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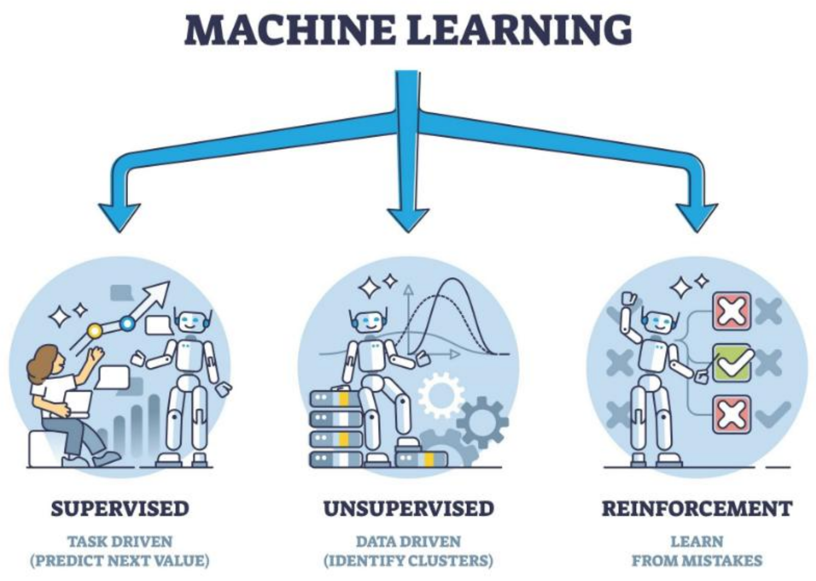
Lab Manual

Machine Learning Description

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that allows computers to learn from data and make decisions or predictions without being explicitly programmed. Instead of following hard-coded instructions, a machine learning model learns patterns from data and improves its performance over time as it sees more examples.

Key Concepts:

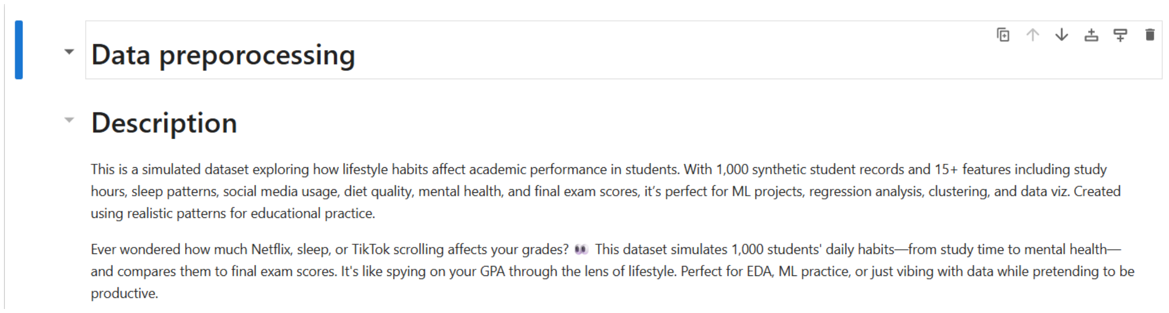
- **Data**: The input used to train and test the model (e.g., numbers, text, images).
- **Model**: A mathematical system that finds patterns in the data.
- **Training**: Teaching the model using known data.
- **Prediction**: Making guesses on new data based on what the model learned.
- **Evaluation**: Checking how well the model performs.



¦LAB - 【Regression】 ¦

Regression is a type of machine learning that helps us **predict a value (number)** based on past data. It's used when the output we want is a **continuous value**, not a category.

Data description:



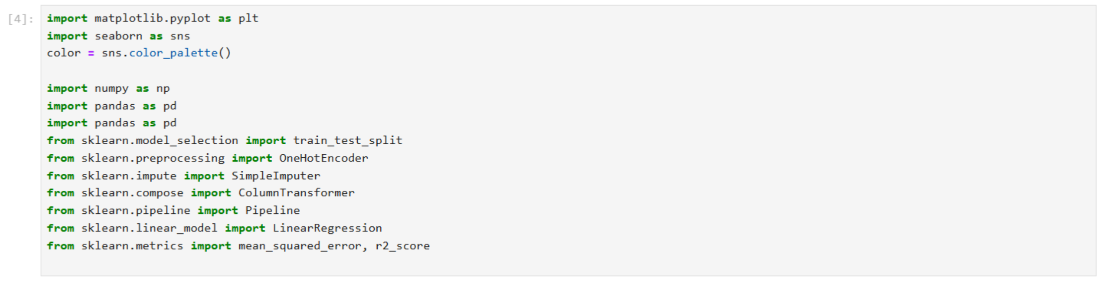
Data preprocessing

Description

This is a simulated dataset exploring how lifestyle habits affect academic performance in students. With 1,000 synthetic student records and 15+ features including study hours, sleep patterns, social media usage, diet quality, mental health, and final exam scores, it's perfect for ML projects, regression analysis, clustering, and data viz. Created using realistic patterns for educational practice.

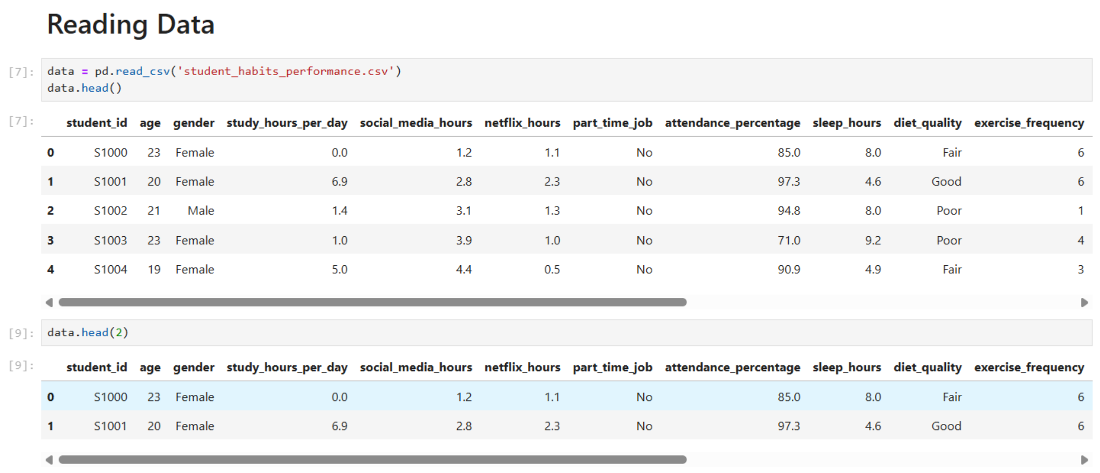
Ever wondered how much Netflix, sleep, or TikTok scrolling affects your grades? 👀 This dataset simulates 1,000 students' daily habits—from study time to mental health—and compares them to final exam scores. It's like spying on your GPA through the lens of lifestyle. Perfect for EDA, ML practice, or just vibing with data while pretending to be productive.

Import libraries:



```
[4]: import matplotlib.pyplot as plt
     import seaborn as sns
     color = sns.color_palette()

     import numpy as np
     import pandas as pd
     import pandas as pd
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import OneHotEncoder
     from sklearn.impute import SimpleImputer
     from sklearn.compose import ColumnTransformer
     from sklearn.pipeline import Pipeline
     from sklearn.linear_model import LinearRegression
     from sklearn.metrics import mean_squared_error, r2_score
```

Reading data:



Reading Data

```
[7]: data = pd.read_csv('student_habits_performance.csv')
     data.head()
```

[7]:

	student_id	age	gender	study_hours_per_day	social_media_hours	netflix_hours	part_time_job	attendance_percentage	sleep_hours	diet_quality	exercise_frequency
0	S1000	23	Female	0.0	1.2	1.1	No	85.0	8.0	Fair	6
1	S1001	20	Female	6.9	2.8	2.3	No	97.3	4.6	Good	6
2	S1002	21	Male	1.4	3.1	1.3	No	94.8	8.0	Poor	1
3	S1003	23	Female	1.0	3.9	1.0	No	71.0	9.2	Poor	4
4	S1004	19	Female	5.0	4.4	0.5	No	90.9	4.9	Fair	3

```
[9]: data.head(2)
```

[9]:

	student_id	age	gender	study_hours_per_day	social_media_hours	netflix_hours	part_time_job	attendance_percentage	sleep_hours	diet_quality	exercise_frequency
0	S1000	23	Female	0.0	1.2	1.1	No	85.0	8.0	Fair	6
1	S1001	20	Female	6.9	2.8	2.3	No	97.3	4.6	Good	6

[11]:
```
data.shape
```
[11]:
```
(1000, 16)
```
[13]:
```
data.sample()
```
[13]:

	student_id	age	gender	study_hours_per_day	social_media_hours	netflix_hours	part_time_job	attendance_percentage	sleep_hours	diet_quality	exercise_frequenc
521	S1521	23	Male	3.5	2.1	1.4	No	82.2	7.7	Fair	

[15]:
```
data.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   student_id                     1000 non-null   object 
 1   age                            1000 non-null   int64  
 2   gender                         1000 non-null   object 
 3   study_hours_per_day            1000 non-null   float64
 4   social_media_hours             1000 non-null   float64
 5   netflix_hours                  1000 non-null   float64
 6   part_time_job                  1000 non-null   object 
 7   attendance_percentage          1000 non-null   float64
 8   sleep_hours                    1000 non-null   float64
 9   diet_quality                   1000 non-null   object 
 10  exercise_frequency             1000 non-null   int64  
 11  parental_education_level       909 non-null    object 
 12  internet_quality               1000 non-null   object 
 13  mental_health_rating           1000 non-null   int64  
 14  extracurricular_participation  1000 non-null   object 
 15  exam_score                     1000 non-null   float64
dtypes: float64(6), int64(3), object(7)
memory usage: 125.1+ KB
```
[17]:
```
data.describe()
```
[17]:

	age	study_hours_per_day	social_media_hours	netflix_hours	attendance_percentage	sleep_hours	exercise_frequency	mental_health_rating	exam_score
count	1000.0000	1000.00000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	20.4980	3.55010	2.505500	1.819700	84.131700	6.470100	3.042000	5.438000	69.601500
std	2.3081	1.46889	1.172422	1.075118	9.399246	1.226377	2.025423	2.847501	16.888564
min	17.0000	0.00000	0.000000	0.000000	56.000000	3.200000	0.000000	1.000000	18.400000
25%	18.7500	2.60000	1.700000	1.000000	78.000000	5.600000	1.000000	3.000000	58.475000
50%	20.0000	3.50000	2.500000	1.800000	84.400000	6.500000	3.000000	5.000000	70.500000
75%	23.0000	4.50000	3.300000	2.525000	91.025000	7.300000	5.000000	8.000000	81.325000
max	24.0000	8.30000	7.200000	5.400000	100.000000	10.000000	6.000000	10.000000	100.000000

Data cleaning:

Handling Missing Values

- Imputation: Filling missing values with mean.

[21]:
```
import pandas as pd
```
[23]:
```
data.isnull().sum()
```
[23]:
```
student_id                        0
age                               0
gender                            0
study_hours_per_day               0
social_media_hours                0
netflix_hours                     0
part_time_job                     0
attendance_percentage             0
sleep_hours                       0
diet_quality                      0
exercise_frequency                0
parental_education_level         91
internet_quality                  0
mental_health_rating              0
extracurricular_participation     0
exam_score                        0
dtype: int64
```
[25]:
```
data.shape
```
[25]:
```
(1000, 16)
```

Drop student_id:

```
[27]:
df = pd.DataFrame(data)
df = df.drop('student_id', axis=1)
df = pd.DataFrame(data)

print(df)
```

Output:

```
    student_id  age  gender  study_hours_per_day  social_media_hours  \
0        S1000   23  Female                  0.0                 1.2
1        S1001   20  Female                  6.9                 2.8
2        S1002   21    Male                  1.4                 3.1
3        S1003   23  Female                  1.0                 3.9
4        S1004   19  Female                  5.0                 4.4
..         ...  ...     ...                  ...                 ...
995      S1995   21  Female                  2.6                 0.5
996      S1996   17  Female                  2.9                 1.0
997      S1997   20    Male                  3.0                 2.6
998      S1998   24    Male                  5.4                 4.1
999      S1999   19  Female                  4.3                 2.9
```

Separate target and features :

```
X = df.drop('exam_score', axis=1)
y = df['exam_score']
```

Separate categorical and numerical columns :

```
categorical_cols = X.select_dtypes(include=['object']).columns.tolist()
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
```

```
categorical_cols
```

```
['gender',
 'part_time_job',
 'diet_quality',
 'parental_education_level',
 'internet_quality',
 'extracurricular_participation']
```

```
numerical_cols
```

```
['age',
 'study_hours_per_day',
 'social_media_hours',
 'netflix_hours',
 'attendance_percentage',
 'sleep_hours',
 'exercise_frequency',
 'mental_health_rating']
```

Create preprocessing for numerical and categorical data :

```
numerical_transformer = SimpleImputer(strategy='mean')
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])
```

Combine both transformers :

```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
```

```
preprocessed_data = preprocessor.fit_transform(data)
print("Transformed data:")
print(preprocessed_data)
```

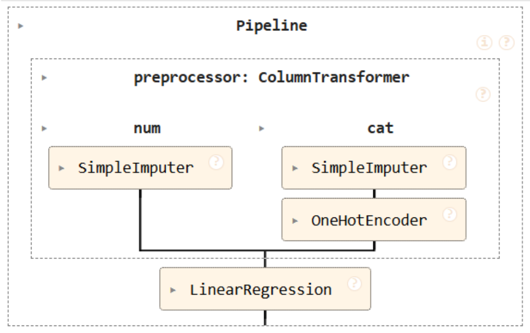
Output:

```
Transformed data:
  (0, 0)	23.0
  (0, 2)	1.2
  (0, 3)	1.1
  (0, 4)	85.0
  (0, 5)	8.0
  (0, 6)	6.0
  (0, 7)	8.0
  (0, 8)	1.0
  (0, 1008)	1.0
  (0, 1011)	1.0
  (0, 1013)	1.0
  (0, 1018)	1.0
  (0, 1019)	1.0
  (0, 1023)	1.0
  (1, 0)	20.0
  (1, 1)	6.9
  (1, 2)	2.8
```

Create a pipeline with preprocessor and linear regression :

```
model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])
```

```
model
```

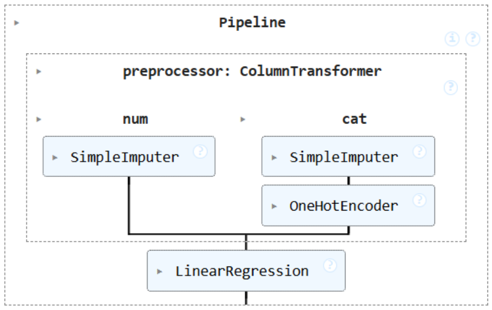


Split data into train and test sets

[51]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

[53]:
```python
model.fit(X_train, y_train)
```

[53]:



Make predictions

```python
y_pred = model.predict(X_test)
```

Evaluate the model

```python
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("R^2 Score:", r2)
```

```
Mean Squared Error: 26.533939976586062
R^2 Score: 0.8965252368374529
```

Part II :

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

df = pd.DataFrame(data)
```

Drop student_id :

```python
df = df.drop(columns=['student_id'])
```

Handle missing values early (for safety in full dataset) :

```python
df.fillna(df.mode().iloc[0], inplace=True)
```

Outlier detection using IQR method on numerical columns :

```python
def remove_outliers(df, cols):
    for col in cols:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower = Q1 - 1.5 * IQR
        upper = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower) & (df[col] <= upper)]
    return df
```

Define numerical columns :

```python
numerical_cols = df.select_dtypes(include=['int64', 'float64']).drop(columns=['exam_score']).columns.tolist()
```

Remove outliers :

```python
7]:  df = remove_outliers(df, numerical_cols)
```

Separate features and target :

```python
X = df.drop('exam_score', axis=1)
y = df['exam_score']
```

Categorical columns :

```python
3]:  categorical_cols = X.select_dtypes(include=['object']).columns.tolist()
```

Preprocessing for numerical features :

```python
numerical_pipeline = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])
```

Preprocessing for categorical features :

```python
categorical_pipeline = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])
```

Combine both into ColumnTransformer :

```
preprocessor = ColumnTransformer(transformers=[
    ('num', numerical_pipeline, numerical_cols),
    ('cat', categorical_pipeline, categorical_cols)
])
```

Full pipeline with Linear Regression :

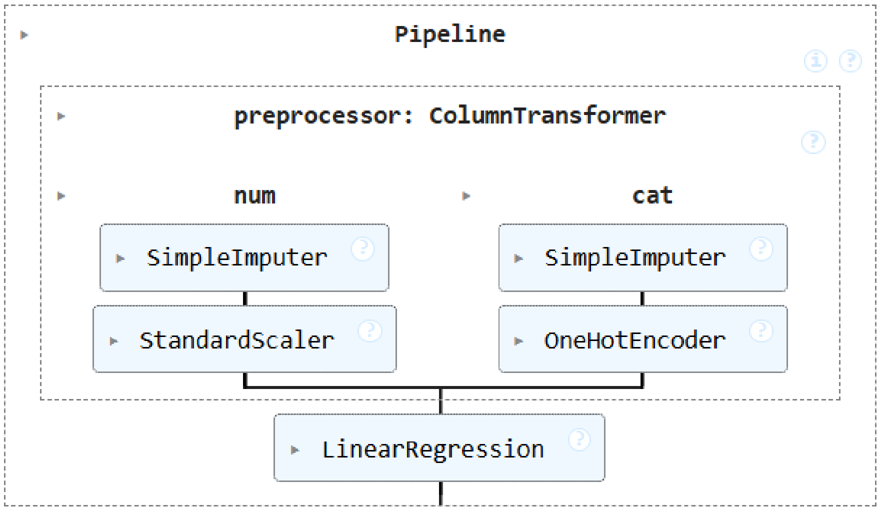
```
model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])
```

Train/test split :

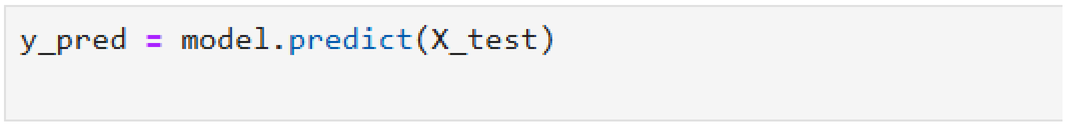
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train the model :

```
model.fit(X_train, y_train)
```

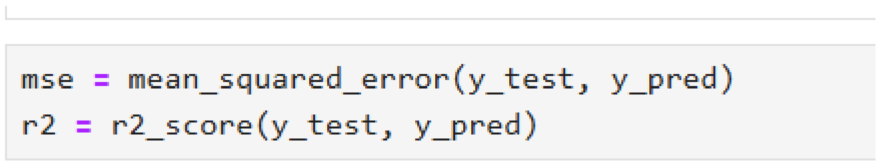


Predictions :



```
y_pred = model.predict(X_test)
```

Evaluation :



```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

Regression Dataset Analysis:

The dataset used in this machine learning lab focuses on predicting a continuous variable, which is ideal for regression analysis. The target variable likely represents a numeric outcome such as student grades, scores, or performance metrics, though the exact variable is not named. The data includes both categorical and numerical features and contains unique student identifiers, which are appropriately removed before modeling.

