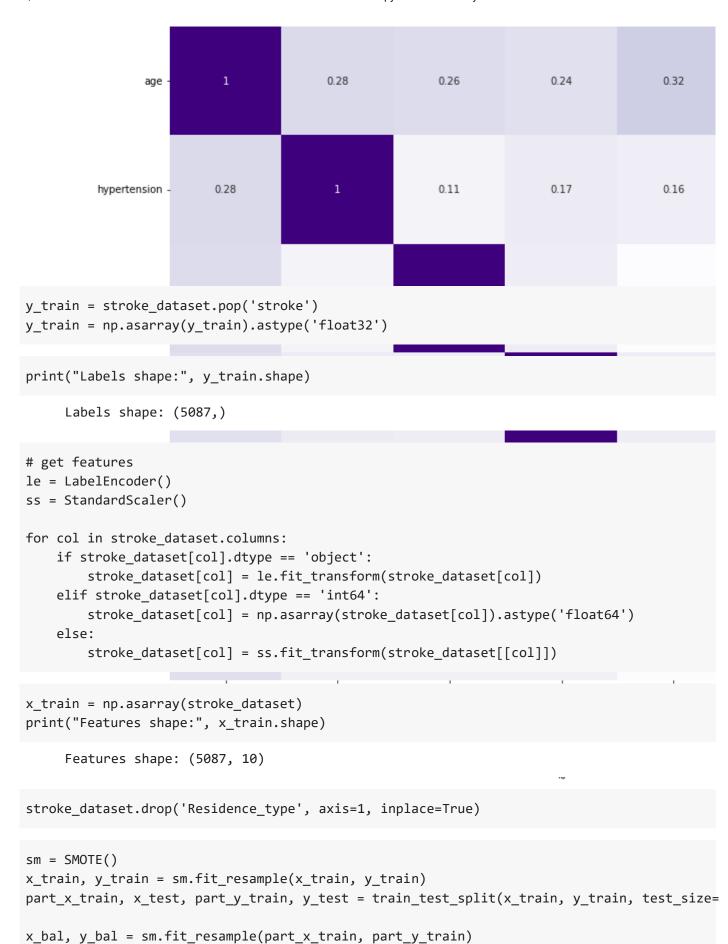
### **REPLACING NULL VALUES**

```
stroke_dataset['bmi'].fillna(stroke_dataset['bmi'].median(), inplace=True)
stroke_dataset.isna().sum()
```

0 gender 0 age hypertension 0 heart\_disease 0 ever married 0 work\_type 0 Residence\_type avg\_glucose\_level bmi 0 0 smoking\_status 0 stroke dtype: int64

### DISPLAYING THE HEAT MAP

```
sns.heatmap(data=stroke_dataset.corr(), annot=True, cmap="Purples")
fig=plt.gcf()
fig.set_size_inches(15,12)
plt.show()
```



## **BUILDING THE MODEL**

x\_test, x\_val, y\_test, y\_val = train\_test\_split(x\_test, y\_test, test\_size=0.5, random\_stat

```
model = models.Sequential()
model.add(layers.Dense(64, activation='relu', input_shape=(x_bal.shape[1],)))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(1, activation='sigmoid'))
early_stopping = EarlyStopping(monitor='val_loss', min_delta=0.01, patience=20, restore_be
model.compile(optimizer=optimizers.Adam(learning_rate=2e-4), loss='binary_crossentropy', m
history = model.fit(x_bal, y_bal, epochs=79, batch_size=128, validation_data=(x_val, y_val
```

```
Epoch 67/79
53/53 [============== ] - 1s 10ms/step - loss: 0.3380 - accuracy:
Epoch 68/79
Epoch 69/79
Epoch 70/79
53/53 [=============== ] - 1s 11ms/step - loss: 0.3223 - accuracy:
Epoch 71/79
53/53 [=============== ] - 1s 11ms/step - loss: 0.3279 - accuracy:
Epoch 72/79
53/53 [============== ] - 1s 10ms/step - loss: 0.3241 - accuracy:
Epoch 73/79
53/53 [=============== ] - 1s 10ms/step - loss: 0.3272 - accuracy:
Epoch 74/79
Epoch 75/79
Epoch 76/79
Epoch 77/79
53/53 [============== ] - 1s 10ms/step - loss: 0.3167 - accuracy:
Epoch 78/79
53/53 [============= ] - 1s 10ms/step - loss: 0.3224 - accuracy:
```

# model.summary()

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	704
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 128)	8320
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 256)	33024
dropout_2 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 256)	65792
dropout_3 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 128)	32896
dropout_4 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 128)	16512
dropout_5 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 128)	16512

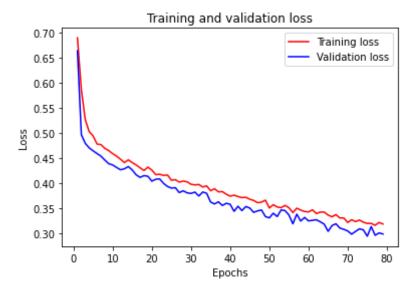
dropout_6 (Dropout)	(None,	128)	0
dense_7 (Dense)	(None,	128)	16512
dropout_7 (Dropout)	(None,	128)	0
dense_8 (Dense)	(None,	64)	8256
dropout_8 (Dropout)	(None,	64)	0
dense_9 (Dense)	(None,	32)	2080
dropout_9 (Dropout)	(None,	32)	0
dense_10 (Dense)	(None,	1)	33

\_\_\_\_\_\_

Total params: 200,641 Trainable params: 200,641 Non-trainable params: 0

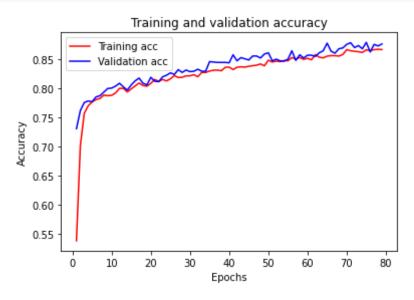
## TRAINING AND VALIDATION LOSS

```
history= history.history
loss_values = history['loss']
val_loss_values = history['val_loss']
epochs = range(1, len(history['accuracy']) + 1)
plt.plot(epochs, loss_values, 'r', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



### TARINING AND VALIDATION ACCURACY

```
plt.clf()
acc_values = history['accuracy']
val_acc_values = history['val_accuracy']
plt.plot(epochs, history['accuracy'], 'r', label='Training acc')
plt.plot(epochs, history['val_accuracy'], 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



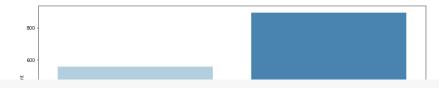
```
y_pred = model.predict(x_test)
y_pred = [1.0 if p > 0.5 else 0 for p in y_pred]
```

46/46 [======== ] - 0s 2ms/step

```
y_pred
      [0,
       1.0,
       1.0,
       1.0,
       1.0,
       1.0,
       0,
       1.0,
       1.0,
       1.0,
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1.0,
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1.0,
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0,
```

```
plt.figure(figsize=(15,6))
sns.countplot(x=y_pred, palette='Blues')
plt.xticks(rotation = 90)
plt.show()
```



print(classification\_report(y\_test, y\_pred))

₽		precision	recall	f1-score	support
	0.0	0.98	0.73	0.84	715
	1.0	0.79	0.99	0.88	736
	accuracy			0.86	1451
	macro avg	0.89	0.86	0.86	1451
	weighted avg	0.88	0.86	0.86	1451