1. Data Preparation and Cleaning

The initial steps involve importing necessary libraries and reading the dataset. One of the key cleaning steps is the removal of the student_id column. This is essential because unique identifiers do not contribute to learning patterns and can bias the model if retained. Handling missing values is done early in Part II, ensuring the dataset remains consistent during training.

Outlier detection and removal are conducted using the IQR (Interquartile Range) method. This helps to maintain the robustness of the regression model by eliminating data points that are likely to distort the results. Proper identification and treatment of outliers prevent overfitting and improve model generalization.

2. Feature Engineering and Preprocessing

The features are separated into categorical and numerical types. This distinction is critical for applying the right preprocessing steps:

- **Numerical Features:** These are scaled or normalized using transformations to ensure that features with large ranges do not dominate the learning process.
- **Categorical Features:** These are typically transformed using one-hot encoding or similar techniques, converting them into numerical format that machine learning algorithms can interpret.

Both preprocessing pipelines are combined using a ColumnTransformer, ensuring that all transformations are applied in a unified manner.

3. Model Construction with Linear Regression

A machine learning pipeline is built using the combined preprocessor and a linear regression model. The pipeline approach ensures that preprocessing and modeling are tightly coupled, making the entire workflow reproducible and clean.

The data is then split into training and testing subsets. This is a standard practice to evaluate model performance on unseen data. The model is trained on the training set and then used to make predictions on the test set.

4. Evaluation

Model evaluation is a key step in assessing performance. Although the specific metrics used are not listed, common regression evaluation metrics include:

- **Mean Absolute Error (MAE)**
- **Mean Squared Error (MSE)**
- **Root Mean Squared Error (RMSE)**
- **R^2 Score (Coefficient of Determination)**

These metrics provide insight into how well the model is performing and how close the predicted values are to the actual targets.

Conclusion

This regression pipeline demonstrates a complete machine learning workflow—from data cleaning and preprocessing to modeling and evaluation. It emphasizes the importance of data handling, especially in mixed-type datasets, and reinforces the value of using pipelines to streamline and organize machine learning tasks. By using linear regression as the model, the lab introduces students to a fundamental technique that is interpretable, fast, and effective for many real-world applications.

¦LAB -【Classification】¦

Classification (Machine Learning)

Classification is a supervised machine learning technique used to predict a **categorical label**. The goal is to assign data points to one of several predefined classes based on input features.

Data description:

A heart attack dataset with 1319 samples and 9 fields: 8 input features (age, gender, heart rate, systolic BP, diastolic BP, blood sugar, CK-MB, Troponin) and 1 output label (heart attack class: positive or negative). The dataset aims to identify key factors contributing to heart attacks.

Import libraries :

```
import pandas as pd
import numpy as np
import os

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import FunctionTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import RandomOverSampler
from sklearn.decomposition import PCA

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier

import tensorflow
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense

from sklearn.metrics import accuracy_score
```

Reading data :

```
import pandas as pd
import numpy as np
data = pd.read_csv("Heart Attack.csv")
```

```
data.head()
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
0	64	1	66	160	83	160.0	1.80	0.012	negative
1	21	1	94	98	46	296.0	6.75	1.060	positive
2	55	1	64	160	77	270.0	1.99	0.003	negative
3	64	1	70	120	55	270.0	13.87	0.122	positive
4	55	1	64	112	65	300.0	1.08	0.003	negative

```
data.tail()
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
1314	44	1	94	122	67	204.0	1.63	0.006	negative
1315	66	1	84	125	55	149.0	1.33	0.172	positive
1316	45	1	85	168	104	96.0	1.24	4.250	positive
1317	54	1	58	117	68	443.0	5.80	0.359	positive
1318	51	1	94	157	79	134.0	50.89	1.770	positive

```
type(data)
```

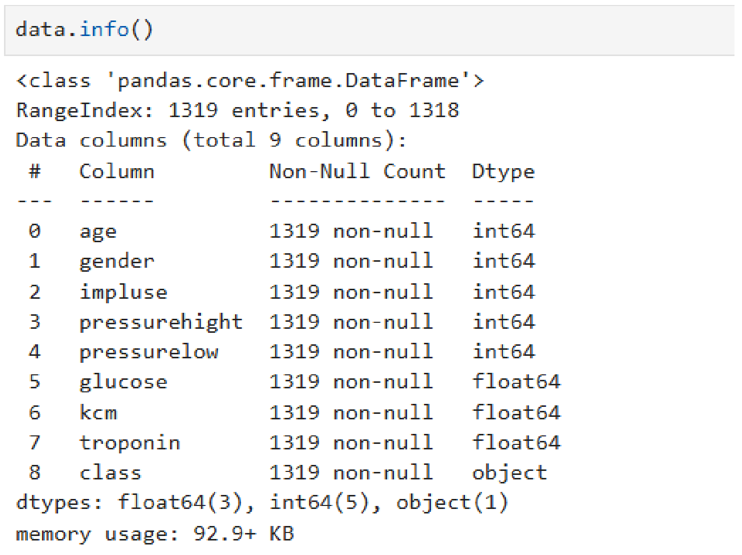
Exploring data :

```
data.sample(3)
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
913	55	1	81	150	51	138.0	17.22	2.800	positive
1055	77	0	82	125	61	115.0	2.14	0.039	positive
855	65	1	67	177	105	120.0	3.68	0.011	negative

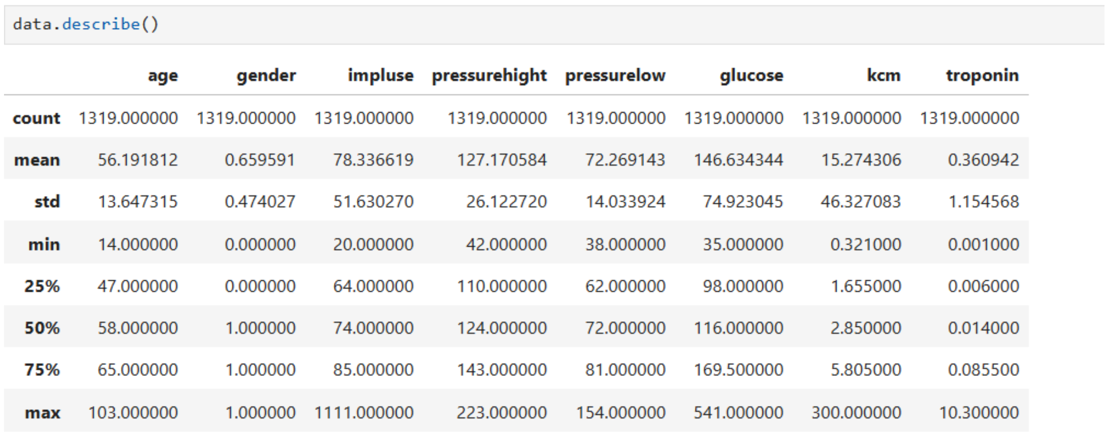
```
data.dtypes
```

```
age                int64
gender             int64
impluse            int64
pressurehight      int64
pressurelow        int64
glucose          float64
kcm              float64
troponin         float64
class             object
dtype: object
```



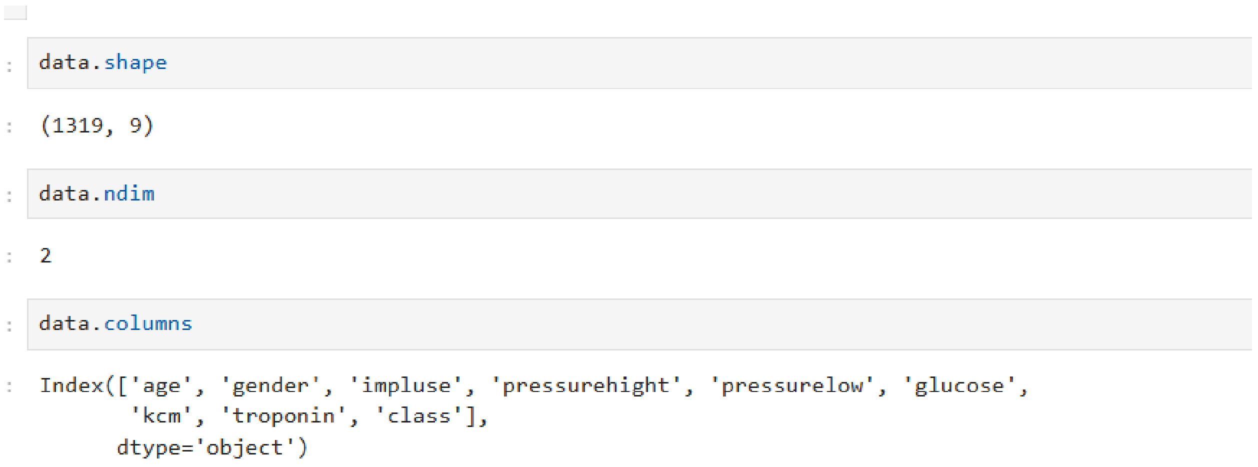
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            1319 non-null   int64  
 1   gender         1319 non-null   int64  
 2   impluse        1319 non-null   int64  
 3   pressurehight  1319 non-null   int64  
 4   pressurelow    1319 non-null   int64  
 5   glucose        1319 non-null   float64
 6   kcm            1319 non-null   float64
 7   troponin       1319 non-null   float64
 8   class          1319 non-null   object 
dtypes: float64(3), int64(5), object(1)
memory usage: 92.9+ KB
```

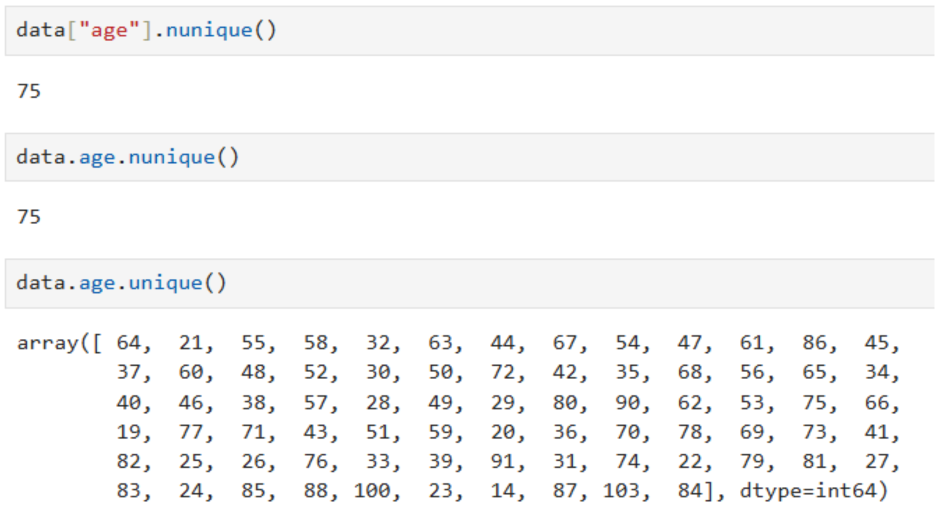


```python
data.describe()
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin
count	1319.000000	1319.000000	1319.000000	1319.000000	1319.000000	1319.000000	1319.000000	1319.000000
mean	56.191812	0.659591	78.336619	127.170584	72.269143	146.634344	15.274306	0.360942
std	13.647315	0.474027	51.630270	26.122720	14.033924	74.923045	46.327083	1.154568
min	14.000000	0.000000	20.000000	42.000000	38.000000	35.000000	0.321000	0.001000
25%	47.000000	0.000000	64.000000	110.000000	62.000000	98.000000	1.655000	0.006000
50%	58.000000	1.000000	74.000000	124.000000	72.000000	116.000000	2.850000	0.014000
75%	65.000000	1.000000	85.000000	143.000000	81.000000	169.500000	5.805000	0.085500
max	103.000000	1.000000	1111.000000	223.000000	154.000000	541.000000	300.000000	10.300000



```
: data.shape

: (1319, 9)

: data.ndim

: 2

: data.columns

: Index(['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose',
         'kcm', 'troponin', 'class'],
        dtype='object')
```



```
data["age"].nunique()
```

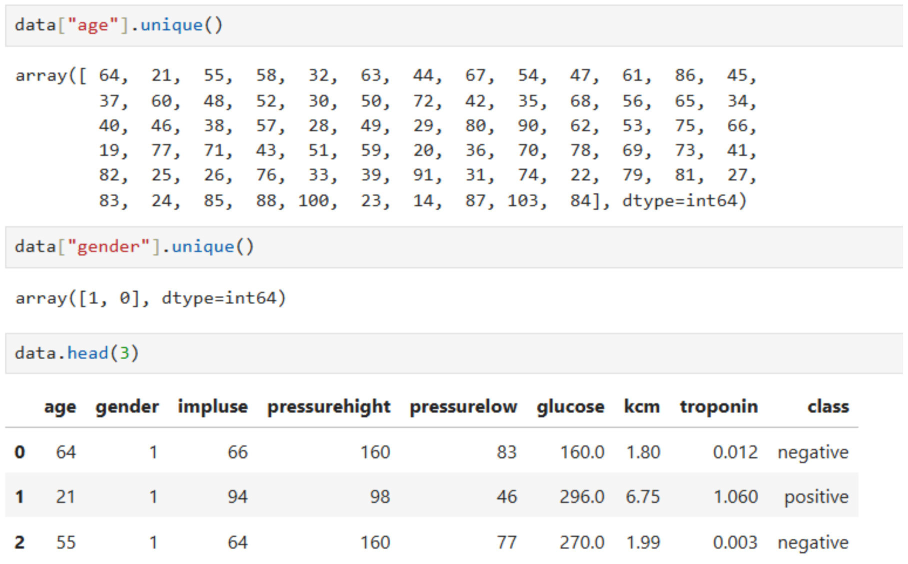
```
75
```

```
data.age.nunique()
```

```
75
```

```
data.age.unique()
```

```
array([ 64,  21,  55,  58,  32,  63,  44,  67,  54,  47,  61,  86,  45,
        37,  60,  48,  52,  30,  50,  72,  42,  35,  68,  56,  65,  34,
        40,  46,  38,  57,  28,  49,  29,  80,  90,  62,  53,  75,  66,
        19,  77,  71,  43,  51,  59,  20,  36,  70,  78,  69,  73,  41,
        82,  25,  26,  76,  33,  39,  91,  31,  74,  22,  79,  81,  27,
        83,  24,  85,  88, 100,  23,  14,  87, 103,  84], dtype=int64)
```



```
data["age"].unique()
```

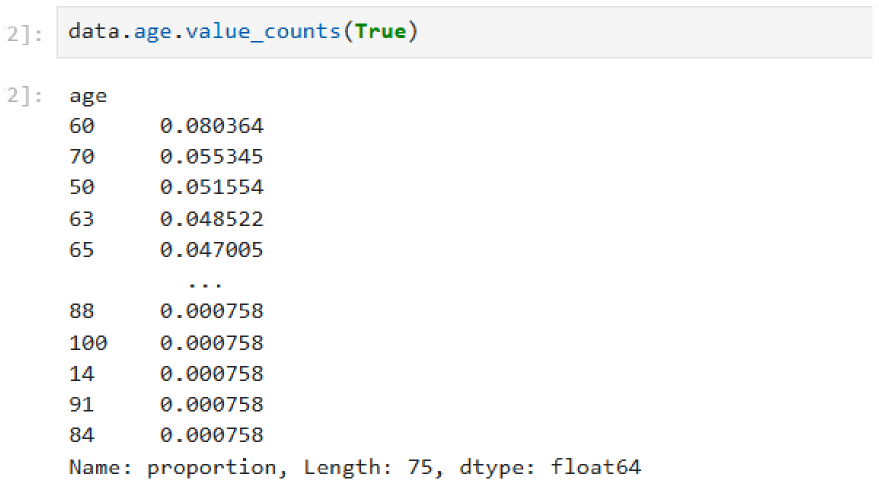
```
array([ 64,  21,  55,  58,  32,  63,  44,  67,  54,  47,  61,  86,  45,
        37,  60,  48,  52,  30,  50,  72,  42,  35,  68,  56,  65,  34,
        40,  46,  38,  57,  28,  49,  29,  80,  90,  62,  53,  75,  66,
        19,  77,  71,  43,  51,  59,  20,  36,  70,  78,  69,  73,  41,
        82,  25,  26,  76,  33,  39,  91,  31,  74,  22,  79,  81,  27,
        83,  24,  85,  88, 100,  23,  14,  87, 103,  84], dtype=int64)
```

```
data["gender"].unique()
```

```
array([1, 0], dtype=int64)
```

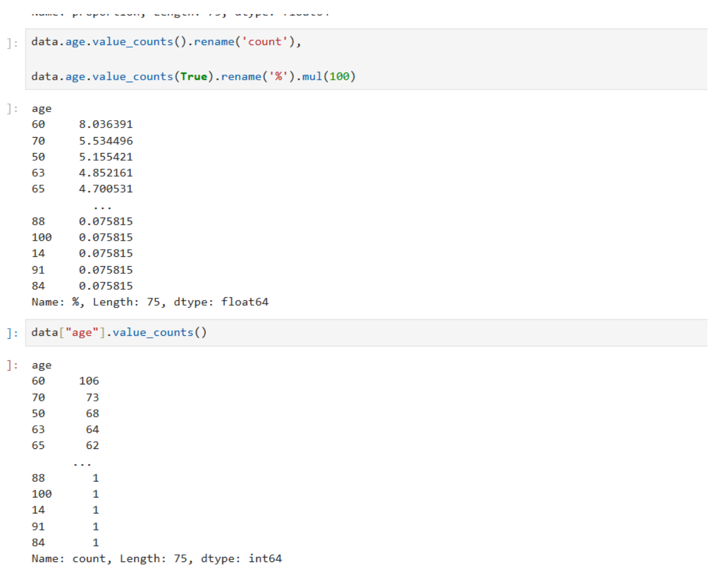
```
data.head(3)
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
0	64	1	66	160	83	160.0	1.80	0.012	negative
1	21	1	94	98	46	296.0	6.75	1.060	positive
2	55	1	64	160	77	270.0	1.99	0.003	negative



```
2]:  data.age.value_counts(True)
```

```
2]:  age
     60     0.080364
     70     0.055345
     50     0.051554
     63     0.048522
     65     0.047005
              ...
     88     0.000758
     100    0.000758
     14     0.000758
     91     0.000758
     84     0.000758
     Name: proportion, Length: 75, dtype: float64
```



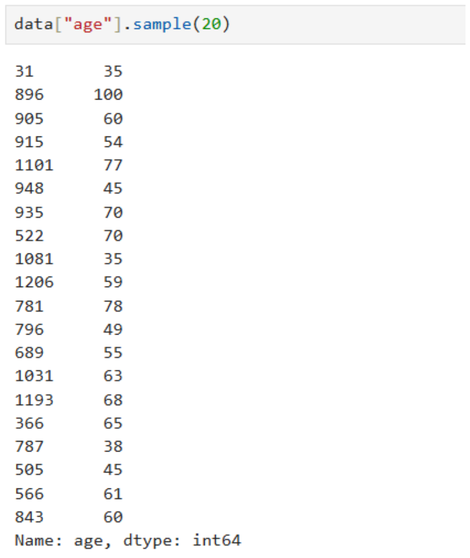
```
Name: proportion, Length: 75, dtype: float64
```

```
]: data.age.value_counts().rename('count'),

   data.age.value_counts(True).rename('%').mul(100)
```

```
]: age
   60     8.036391
   70     5.534496
   50     5.155421
   63     4.852161
   65     4.700531
            ...
   88     0.075815
   100    0.075815
   14     0.075815
   91     0.075815
   84     0.075815
   Name: %, Length: 75, dtype: float64
```

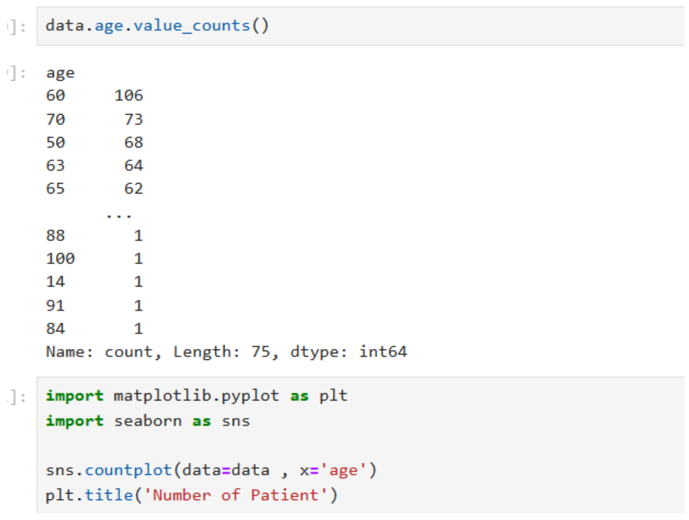
```
]: data["age"].value_counts()
```

```
]: age
   60     106
   70      73
   50      68
   63      64
   65      62
         ...
   88       1
   100      1
   14       1
   91       1
   84       1
   Name: count, Length: 75, dtype: int64
```



```
data["age"].sample(20)
```

```
31       35
896     100
905      60
915      54
1101     77
948      45
935      70
522      70
1081     35
1206     59
781      78
796      49
689      55
1031     63
1193     68
366      65
787      38
505      45
566      61
843      60
Name: age, dtype: int64
```

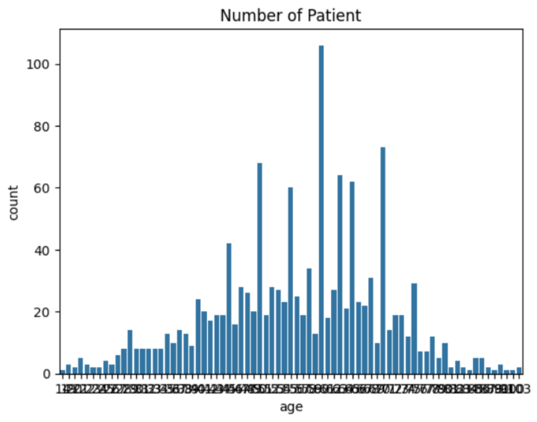


```
]: data.age.value_counts()
```

```
]: age
   60     106
   70      73
   50      68
   63      64
   65      62
         ...
   88       1
   100      1
   14       1
   91       1
   84       1
   Name: count, Length: 75, dtype: int64
```

```
]: import matplotlib.pyplot as plt
   import seaborn as sns

   sns.countplot(data=data , x='age')
   plt.title('Number of Patient')
```

```
: Text(0.5, 1.0, 'Number of Patient')
```



```
]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            1319 non-null   int64  
 1   gender         1319 non-null   int64  
 2   impluse        1319 non-null   int64  
 3   pressurehight  1319 non-null   int64  
 4   pressurelow    1319 non-null   int64  
 5   glucose        1319 non-null   float64
 6   kcm            1319 non-null   float64
 7   troponin       1319 non-null   float64
 8   class          1319 non-null   object 
dtypes: float64(3), int64(5), object(1)
memory usage: 92.9+ KB
```

```
]: data.sample(20)
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
1235	47	1	93	105	71	113.0	1.730	0.434	positive
583	44	1	74	155	77	81.0	61.100	0.044	positive
664	62	1	75	134	85	109.0	5.770	0.010	negative
510	52	1	77	122	58	122.0	51.900	0.017	positive
1010	35	1	60	109	65	222.0	3.270	0.003	negative
201	75	0	66	150	95	115.0	2.960	0.280	positive
56	49	1	59	110	65	149.0	3.180	0.003	negative
1174	37	0	83	102	68	104.0	1.350	0.007	negative
646	70	1	80	125	75	150.0	5.020	0.016	positive
527	63	0	96	112	62	244.0	1.950	0.003	negative
1221	52	1	62	143	75	100.0	6.410	0.055	positive
825	57	1	82	138	93	297.0	6.750	0.020	positive

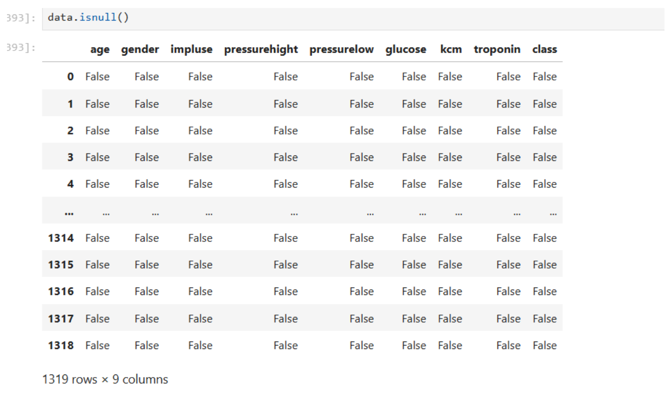
```
: data.columns
```

```
: Index(['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose',
         'kcm', 'troponin', 'class'],
        dtype='object')
```

```
: data["age"].value_counts()
```

```
: age
  60     106
  70      73
  50      68
  63      64
  65      62
        ... 
  88       1
  100      1
  14       1
  91       1
  84       1
  Name: count, Length: 75, dtype: int64
```

Missing values :

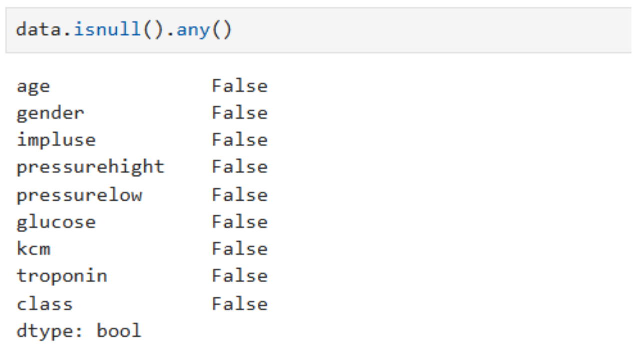


```
393]: data.isnull()
```

393]:

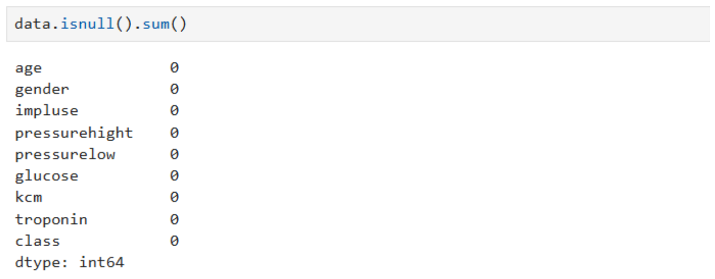
	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
1314	False	False	False	False	False	False	False	False	False
1315	False	False	False	False	False	False	False	False	False
1316	False	False	False	False	False	False	False	False	False
1317	False	False	False	False	False	False	False	False	False
1318	False	False	False	False	False	False	False	False	False

1319 rows × 9 columns



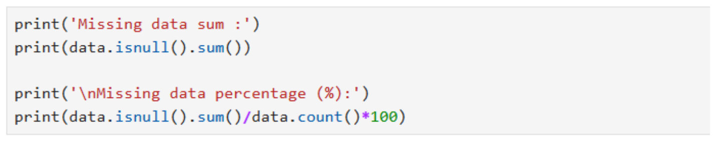
```
data.isnull().any()
```

```
age              False
gender           False
impluse          False
pressurehight    False
pressurelow      False
glucose          False
kcm              False
troponin         False
class            False
dtype: bool
```

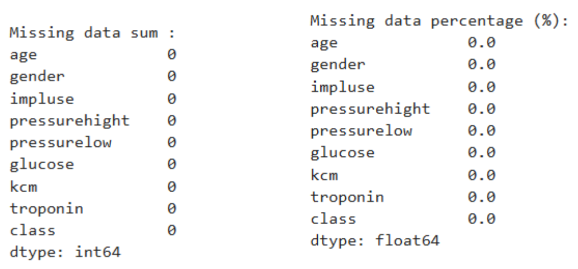


```
data.isnull().sum()
```

```
age              0
gender           0
impluse          0
pressurehight    0
pressurelow      0
glucose          0
kcm              0
troponin         0
class            0
dtype: int64
```



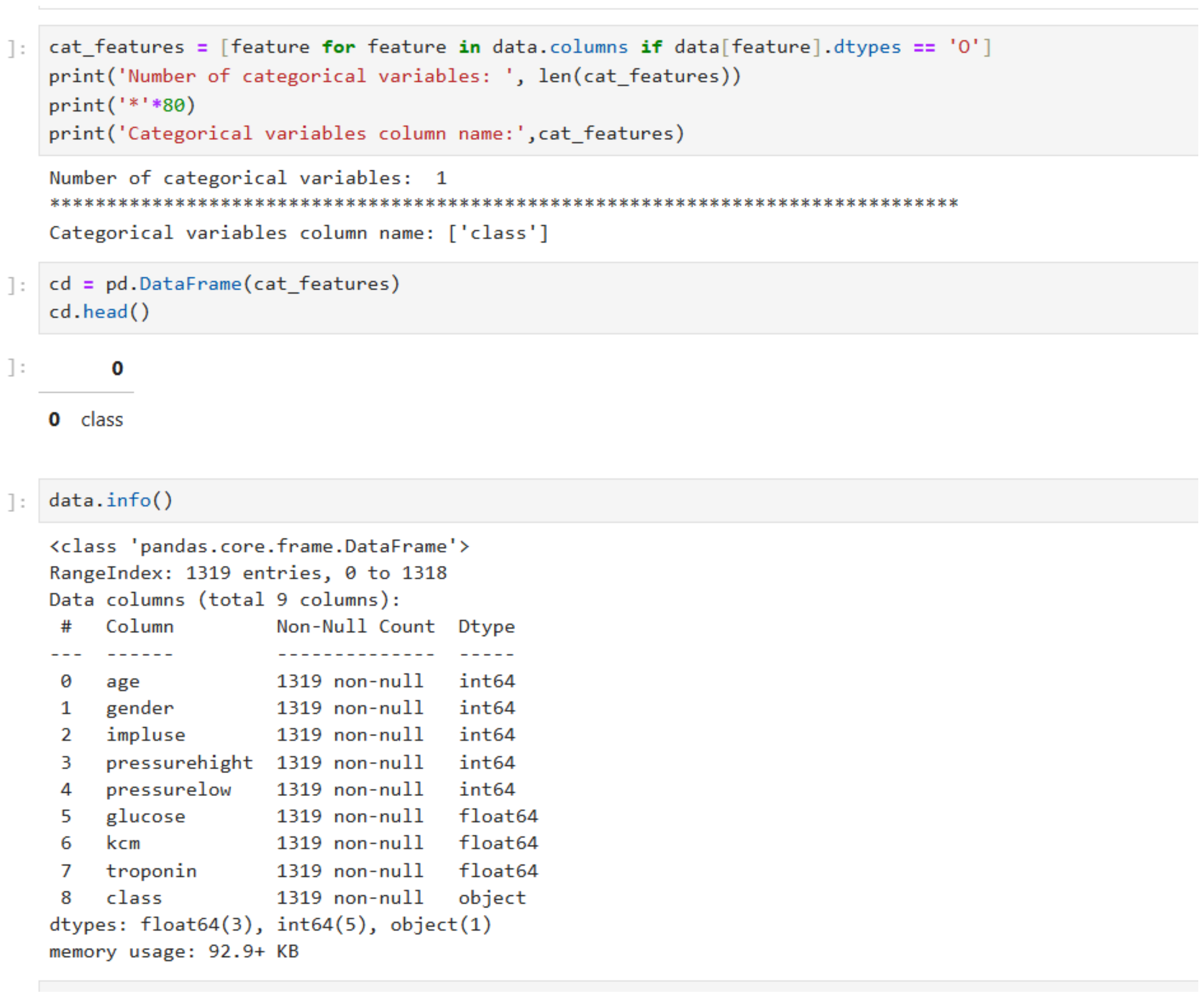
```
print('Missing data sum :')
print(data.isnull().sum())

print('\nMissing data percentage (%):')
print(data.isnull().sum()/data.count()*100)
```



```
Missing data sum :
age              0
gender           0
impluse          0
pressurehight    0
pressurelow      0
glucose          0
kcm              0
troponin         0
class            0
dtype: int64
```

```
Missing data percentage (%):
age              0.0
gender           0.0
impluse          0.0
pressurehight    0.0
pressurelow      0.0
glucose          0.0
kcm              0.0
troponin         0.0
class            0.0
dtype: float64
```

Seperate Categorical and Numerical Features :



```
]: cat_features = [feature for feature in data.columns if data[feature].dtypes == 'O']
   print('Number of categorical variables: ', len(cat_features))
   print('*'*80)
   print('Categorical variables column name:',cat_features)
```

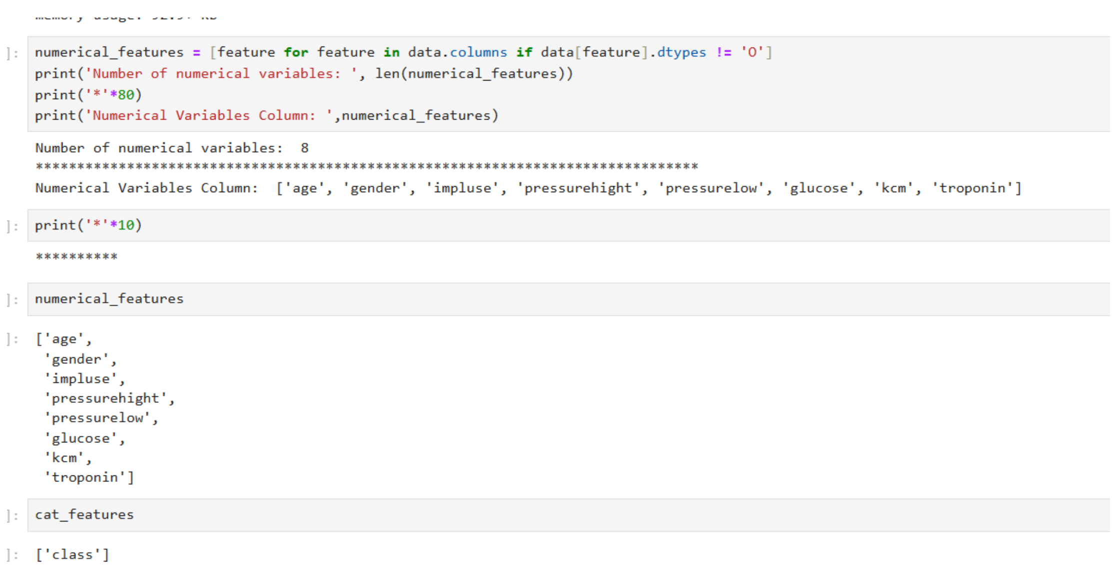
```
Number of categorical variables:  1
********************************************************************************
Categorical variables column name: ['class']
```

```
]: cd = pd.DataFrame(cat_features)
   cd.head()
```

```
]:      0
   0  class
```

```
]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            1319 non-null   int64  
 1   gender         1319 non-null   int64  
 2   impluse        1319 non-null   int64  
 3   pressurehight  1319 non-null   int64  
 4   pressurelow    1319 non-null   int64  
 5   glucose        1319 non-null   float64
 6   kcm            1319 non-null   float64
 7   troponin       1319 non-null   float64
 8   class          1319 non-null   object 
dtypes: float64(3), int64(5), object(1)
memory usage: 92.9+ KB
```



memory usage: 92.9+ KB

```
]: numerical_features = [feature for feature in data.columns if data[feature].dtypes != 'O']
   print('Number of numerical variables: ', len(numerical_features))
   print('*'*80)
   print('Numerical Variables Column: ',numerical_features)
```

```
Number of numerical variables:  8
********************************************************************************
Numerical Variables Column:  ['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose', 'kcm', 'troponin']
```

```
]: print('*'*10)
```

```
**********
```

```
]: numerical_features
```

```
]: ['age',
    'gender',
    'impluse',
    'pressurehight',
    'pressurelow',
    'glucose',
    'kcm',
    'troponin']
```

```
]: cat_features
```

```
]: ['class']
```

Checking Duplicating Values :

```
]: data.gender.duplicated()
```

```
]: 0       False
   1        True
   2        True
   3        True
   4        True
            ...
   1314     True
   1315     True
   1316     True
   1317     True
   1318     True
   Name: gender, Length: 1319, dtype: bool
```

```
]: data.duplicated().sum()
```

```
]: 0
```

```
]: data['gender'].unique()
```

```
]: array([1, 0], dtype=int64)
```

```
23]: data['age'].sample(10)
```

```
23]: 1175    60
     1024    65
     679     43
     930     74
     509     65
     992     72
     1265    41
     368     59
     768     58
     763     70
     Name: age, dtype: int64
```

```
25]: data['age'].unique()
```

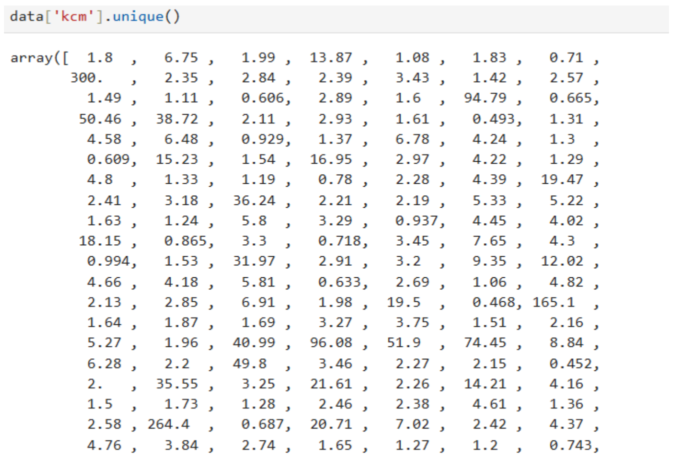
```
25]: array([ 64,  21,  55,  58,  32,  63,  44,  67,  54,  47,  61,  86,  45,
             37,  60,  48,  52,  30,  50,  72,  42,  35,  68,  56,  65,  34,
             40,  46,  38,  57,  28,  49,  29,  80,  90,  62,  53,  75,  66,
             19,  77,  71,  43,  51,  59,  20,  36,  70,  78,  69,  73,  41,
             82,  25,  26,  76,  33,  39,  91,  31,  74,  22,  79,  81,  27,
             83,  24,  85,  88, 100,  23,  14,  87, 103,  84], dtype=int64)
```

```
data['impluse'].unique()
```

```
array([  66,   94,   64,   70,   61,   40,   60,   76,   81,   73,   72,
         92,  135,   63,   65,  125,   62,   58,   93,   96,   95,   97,
         91,   87,   77,   80,   82,   83,   78,   90,   59,   57,   98,
       1111,  102,  103,  105,   74,   85,   75,   71,   68,   67,   56,
         89,   88,   86,   79,  100,   69,   84,  110,  120,  122,  119,
        116,  114,   55,   53,   54,  117,  112,  108,  134,  111,  101,
        113,   51,   52,   99,  132,   50,  107,  104,   49,   46,   20,
         36,   45], dtype=int64)
```

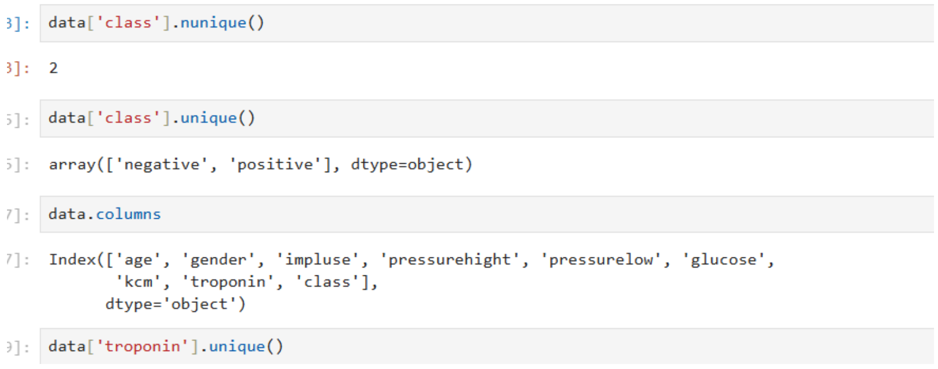
```
: data['glucose'].unique()
```

```
: array([160. , 296. , 270. , 300. ,  87. , 102. , 135. , 100. , 198. ,
          92. ,  97. , 319. , 134. ,  96. , 274. ,  89. , 301. , 227. ,
         107. , 269. , 111. , 101. ,  95. , 279. , 166. , 321. ,  98. ,
         105. , 136. ,  82. , 117. , 120. , 208. , 125. , 103. ,  93. ,
          99. , 228. , 238. , 133. , 113. ,  91. , 114. , 149. , 110. ,
         251. , 191. , 334. , 109. , 201. , 167. ,  85. , 112. , 123. ,
          86. , 177. ,  90. , 115. , 392. , 147. , 141. , 222. , 174. ,
         162. , 219. , 189. , 193. , 181. , 387. , 121. , 294. , 116. ,
          88. , 240. , 132. , 159. ,  81. , 266. , 142. , 244. , 130. ,
         182. ,  94. ,  83. , 241. , 318. ,  66. , 156. , 108. , 322. ,
         187. , 122. , 362. , 180. , 127. , 131. ,  84. , 137. , 242. ,
         106. , 197. , 152. , 169. , 347. , 104. , 165. , 126. , 215. ,
          61. ,  80. , 195. , 150. , 194. , 233. , 462. , 422. , 245. ,
```

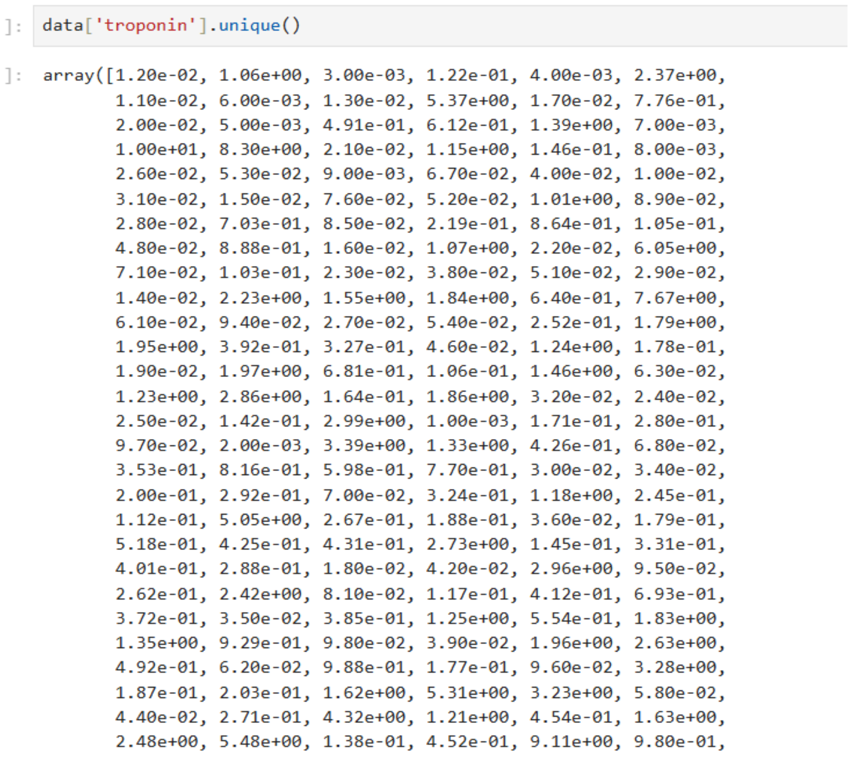


```
data['kcm'].unique()
```

```
array([  1.8  ,   6.75 ,   1.99 ,  13.87 ,   1.08 ,   1.83 ,   0.71 ,
       300.   ,   2.35 ,   2.84 ,   2.39 ,   3.43 ,   1.42 ,   2.57 ,
         1.49 ,   1.11 ,   0.606,   2.89 ,   1.6  ,  94.79 ,   0.665,
        50.46 ,  38.72 ,   2.11 ,   2.93 ,   1.61 ,   0.493,   1.31 ,
         4.58 ,   6.48 ,   0.929,   1.37 ,   6.78 ,   4.24 ,   1.3  ,
         0.609,  15.23 ,   1.54 ,  16.95 ,   2.97 ,   4.22 ,   1.29 ,
         4.8  ,   1.33 ,   1.19 ,   0.78 ,   2.28 ,   4.39 ,  19.47 ,
         2.41 ,   3.18 ,  36.24 ,   2.21 ,   2.19 ,   5.33 ,   5.22 ,
         1.63 ,   1.24 ,   5.8  ,   3.29 ,   0.937,   4.45 ,   4.02 ,
        18.15 ,   0.865,   3.3  ,   0.718,   3.45 ,   7.65 ,   4.3  ,
         0.994,   1.53 ,  31.97 ,   2.91 ,   3.2  ,   9.35 ,  12.02 ,
         4.66 ,   4.18 ,   5.81 ,   0.633,   2.69 ,   1.06 ,   4.82 ,
         2.13 ,   2.85 ,   6.91 ,   1.98 ,  19.5  ,   0.468, 165.1  ,
         1.64 ,   1.87 ,   1.69 ,   3.27 ,   3.75 ,   1.51 ,   2.16 ,
         5.27 ,   1.96 ,  40.99 ,  96.08 ,  51.9  ,  74.45 ,   8.84 ,
         6.28 ,   2.2  ,  49.8  ,   3.46 ,   2.27 ,   2.15 ,   0.452,
         2.   ,  35.55 ,   3.25 ,  21.61 ,   2.26 ,  14.21 ,   4.16 ,
         1.5  ,   1.73 ,   1.28 ,   2.46 ,   2.38 ,   4.61 ,   1.36 ,
         2.58 , 264.4  ,   0.687,  20.71 ,   7.02 ,   2.42 ,   4.37 ,
         4.76 ,   3.84 ,   2.74 ,   1.65 ,   1.27 ,   1.2  ,   0.743,
```



```
3]:  data['class'].nunique()

3]:  2

5]:  data['class'].unique()

5]:  array(['negative', 'positive'], dtype=object)

7]:  data.columns

7]:  Index(['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose',
            'kcm', 'troponin', 'class'],
           dtype='object')

9]:  data['troponin'].unique()
```



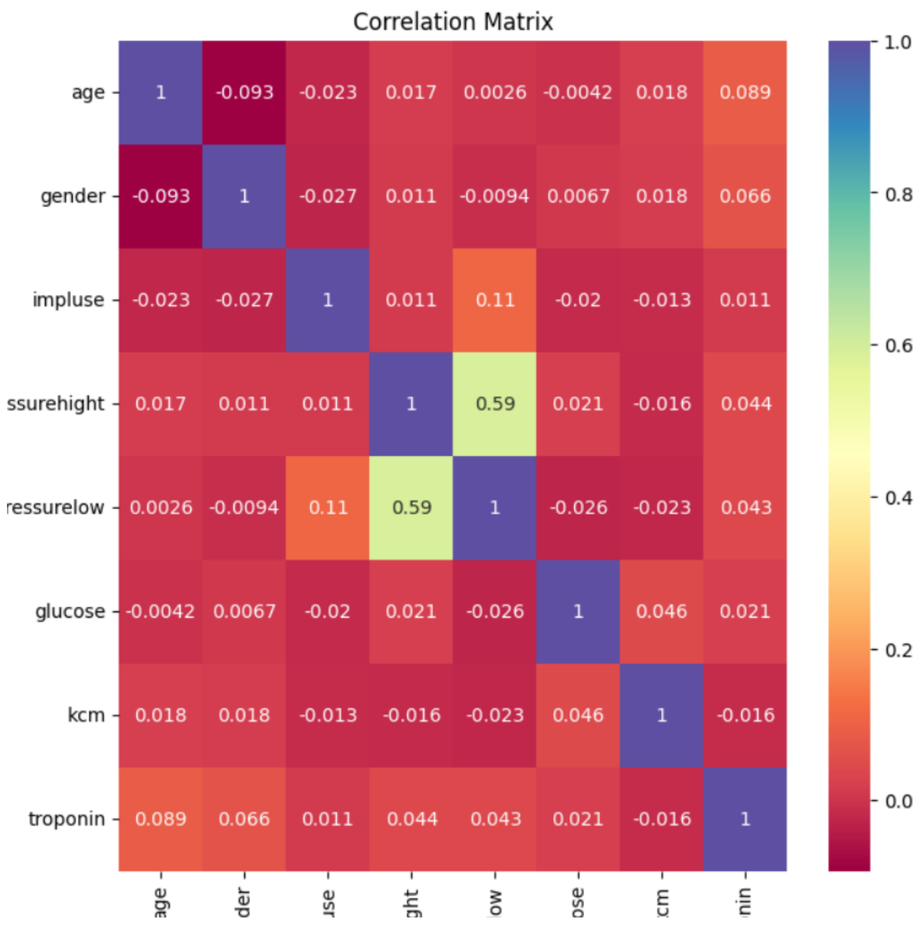
```
]:  data['troponin'].unique()

]:  array([1.20e-02, 1.06e+00, 3.00e-03, 1.22e-01, 4.00e-03, 2.37e+00,
           1.10e-02, 6.00e-03, 1.30e-02, 5.37e+00, 1.70e-02, 7.76e-01,
           2.00e-02, 5.00e-03, 4.91e-01, 6.12e-01, 1.39e+00, 7.00e-03,
           1.00e+01, 8.30e+00, 2.10e-02, 1.15e+00, 1.46e-01, 8.00e-03,
           2.60e-02, 5.30e-02, 9.00e-03, 6.70e-02, 4.00e-02, 1.00e-02,
           3.10e-02, 1.50e-02, 7.60e-02, 5.20e-02, 1.01e+00, 8.90e-02,
           2.80e-02, 7.03e-01, 8.50e-02, 2.19e-01, 8.64e-01, 1.05e-01,
           4.80e-02, 8.88e-01, 1.60e-02, 1.07e+00, 2.20e-02, 6.05e+00,
           7.10e-02, 1.03e-01, 2.30e-02, 3.80e-02, 5.10e-02, 2.90e-02,
           1.40e-02, 2.23e+00, 1.55e+00, 1.84e+00, 6.40e-01, 7.67e+00,
           6.10e-02, 9.40e-02, 2.70e-02, 5.40e-02, 2.52e-01, 1.79e+00,
           1.95e+00, 3.92e-01, 3.27e-01, 4.60e-02, 1.24e+00, 1.78e-01,
           1.90e-02, 1.97e+00, 6.81e-01, 1.06e-01, 1.46e+00, 6.30e-02,
           1.23e+00, 2.86e+00, 1.64e-01, 1.86e+00, 3.20e-02, 2.40e-02,
           2.50e-02, 1.42e-01, 2.99e+00, 1.00e-03, 1.71e-01, 2.80e-01,
           9.70e-02, 2.00e-03, 3.39e+00, 1.33e+00, 4.26e-01, 6.80e-02,
           3.53e-01, 8.16e-01, 5.98e-01, 7.70e-01, 3.00e-02, 3.40e-02,
           2.00e-01, 2.92e-01, 7.00e-02, 3.24e-01, 1.18e+00, 2.45e-01,
           1.12e-01, 5.05e+00, 2.67e-01, 1.88e-01, 3.60e-02, 1.79e-01,
           5.18e-01, 4.25e-01, 4.31e-01, 2.73e+00, 1.45e-01, 3.31e-01,
           4.01e-01, 2.88e-01, 1.80e-02, 4.20e-02, 2.96e+00, 9.50e-02,
           2.62e-01, 2.42e+00, 8.10e-02, 1.17e-01, 4.12e-01, 6.93e-01,
           3.72e-01, 3.50e-02, 3.85e-01, 1.25e+00, 5.54e-01, 1.83e+00,
           1.35e+00, 9.29e-01, 9.80e-02, 3.90e-02, 1.96e+00, 2.63e+00,
           4.92e-01, 6.20e-02, 9.88e-01, 1.77e-01, 9.60e-02, 3.28e+00,
           1.87e-01, 2.03e-01, 1.62e+00, 5.31e+00, 3.23e+00, 5.80e-02,
           4.40e-02, 2.71e-01, 4.32e+00, 1.21e+00, 4.54e-01, 1.63e+00,
           2.48e+00, 5.48e+00, 1.38e-01, 4.52e-01, 9.11e+00, 9.80e-01,
]: data['age'].nunique()
```

```
]: 75
```

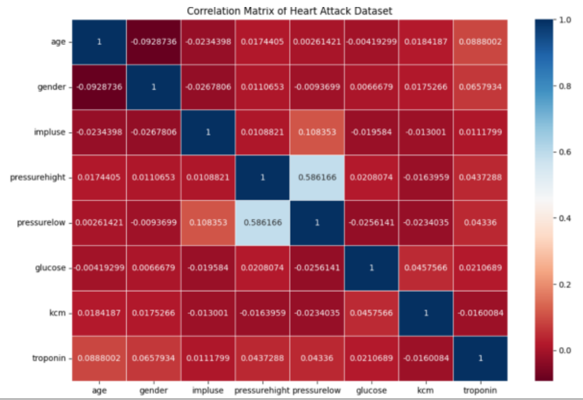
```
]: data['age'].unique()
```

```
]: array([ 64,  21,  55,  58,  32,  63,  44,  67,  54,  47,  61,  86,  45,
         37,  60,  48,  52,  30,  50,  72,  42,  35,  68,  56,  65,  34,
         40,  46,  38,  57,  28,  49,  29,  80,  90,  62,  53,  75,  66,
         19,  77,  71,  43,  51,  59,  20,  36,  70,  78,  69,  73,  41,
         82,  25,  26,  76,  33,  39,  91,  31,  74,  22,  79,  81,  27,
         83,  24,  85,  88, 100,  23,  14,  87, 103,  84], dtype=int64)
```

```
]: corr = data.drop(columns=['class']).corr()

   plt.figure(figsize=(8, 8))
   sns.heatmap(data=corr, annot=True, cmap='Spectral')
   plt.title("Correlation Matrix")
   plt.show()
```



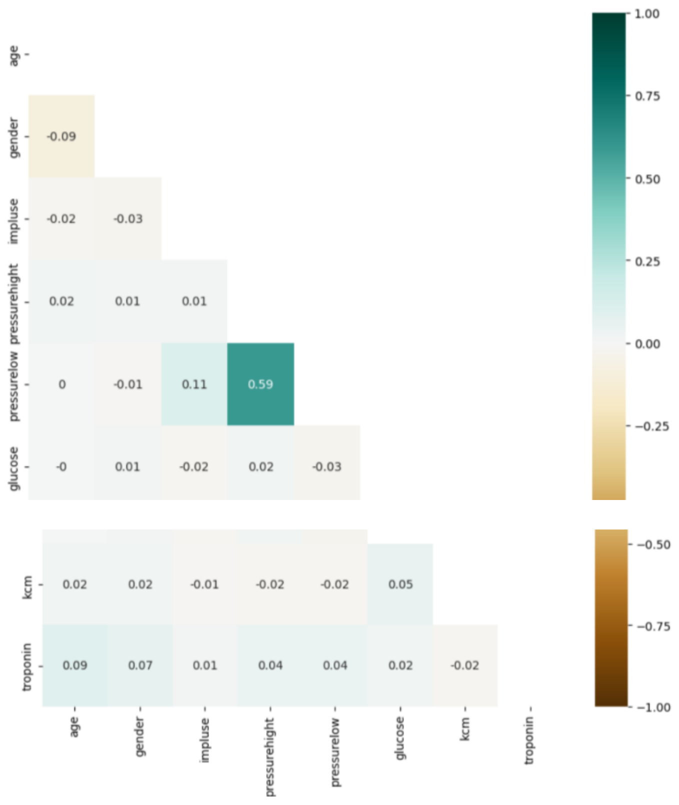
```
fig = plt.figure(figsize=(12, 8))
corr = data.drop(columns=['class']).corr()
sns.heatmap(corr, linewidths=0.5, cmap="RdBu", annot=True, fmt="g")
plt.title("Correlation Matrix of Heart Attack Dataset")
plt.show()
```



```
corr_matrix = data.drop(columns=['class']).corr().round(2)
corr_matrix
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin
age	1.00	-0.09	-0.02	0.02	0.00	-0.00	0.02	0.09
gender	-0.09	1.00	-0.03	0.01	-0.01	0.01	0.02	0.07
impluse	-0.02	-0.03	1.00	0.01	0.11	-0.02	-0.01	0.01
pressurehight	0.02	0.01	0.01	1.00	0.59	0.02	-0.02	0.04
pressurelow	0.00	-0.01	0.11	0.59	1.00	-0.03	-0.02	0.04
glucose	-0.00	0.01	-0.02	0.02	-0.03	1.00	0.05	0.02
kcm	0.02	0.02	-0.01	-0.02	-0.02	0.05	1.00	-0.02
troponin	0.09	0.07	0.01	0.04	0.04	0.02	-0.02	1.00

```
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

plt.figure(figsize=(10,10))
sns.heatmap(corr_matrix, center=0, vmin=-1, vmax=1, mask=mask, annot=True, cmap='BrBG')
plt.show()
```



```
[1451]: cat_features = [feature for feature in data.columns if data[feature].dtypes == 'O']
        print('Number of categorical variables: ', len(cat_features))
        print('*'*80)
        print('Categorical variables column name:',cat_features)
```

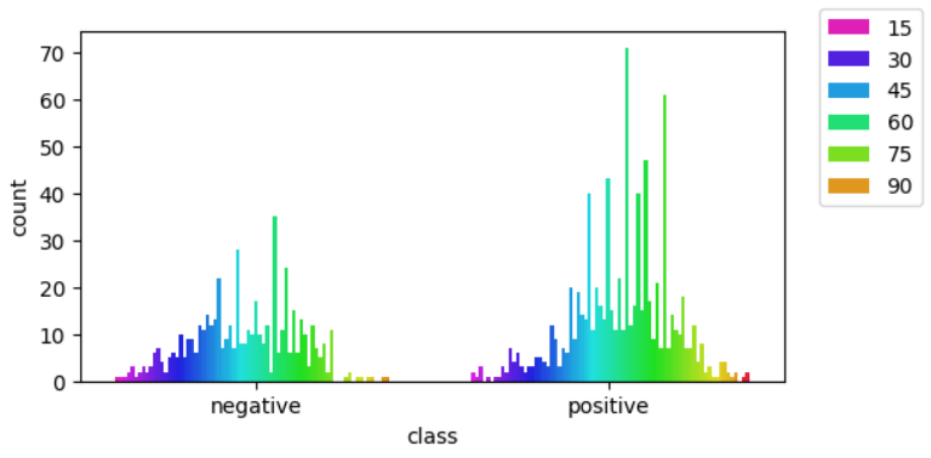
```
Number of categorical variables:  1
********************************************************************************
Categorical variables column name: ['class']
```

```
[1453]: numerical_features = [feature for feature in data.columns if data[feature].dtypes != 'O']
        print('Number of numerical variables: ', len(numerical_features))
        print('*'*80)
        print('Numerical Variables Column: ',numerical_features)
```

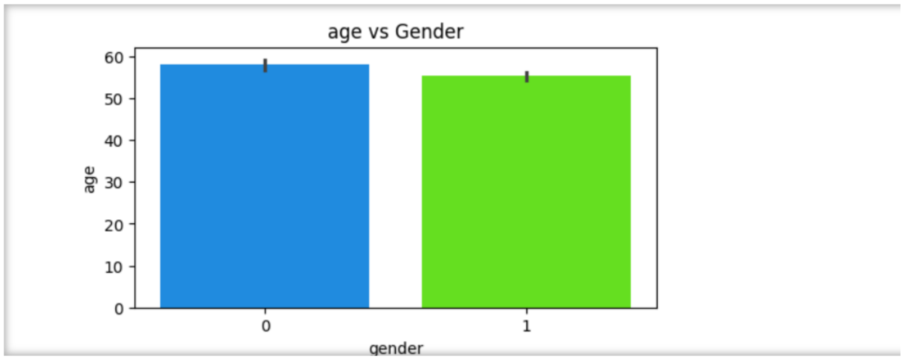
```
Number of numerical variables:  8
********************************************************************************
Numerical Variables Column:  ['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose', 'kcm', 'troponin']
```

Visualizing Categorical Features :

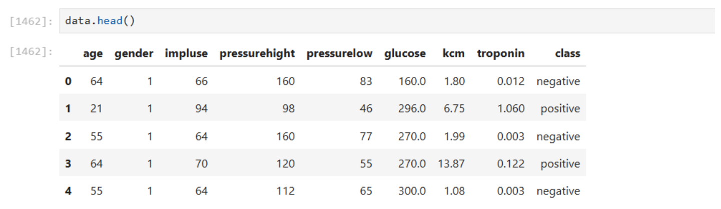
```
: for col in cat_features[:]:
      plt.figure(figsize=(6,3), dpi=100)
      sns.countplot(data=data,x=col,hue ='age',palette='gist_rainbow_r')
      plt.legend(loc=(1.05,0.5))
```



```
9]: numerical_features = ['age', 'impluse', 'pressurehight', 'pressurelow', 'glucose', 'kcm', 'troponin']

    for col in numerical_features:
        plt.figure(figsize=(6, 3), dpi=100)
        sns.barplot(data=data, x='gender', y=col, hue='gender', palette='gist_rainbow_r', legend=False)
        plt.title(f'{col} vs Gender')
        plt.show()
```



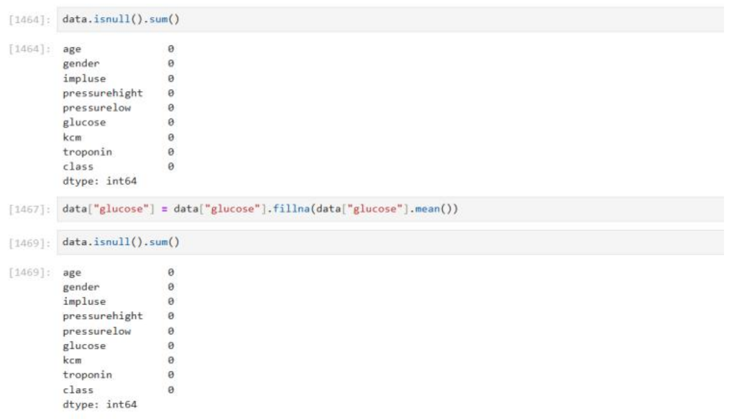
Handling Missing Values :



```
[1462]: data.head()
```

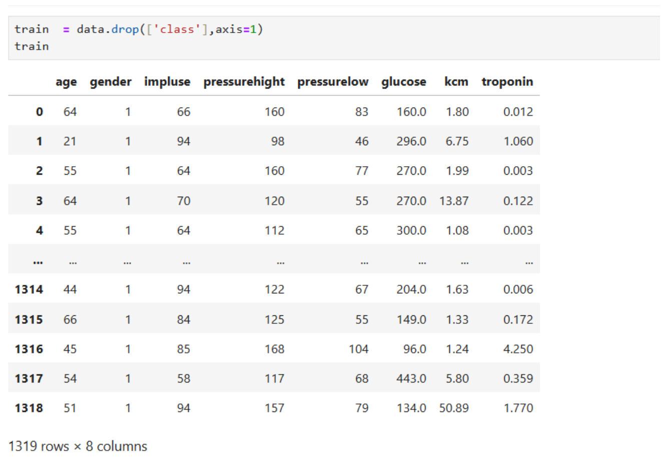
[1462]:

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class
0	64	1	66	160	83	160.0	1.80	0.012	negative
1	21	1	94	98	46	296.0	6.75	1.060	positive
2	55	1	64	160	77	270.0	1.99	0.003	negative
3	64	1	70	120	55	270.0	13.87	0.122	positive
4	55	1	64	112	65	300.0	1.08	0.003	negative



```
[1464]: data.isnull().sum()

[1464]: age              0
        gender           0
        impluse          0
        pressurehight    0
        pressurelow      0
        glucose          0
        kcm              0
        troponin         0
        class            0
        dtype: int64

[1467]: data["glucose"] = data["glucose"].fillna(data["glucose"].mean())

[1469]: data.isnull().sum()

[1469]: age              0
        gender           0
        impluse          0
        pressurehight    0
        pressurelow      0
        glucose          0
        kcm              0
        troponin         0
        class            0
        dtype: int64
```

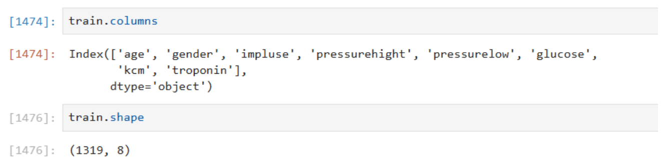
dropping irrelevant feature :



```
train  = data.drop(['class'],axis=1)
train
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin
0	64	1	66	160	83	160.0	1.80	0.012
1	21	1	94	98	46	296.0	6.75	1.060
2	55	1	64	160	77	270.0	1.99	0.003
3	64	1	70	120	55	270.0	13.87	0.122
4	55	1	64	112	65	300.0	1.08	0.003
...	...	...	...	...	...	...	...	...
1314	44	1	94	122	67	204.0	1.63	0.006
1315	66	1	84	125	55	149.0	1.33	0.172
1316	45	1	85	168	104	96.0	1.24	4.250
1317	54	1	58	117	68	443.0	5.80	0.359
1318	51	1	94	157	79	134.0	50.89	1.770

1319 rows × 8 columns



```
[1474]: train.columns

[1474]: Index(['age', 'gender', 'impluse', 'pressurehight', 'pressurelow', 'glucose',
               'kcm', 'troponin'],
              dtype='object')

[1476]: train.shape

[1476]: (1319, 8)
```

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1319 entries, 0 to 1318
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   age            1319 non-null   int64  
 1   gender         1319 non-null   int64  
 2   impluse        1319 non-null   int64  
 3   pressurehight  1319 non-null   int64  
 4   pressurelow    1319 non-null   int64  
 5   glucose        1319 non-null   float64
 6   kcm            1319 non-null   float64
 7   troponin       1319 non-null   float64
dtypes: float64(3), int64(5)
memory usage: 82.6 KB
```

```
train_data_cat = train.select_dtypes("object")
train_data_num = train.select_dtypes("number")
```

```
train_data_cat.head(3)
```

0
1
2

```
train_data_num.head(3)
```

	age	gender	impluse	pressurehight	pressurelow	glucose	kcm	troponin
0	64	1	66	160	83	160.0	1.80	0.012
1	21	1	94	98	46	296.0	6.75	1.060
2	55	1	64	160	77	270.0	1.99	0.003

Converting categorical features into numerical :

```
]: data_encoded = pd.get_dummies(data, columns=['gender'])
   data_encoded.head()
```

]:

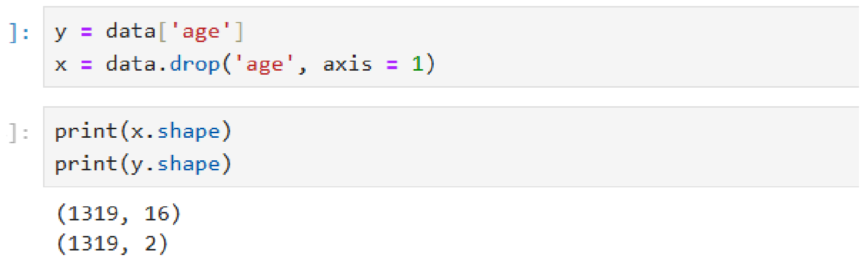
	age	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class	gender_0	gender_1
0	64	66	160	83	160.0	1.80	0.012	negative	False	True
1	21	94	98	46	296.0	6.75	1.060	positive	False	True
2	55	64	160	77	270.0	1.99	0.003	negative	False	True
3	64	70	120	55	270.0	13.87	0.122	positive	False	True
4	55	64	112	65	300.0	1.08	0.003	negative	False	True

```
89]: data = pd.concat([data_encoded, train_data_num], axis=1, join="outer")
     data.head()
```

89]:

	age	impluse	pressurehight	pressurelow	glucose	kcm	troponin	class	gender_0	gender_1	age	gender	impluse	pressurehight	pressurelow	glucose	kcm
0	64	66	160	83	160.0	1.80	0.012	negative	False	True	64	1	66	160	83	160.0	1.80
1	21	94	98	46	296.0	6.75	1.060	positive	False	True	21	1	94	98	46	296.0	6.75
2	55	64	160	77	270.0	1.99	0.003	negative	False	True	55	1	64	160	77	270.0	1.99
3	64	70	120	55	270.0	13.87	0.122	positive	False	True	64	1	70	120	55	270.0	13.87
4	55	64	112	65	300.0	1.08	0.003	negative	False	True	55	1	64	112	65	300.0	1.08

seperate dependant and independant feature :

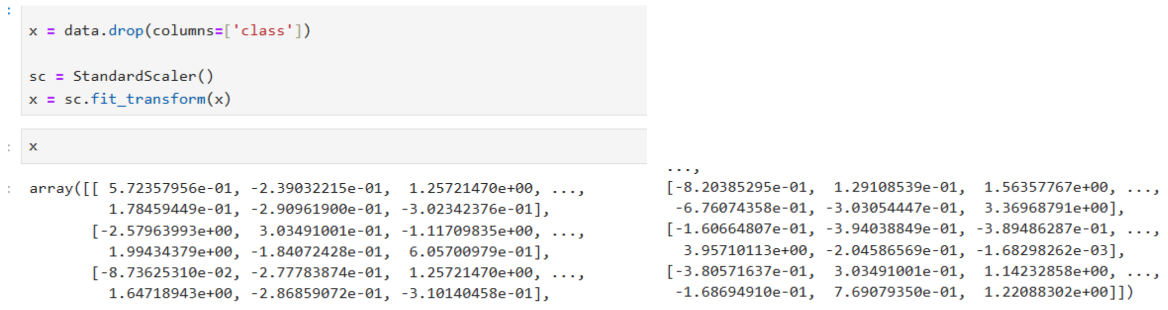


```
y = data['age']
x = data.drop('age', axis = 1)
```

```
print(x.shape)
print(y.shape)
```

```
(1319, 16)
(1319, 2)
```

scailing the data :

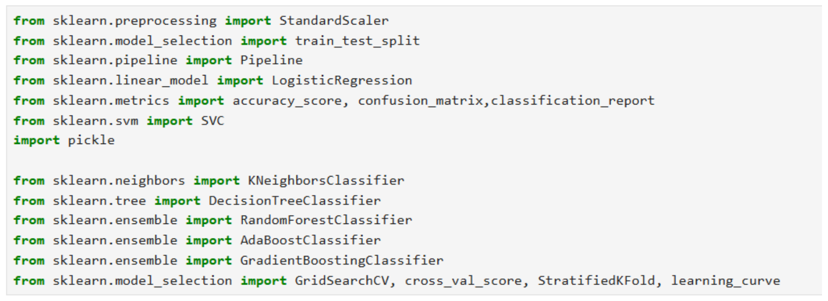


```
x = data.drop(columns=['class'])

sc = StandardScaler()
x = sc.fit_transform(x)
```

```
x
```

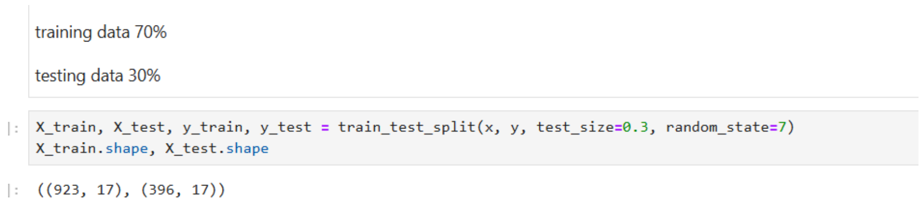
```
array([[ 5.72357956e-01, -2.39032215e-01,  1.25721470e+00, ...,
         1.78459449e-01, -2.90961900e-01, -3.02342376e-01],
       [-2.57963993e+00,  3.03491001e-01, -1.11709835e+00, ...,
         1.99434379e+00, -1.84072428e-01,  6.05700979e-01],
       [-8.73625310e-02, -2.77783874e-01,  1.25721470e+00, ...,
         1.64718943e+00, -2.86859072e-01, -3.10140458e-01],
       ...,
       [-8.20385295e-01,  1.29108539e-01,  1.56357767e+00, ...,
        -6.76074358e-01, -3.03054447e-01,  3.36968791e+00],
       [-1.60664807e-01, -3.94038849e-01, -3.89486287e-01, ...,
         3.95710113e+00, -2.04586569e-01, -1.68298262e-03],
       [-3.80571637e-01,  3.03491001e-01,  1.14232858e+00, ...,
        -1.68694910e-01,  7.69079350e-01,  1.22088302e+00]])
```

Splitting data into Training and Testing :



```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
from sklearn.svm import SVC
import pickle

from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score, StratifiedKFold, learning_curve
```

Splitting the dataset :



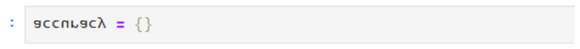
training data 70%

testing data 30%

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=7)
X_train.shape, X_test.shape
```

```
((923, 17), (396, 17))
```

Building Classifiers :



```
accuracy = {}
```

Confusion Matrix :

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score
```

Step 1: Encode 'class' as 0 (negative) and 1 (positive):

```python
data['class'] = data['class'].map({'negative': 0, 'positive': 1})
```

Step 2: Separate features (X) and target (y) :

```python
X = data.drop(columns=['class'])
y = data['class']
```

Step 3: Scale the numeric features (StandardScaler) :

```python
sc = StandardScaler()
X_scaled = sc.fit_transform(X)
```

Step 4: Split the data into training and testing sets (70% training, 30% testing) :

```python
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42)
```

Step 5: Initialize and train the Logistic Regression model :

```python
lr = LogisticRegression(max_iter=200)
lr.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=200)
```

Step 6: Make predictions on the test data :

```python
y_pred = lr.predict(X_test)
```

Step 7: Calculate accuracy :

```python
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')
```

```
Accuracy: 79.55%
```

Step 8: Generate confusion matrix :

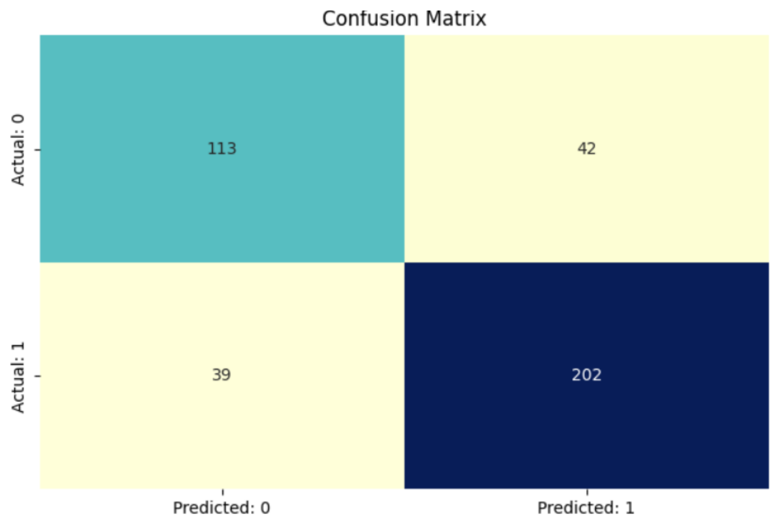
```
cm = confusion_matrix(y_test, y_pred)
```

Step 9: Create a DataFrame for confusion matrix visualization

```
conf_matrix = pd.DataFrame(data=cm, columns=['Predicted: 0', 'Predicted: 1'],
                           index=['Actual: 0', 'Actual: 1'])
```

Step 10: Plot confusion matrix with heatmap

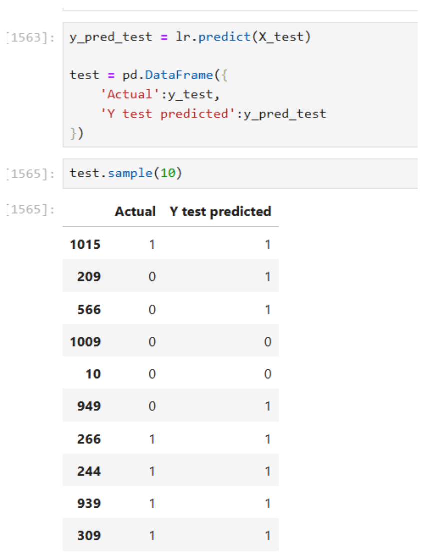
```
]:
plt.figure(figsize=(8, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu", cbar=False)
plt.title("Confusion Matrix")
plt.show()
```



Classification report :

```
:
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
data['class'] = le.fit_transform(data['class'])
```

Predicting :



[1563]:

```
y_pred_test = lr.predict(X_test)

test = pd.DataFrame({
    'Actual':y_test,
    'Y test predicted':y_pred_test
})
```

[1565]:

```
test.sample(10)
```

[1565]:

	Actual	Y test predicted
1015	1	1
209	0	1
566	0	1
1009	0	0
10	0	0
949	0	1
266	1	1
244	1	1
939	1	1
309	1	1

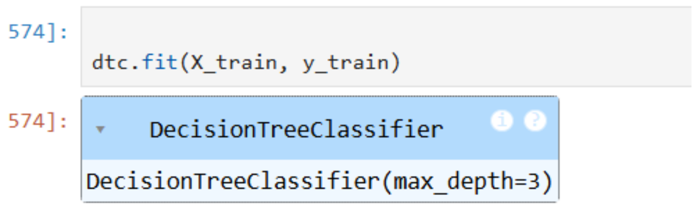
DecisionTreeClassifier :

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
```

Initialize the DecisionTreeClassifier with max_depth=3 :

```
dtc = DecisionTreeClassifier(max_depth=3)
```

Fit the model on the training data (make sure X_train and y_train are properly prepared) :



574]:

```
dtc.fit(X_train, y_train)
```

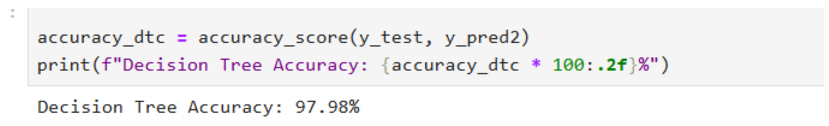
574]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3)
```

Predict on the test set :

```
y_pred2 = dtc.predict(X_test)
```

Calculate and print the accuracy score :



```
accuracy_dtc = accuracy_score(y_test, y_pred2)
print(f"Decision Tree Accuracy: {accuracy_dtc * 100:.2f}%")
```

```
Decision Tree Accuracy: 97.98%
```

Store the accuracy in the accuracy dictionary :

```
accuracy = {}
accuracy[str(dtc)] = accuracy_dtc * 100
```

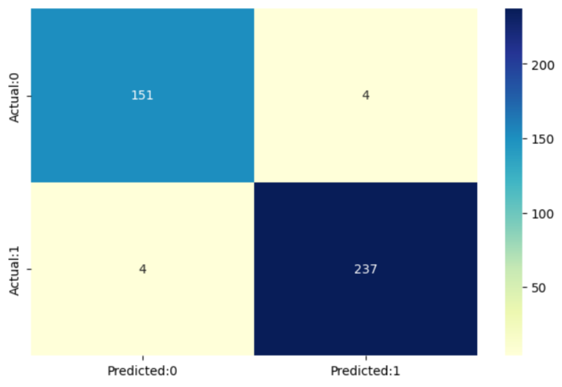
Optionally, print the accuracy dictionary :

```
print("Accuracy dictionary:", accuracy)
```

```
Accuracy dictionary: {'DecisionTreeClassifier(max_depth=3)': 97.97979797979798}
```

```
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,y_pred2)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

```
<Axes: >
```



```
print(classification_report(y_test,y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       155
           1       0.98      0.98      0.98       241

    accuracy                           0.98       396
   macro avg       0.98      0.98      0.98       396
weighted avg       0.98      0.98      0.98       396
```

```
y_pred_test = dtc.predict(X_test)

test = pd.DataFrame({
    'Actual':y_test,
    'Y test predicted':y_pred_test
})
```

94]:

```
test.head(5)
```

94]:

	Actual	Y test predicted
677	1	1
1046	0	0
610	0	0
49	0	0
1284	1	1

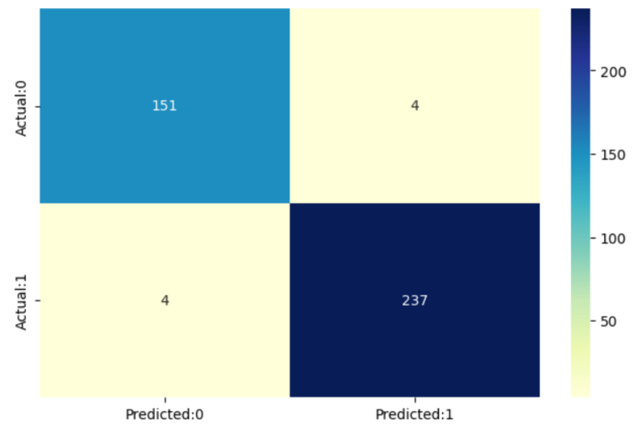
```
rfc = RandomForestClassifier(max_depth=5)
rfc.fit(X_train, y_train)
y_pred3 = rfc.predict(X_test)
print(accuracy_score(y_test, y_pred3))
accuracy[str(rfc)] = accuracy_score(y_test, y_pred3)*100
```

```
0.9797979797979798
```

```
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,y_pred3)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

```
<Axes: >
```

```
<Axes: >
```

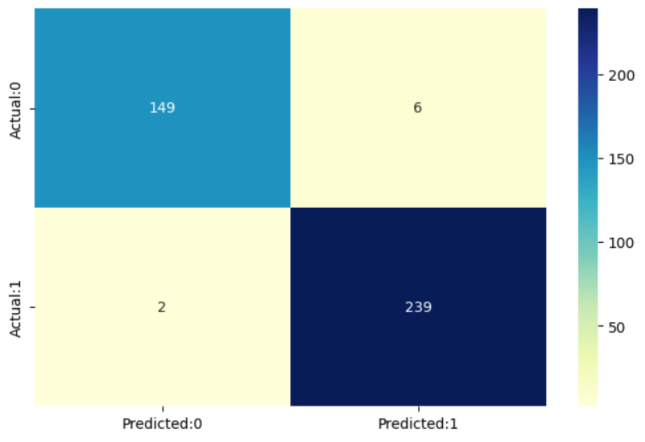


```
gbc = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1)
gbc.fit(X_train, y_train)
y_pred4 = gbc.predict(X_test)
print(accuracy_score(y_test, y_pred4))
accuracy[str(gbc)] = accuracy_score(y_test, y_pred4)*100
```

```
0.9797979797979798
```

```
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,y_pred4)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

```
<Axes: >
```



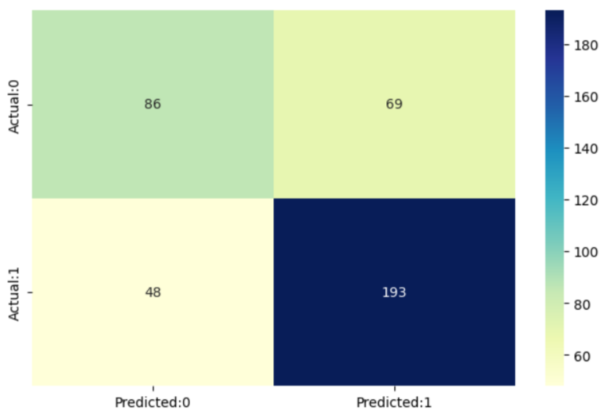
SVM :

```
svc = SVC()
svc.fit(X_train, y_train)
y_pred5 = svc.predict(X_test)
print(accuracy_score(y_test, y_pred5))
accuracy[str(svc)] = accuracy_score(y_test, y_pred5)*100
```

```
0.7045454545454546
```

```
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,y_pred5)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

```
<Axes: >
```



```
accuracy
```

```
{'DecisionTreeClassifier(max_depth=3)': 97.97979797979798,
 'RandomForestClassifier(max_depth=5)': 97.97979797979798,
 'GradientBoostingClassifier()': 97.97979797979798,
 'SVC()': 70.45454545454545}
```

Handling this data using SMOTE :

```
from imblearn.over_sampling import SMOTE
```

```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
import pandas as pd
```

Assuming 'data' is your dataframe and 'class' is the target column :

```
X = data.drop('class', axis=1)
y = data['class']
```

Step 1: Split the dataset into training and testing sets (80% train, 20% test) :

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 2: Apply SMOTE to the training set to balance the classes :

```
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

Step 3: Standardize the features using Standard Scaler (optional but recommended) :

```
scaler = StandardScaler()
X_train_res = scaler.fit_transform(X_train_res)
X_test = scaler.transform(X_test)
```

Step 4: Initialize and train the Decision Tree Classifier :

```
]: dtc = DecisionTreeClassifier(max_depth=3)
   dtc.fit(X_train_res, y_train_res)
```

```
]:  DecisionTreeClassifier
   DecisionTreeClassifier(max_depth=3)
```

Step 5: Make predictions on the test set :

```
y_pred2 = dtc.predict(X_test)
```

Step 6: Calculate and print the accuracy score :

```
accuracy_dtc = accuracy_score(y_test, y_pred2)
print(f"Decision Tree Accuracy with SMOTE: {accuracy_dtc * 100:.2f}%")
```

```
Decision Tree Accuracy with SMOTE: 97.73%
```

Splitting the oversampling data :

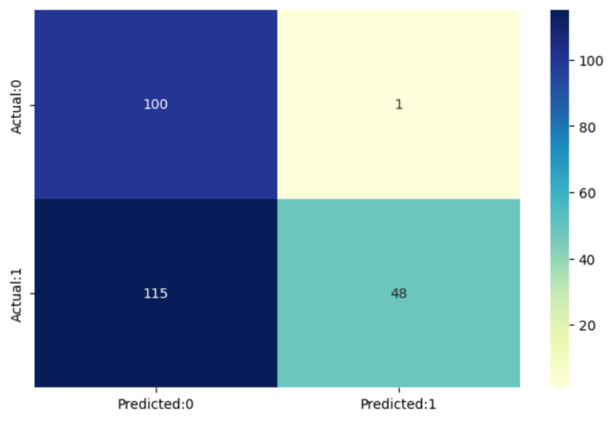
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1055, 17)
(264, 17)
(1055,)
(264,)
```

```
lr = LogisticRegression(max_iter=200)
lr.fit(X_train, y_train)
y_pred1 = lr.predict(X_test)
print(accuracy_score(y_test, y_pred1))
accuracy[str(lr)] = accuracy_score(y_test, y_pred1)*100
```

```
0.5606060606060606
```

```
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,y_pred1)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```



```
print(classification_report(y_test,y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.47      0.99      0.63       101
           1       0.98      0.29      0.45       163

    accuracy                           0.56       264
   macro avg       0.72      0.64      0.54       264
weighted avg       0.78      0.56      0.52       264
```

```
y_pred_test = lr.predict(X_test)

test = pd.DataFrame({
    'Actual':y_test,
    'Y test predicted':y_pred_test
})
```

```
test.head()
```

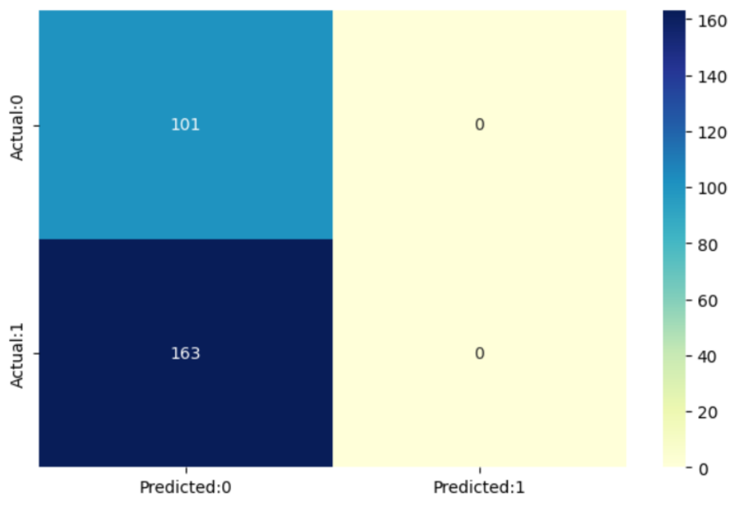
	Actual	Y test predicted
677	1	0
1046	0	0
610	0	0
49	0	0
1284	1	0

```
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train,y_train)
knn_predict = knn_model.predict(X_test)
print(accuracy_score(y_test, knn_predict))
accuracy[str(lr)] = accuracy_score(y_test, knn_predict)*100
```

```
0.38257575757575757
```

```python
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(y_test,knn_predict)

conf_matrix=pd.DataFrame(data=cm,columns=['Predicted:0','Predicted:1'],index=['Actual:0','Actual:1'])
plt.figure(figsize = (8,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu")
```

```
<Axes: >
```



```python
print(classification_report(y_test,knn_predict))
```

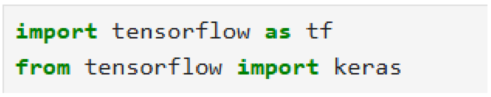
```
              precision    recall  f1-score   support

           0       0.38      1.00      0.55       101
           1       0.00      0.00      0.00       163

    accuracy                           0.38       264
   macro avg       0.19      0.50      0.28       264
weighted avg       0.15      0.38      0.21       264
```

```python
y_pred_test = knn_model.predict(X_test)

test = pd.DataFrame({
    'Actual':y_test,
    'Y test predicted':y_pred_test
})
```

```python
test.sample(10)
```

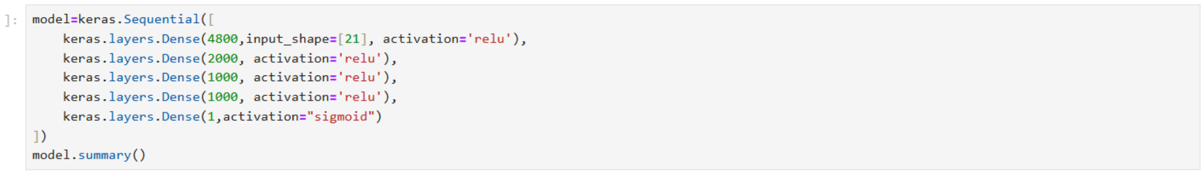
	Actual	Y test predicted
220	0	0
240	1	0
1125	0	0
1134	1	0
351	1	0
54	1	0
724	1	0
231	0	0
1046	0	0
778	1	0

Deep Learning :

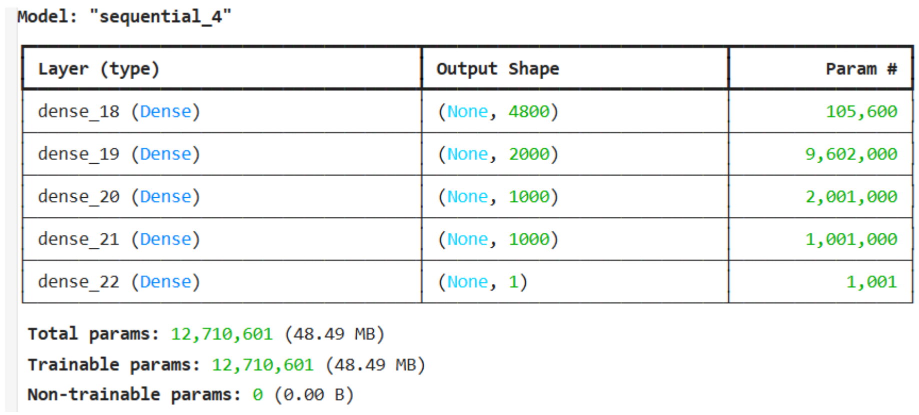


```python
import tensorflow as tf
from tensorflow import keras
```

Create neural network



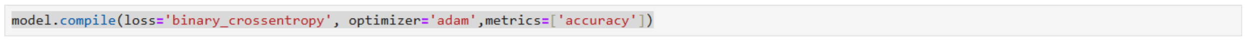
```python
]: model=keras.Sequential([
       keras.layers.Dense(4800,input_shape=[21], activation='relu'),
       keras.layers.Dense(2000, activation='relu'),
       keras.layers.Dense(1000, activation='relu'),
       keras.layers.Dense(1000, activation='relu'),
       keras.layers.Dense(1,activation="sigmoid")
   ])
   model.summary()
```



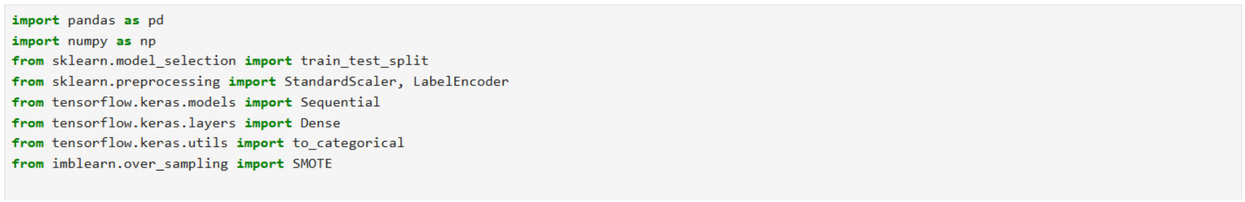
Model: "sequential_4"

Layer (type)	Output Shape	Param #
dense_18 (Dense)	(None, 4800)	105,600
dense_19 (Dense)	(None, 2000)	9,602,000
dense_20 (Dense)	(None, 1000)	2,001,000
dense_21 (Dense)	(None, 1000)	1,001,000
dense_22 (Dense)	(None, 1)	1,001

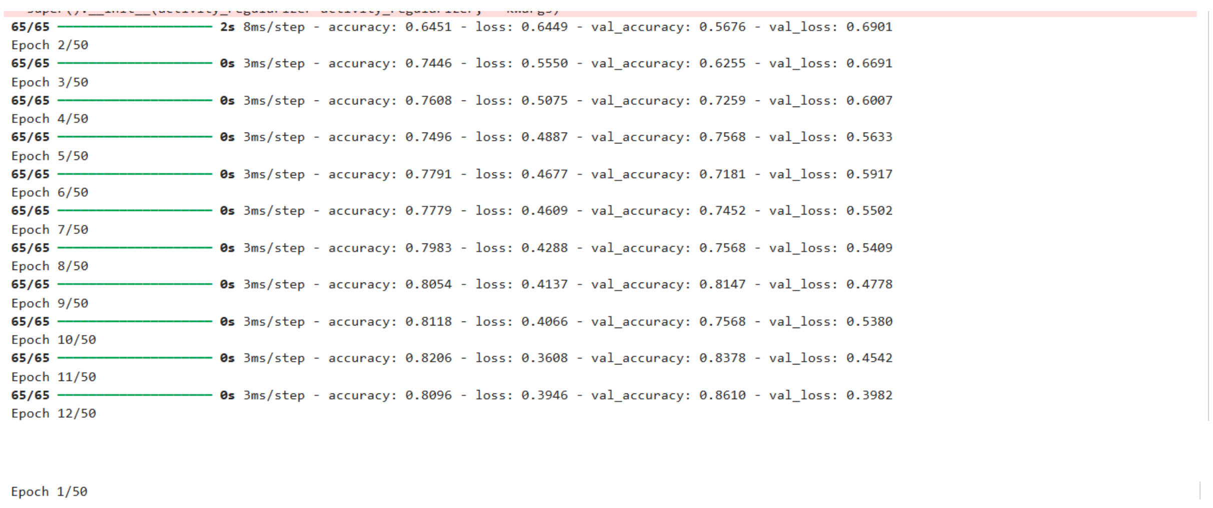
Total params: 12,710,601 (48.49 MB)
Trainable params: 12,710,601 (48.49 MB)
Non-trainable params: 0 (0.00 B)



```python
model.compile(loss='binary_crossentropy', optimizer='adam',metrics=['accuracy'])
```



```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
from imblearn.over_sampling import SMOTE
```



```
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
65/65 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.6451 - loss: 0.6449 - val_accuracy: 0.5676 - val_loss: 0.6901
Epoch 2/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7446 - loss: 0.5550 - val_accuracy: 0.6255 - val_loss: 0.6691
Epoch 3/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7608 - loss: 0.5075 - val_accuracy: 0.7259 - val_loss: 0.6007
Epoch 4/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7496 - loss: 0.4887 - val_accuracy: 0.7568 - val_loss: 0.5633
Epoch 5/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7791 - loss: 0.4677 - val_accuracy: 0.7181 - val_loss: 0.5917
Epoch 6/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7779 - loss: 0.4609 - val_accuracy: 0.7452 - val_loss: 0.5502
Epoch 7/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7983 - loss: 0.4288 - val_accuracy: 0.7568 - val_loss: 0.5409
Epoch 8/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8054 - loss: 0.4137 - val_accuracy: 0.8147 - val_loss: 0.4778
Epoch 9/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8118 - loss: 0.4066 - val_accuracy: 0.7568 - val_loss: 0.5380
Epoch 10/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8206 - loss: 0.3608 - val_accuracy: 0.8378 - val_loss: 0.4542
Epoch 11/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8096 - loss: 0.3946 - val_accuracy: 0.8610 - val_loss: 0.3982
Epoch 12/50


Epoch 1/50
```

Step 1: Encode the target variable if it's categorical :

```
e = LabelEncoder()
data['class'] = le.fit_transform(data['class'])  # Converts string labels to 0, 1, ...
```

Step 2: Split data into features and target :

```
X = data.drop('class', axis=1)
y = data['class']
```

Step 3: Train-test split :

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 4: Balance the training set using SMOTE :

```
sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
```

Step 5: Scale the features :

```
scaler = StandardScaler()
X_train_res = scaler.fit_transform(X_train_res)
X_test = scaler.transform(X_test)
```

Step 6: Convert target to categorical (for binary/multiclass classification) :

```
y_train_cat = to_categorical(y_train_res)
y_test_cat = to_categorical(y_test)
```

Step 7: Build the Neural Network model

[1694]:

```
model = Sequential()
model.add(Dense(32, input_dim=X_train_res.shape[1], activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(y_train_cat.shape[1], activation='softmax'))  # softmax for multi-class
```

Step 8: Compile the model :

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

Step 9: Train the model :

```
model.fit(X_train_res, y_train_cat, epochs=50, batch_size=16, verbose=1, validation_split=0.2)
```

```
Epoch 1/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.5409 - loss: 0.7340 - val_accuracy: 0.6100 - val_loss: 0.6667
Epoch 2/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7017 - loss: 0.5818 - val_accuracy: 0.6448 - val_loss: 0.6386
Epoch 3/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7129 - loss: 0.5378 - val_accuracy: 0.7568 - val_loss: 0.5709
Epoch 4/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7527 - loss: 0.4969 - val_accuracy: 0.8224 - val_loss: 0.4970
Epoch 5/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7537 - loss: 0.4869 - val_accuracy: 0.8610 - val_loss: 0.4364
Epoch 6/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7921 - loss: 0.4500 - val_accuracy: 0.8726 - val_loss: 0.4362
Epoch 7/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7878 - loss: 0.4422 - val_accuracy: 0.9189 - val_loss: 0.3263
Epoch 8/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7823 - loss: 0.4405 - val_accuracy: 0.9151 - val_loss: 0.3001
Epoch 9/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8124 - loss: 0.4081 - val_accuracy: 0.8764 - val_loss: 0.3472
Epoch 10/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8170 - loss: 0.3855 - val_accuracy: 0.9073 - val_loss: 0.2789
Epoch 11/50
65/65 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.8409 - loss: 0.3649 - val_accuracy: 0.8880 - val_loss: 0.2996
```

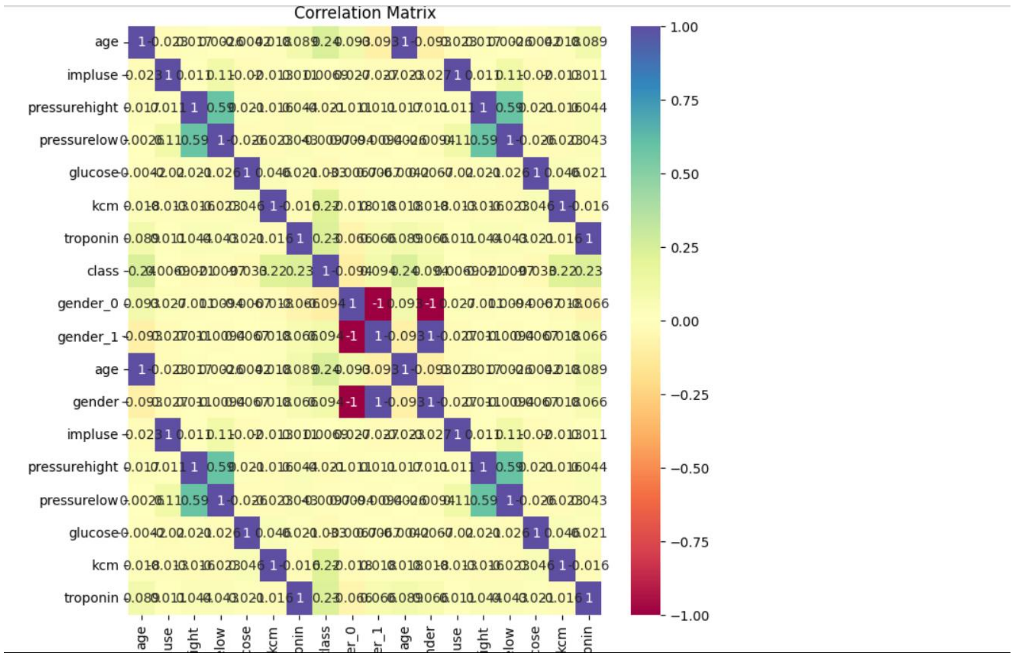
Step 10: Evaluate the model :

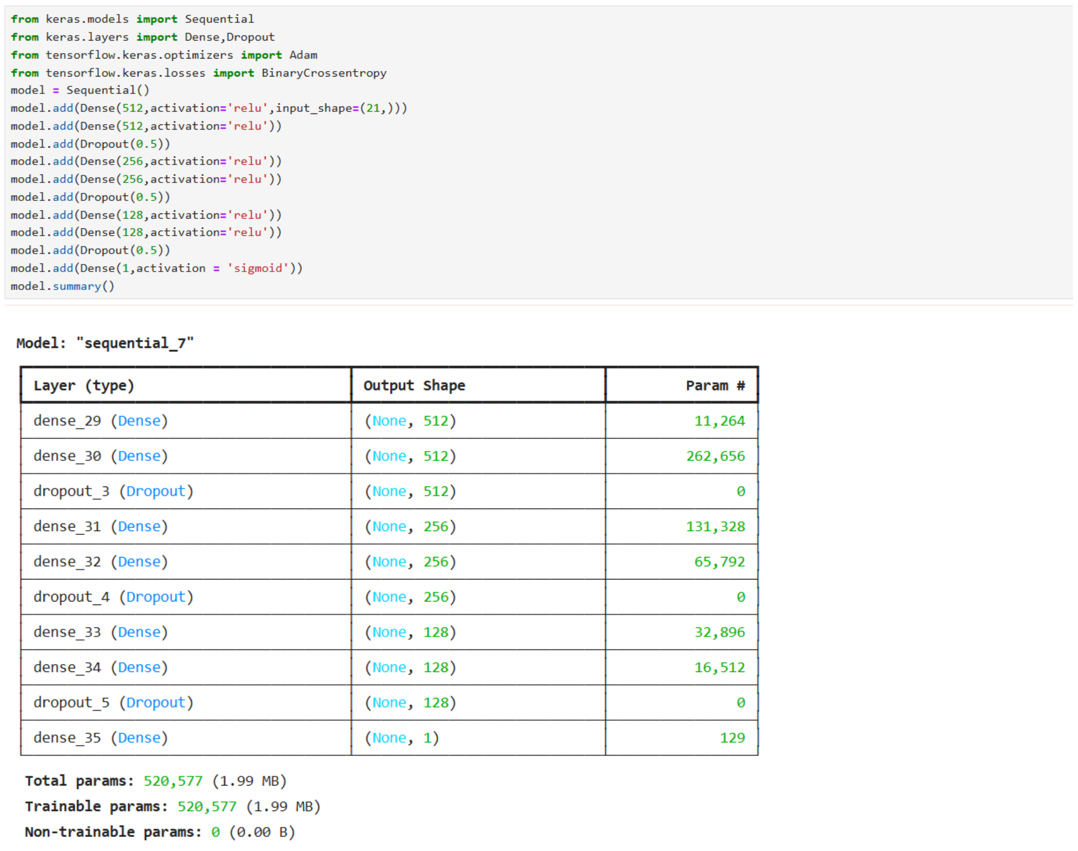
```
3]: loss, accuracy = model.evaluate(X_test, y_test_cat, verbose=0)
    print(f"\nTest Accuracy: {accuracy*100:.2f}%")
```

```
Test Accuracy: 80.68%
```

```
5]: corr = data.corr()
    plt.figure(figsize=(8,8))
    sns.heatmap(data=corr, annot=True, cmap='Spectral').set(title="Correlation Matrix")
```

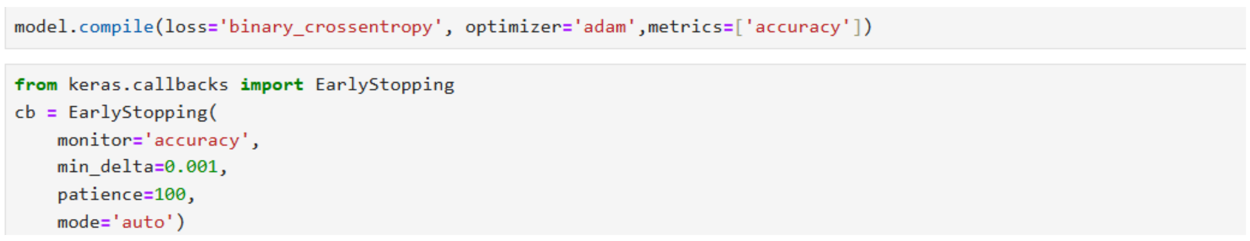
```
5]: [Text(0.5, 1.0, 'Correlation Matrix')]
```





```python
from keras.models import Sequential
from keras.layers import Dense,Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
model = Sequential()
model.add(Dense(512,activation='relu',input_shape=(21,)))
model.add(Dense(512,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(256,activation='relu'))
model.add(Dense(256,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(128,activation='relu'))
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1,activation = 'sigmoid'))
model.summary()
```

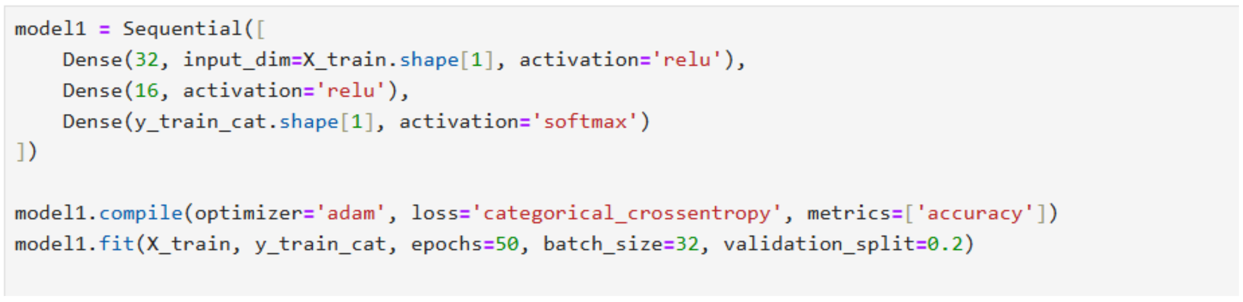
```
Model: "sequential_7"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                       ┃ Output Shape              ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ dense_29 (Dense)                   │ (None, 512)               │          11,264 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_30 (Dense)                   │ (None, 512)               │         262,656 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dropout_3 (Dropout)                │ (None, 512)               │               0 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_31 (Dense)                   │ (None, 256)               │         131,328 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_32 (Dense)                   │ (None, 256)               │          65,792 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dropout_4 (Dropout)                │ (None, 256)               │               0 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_33 (Dense)                   │ (None, 128)               │          32,896 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_34 (Dense)                   │ (None, 128)               │          16,512 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dropout_5 (Dropout)                │ (None, 128)               │               0 │
├────────────────────────────────────┼───────────────────────────┼─────────────────┤
│ dense_35 (Dense)                   │ (None, 1)                 │             129 │
└────────────────────────────────────┴───────────────────────────┴─────────────────┘

 Total params: 520,577 (1.99 MB)
 Trainable params: 520,577 (1.99 MB)
 Non-trainable params: 0 (0.00 B)
```



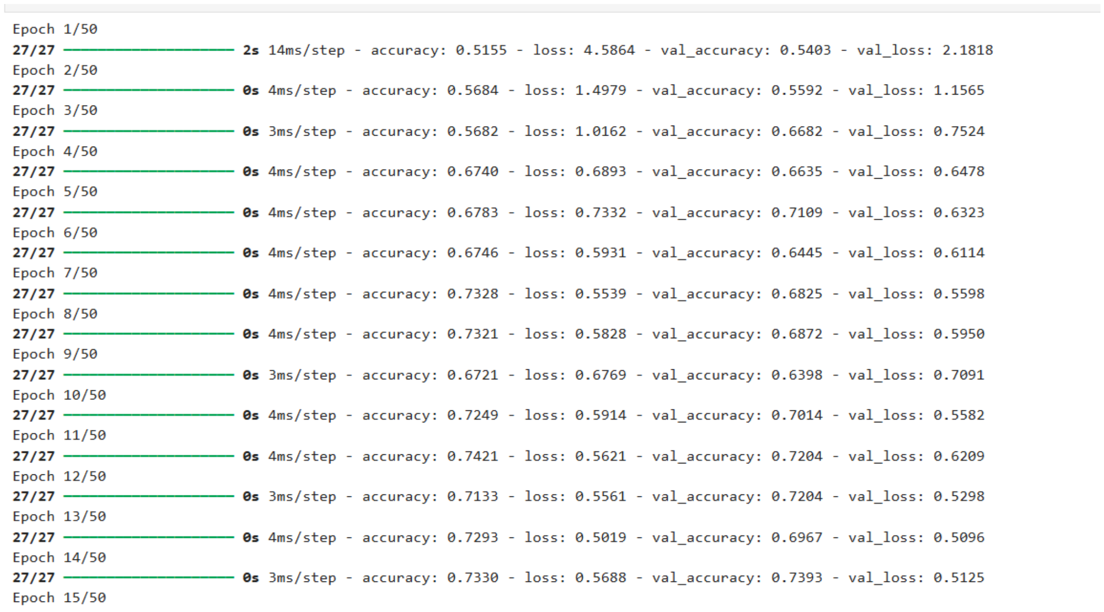
```python
model.compile(loss='binary_crossentropy', optimizer='adam',metrics=['accuracy'])
```

```python
from keras.callbacks import EarlyStopping
cb = EarlyStopping(
    monitor='accuracy',
    min_delta=0.001,
    patience=100,
    mode='auto')
```

Model 1: Simple Feedforward Neural Network :

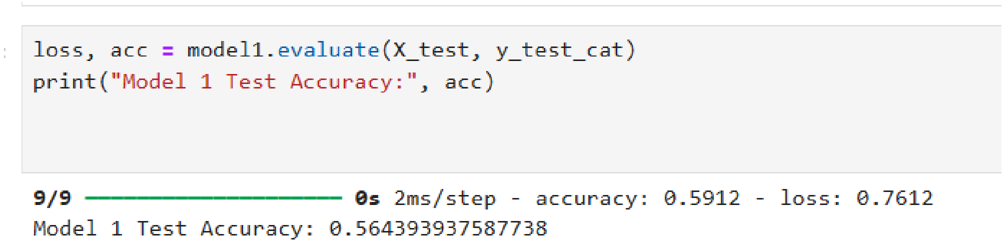


```python
model1 = Sequential([
    Dense(32, input_dim=X_train.shape[1], activation='relu'),
    Dense(16, activation='relu'),
    Dense(y_train_cat.shape[1], activation='softmax')
])

model1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model1.fit(X_train, y_train_cat, epochs=50, batch_size=32, validation_split=0.2)
```



```
Epoch 1/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.5155 - loss: 4.5864 - val_accuracy: 0.5403 - val_loss: 2.1818
Epoch 2/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5684 - loss: 1.4979 - val_accuracy: 0.5592 - val_loss: 1.1565
Epoch 3/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5682 - loss: 1.0162 - val_accuracy: 0.6682 - val_loss: 0.7524
Epoch 4/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.6740 - loss: 0.6893 - val_accuracy: 0.6635 - val_loss: 0.6478
Epoch 5/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.6783 - loss: 0.7332 - val_accuracy: 0.7109 - val_loss: 0.6323
Epoch 6/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.6746 - loss: 0.5931 - val_accuracy: 0.6445 - val_loss: 0.6114
Epoch 7/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7328 - loss: 0.5539 - val_accuracy: 0.6825 - val_loss: 0.5598
Epoch 8/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7321 - loss: 0.5828 - val_accuracy: 0.6872 - val_loss: 0.5950
Epoch 9/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.6721 - loss: 0.6769 - val_accuracy: 0.6398 - val_loss: 0.7091
Epoch 10/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7249 - loss: 0.5914 - val_accuracy: 0.7014 - val_loss: 0.5582
Epoch 11/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7421 - loss: 0.5621 - val_accuracy: 0.7204 - val_loss: 0.6209
Epoch 12/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7133 - loss: 0.5561 - val_accuracy: 0.7204 - val_loss: 0.5298
Epoch 13/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7293 - loss: 0.5019 - val_accuracy: 0.6967 - val_loss: 0.5096
Epoch 14/50
27/27 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7330 - loss: 0.5688 - val_accuracy: 0.7393 - val_loss: 0.5125
Epoch 15/50
```

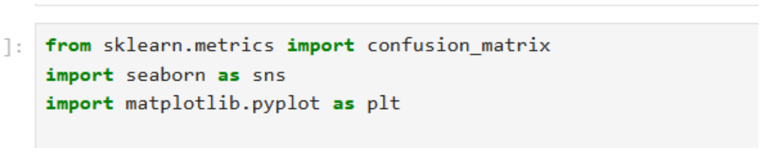
Evaluate:



```python
loss, acc = model1.evaluate(X_test, y_test_cat)
print("Model 1 Test Accuracy:", acc)
```

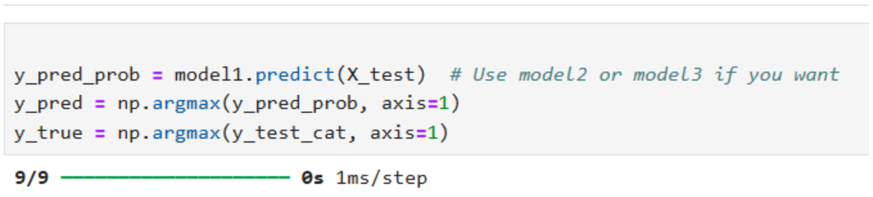
```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.5912 - loss: 0.7612
Model 1 Test Accuracy: 0.564393937587738
```

Confusion matrix :



```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
```

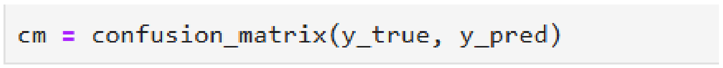
Step 1: Predict using the model :



```python
y_pred_prob = model1.predict(X_test)  # Use model2 or model3 if you want
y_pred = np.argmax(y_pred_prob, axis=1)
y_true = np.argmax(y_test_cat, axis=1)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

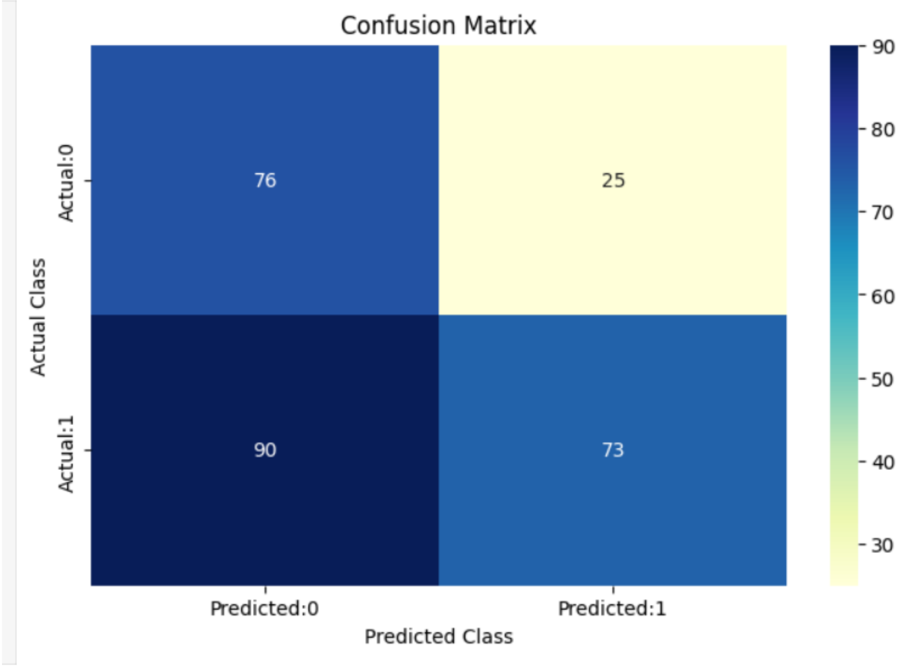
Step 2: Create confusion matrix:



```python
cm = confusion_matrix(y_true, y_pred)
```

Step 3: Convert to DataFrame and plot :

```
conf_matrix = pd.DataFrame(data=cm,
                           columns=['Predicted:0', 'Predicted:1'],
                           index=['Actual:0', 'Actual:1'])

plt.figure(figsize=(8, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="YlGnBu")
plt.title("Confusion Matrix")
plt.ylabel("Actual Class")
plt.xlabel("Predicted Class")
plt.show()
```



Classification Dataset Analysis:

The classification problem in this lab uses a heart attack dataset consisting of 1319 samples and 9 fields. Out of these, 8 are input features (including age, gender, heart rate, blood pressure readings, blood sugar, CK-MB, and Troponin levels), and 1 is the target variable—a binary class indicating whether the individual is at risk of a heart attack (positive or negative).

---

1. Data Exploration and Cleaning

Initial steps involve loading and exploring the dataset to understand the structure and detect any issues such as:

- Missing values, which are handled appropriately to prevent biases during training.
- Irrelevant or duplicate features, such as unnecessary identifiers, are dropped.
- Categorical variables (like gender) are converted into numerical format using encoding techniques.

Data visualization is used to examine the distribution of categorical features and identify class imbalances. This helps in deciding whether resampling methods like SMOTE are needed.

---

2. Feature Engineering

The features are split into:

- Numerical features (e.g., age, heart rate, CK-MB)
- Categorical features (e.g., gender)

Feature scaling is performed using StandardScaler to bring all numeric values into a similar range. This step is especially crucial for algorithms like SVM and Logistic Regression, which are sensitive to feature scale.

The target variable is encoded:

- 0 for negative (no heart attack)
- 1 for positive (heart attack risk)

---

3. Splitting the Dataset

The dataset is split into training and testing sets (commonly 70% training, 30% testing), which ensures the model is evaluated on unseen data and helps prevent overfitting.

In cases of class imbalance, SMOTE (Synthetic Minority Over-sampling Technique) is used to balance the dataset. This improves performance metrics like recall and F1-score, especially for the minority class.

---

4. Model Training and Evaluation

Various classification algorithms are applied:

Logistic Regression

- A baseline linear classifier that performs well on linearly separable data.
- Evaluation includes accuracy, confusion matrix, and a classification report (precision, recall, F1-score).

Decision Tree Classifier

- A non-linear model that splits data based on feature thresholds.
- Limited tree depth (e.g., max_depth=3) is used to avoid overfitting and enhance interpretability.

Support Vector Machine (SVM)

- A powerful classifier that works well on high-dimensional data.
- Feature scaling is especially important here.

Neural Networks (Deep Learning)

- A feedforward neural network is created for binary classification.
- The model is compiled, trained, and evaluated using metrics such as accuracy and confusion matrix.
- Neural networks handle non-linear relationships well but require more data and computation.

---

5. Evaluation Metrics

Each model is evaluated using:

- Accuracy – overall correctness
- Confusion Matrix – breakdown of true/false positives and negatives
- Precision & Recall – performance on each class
- F1-Score – harmonic mean of precision and recall

These metrics help identify which model is best suited for the classification task, especially when class distribution is imbalanced.

Conclusion

This classification pipeline demonstrates a full ML workflow: from data loading and preprocessing to model training and evaluation. By using different classifiers and handling imbalanced data with SMOTE, this lab provides a comprehensive understanding of binary classification. The dataset and features used (age, blood pressure, biomarkers) reflect real-world medical diagnostics, making this an impactful use case in healthcare AI.
