B.S. Abdur Rahman Crescent Institute of Science & Technology

Deemed to be University u/s 3 of the UGC Act, 1956

DEPARTMENT OF COMPUTER APPLICATIONS

CADX116 - MACHINE LEARNING ALGORITHMS LABORATORY

B.S. Abdur Rahman
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LAB RECORD

NAME **:** ____________________________________

RRN **:** ____________________________________

LAB **:** ***CADX116 - MACHINE LEARNING ALGORITHMS LABORATORY***

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DEPARTMENT OF COMPUTER APPLICATIONS

ACADEMIC YEAR (JULY 2024 - DECEMBER 2024)

COURSE CODE : CADX116

COURSE NAME : MACHINE LEARNING ALGORITHMS LABORATORY

PROGRAMME : BCA (DATA SCIENCE)

SEMESTER : V

B.S. Abdur Rahman

Crescent

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BONAFIDE CERTIFICATE

This is a Certified Record Book of ____________________________________

RRN: ________________________________ *submitted for the Semester End Practical Examination held on* ______________________, *for the* ***CADX116 - MACHINE LEARNING ALGORITHMS LABORATORY*** *during* ***2024 - 2025***.

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Signature of Faculty

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EX.NO :

DATE :

IMPLEMENT NAÏVE BAYES CLASSIFIER

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     from sklearn import tree
     from sklearn.preprocessing import LabelEncoder
     from sklearn.naive_bayes import GaussianNB
```

Step 2:

```
[ ]  data=pd.read_csv("Naive_Bayes_PlayTennis.csv")
     print("the First 5 values of data is :\n")
     data.head()
```

Output:

the First 5 values of data is :

	Outlook	Temperature	Humidity	Windy	Play Tennis
0	Sunny	Hot	High	False	No
1	Sunny	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Rainy	Mild	High	False	Yes
4	Rainy	Cool	Normal	False	Yes

Step 3:

```
[ ]  X=data.iloc[:,:-1]
     print("the First 5 values of data is :\n")
     X.head()
```

Output:

the First 5 values of data is :

	Outlook	Temperature	Humidity	Windy
0	Sunny	Hot	High	False
1	Sunny	Hot	High	True
2	Overcast	Hot	High	False
3	Rainy	Mild	High	False
4	Rainy	Cool	Normal	False

Step 4:

```
[ ]    y=data.iloc[:,-1]
       print("the First 5 values of data is :\n")
       y.head()
```

Output:

the First 5 values of data is :

```
0    No
1    No
2    Yes
3    Yes
4    Yes
Name: PlayTennis, dtype: object
```

Step 5:

```
[ ]    for column in X.columns:
          X[column]=LabelEncoder().fit_transform(X[column])
       X.head()
```

Output:

	Outlook	Temperature	Humidity	Windy
0	2	1	0	0
1	2	1	0	1
2	0	1	0	0
3	1	2	0	0
4	1	0	1	0

Step 6:

```
[ ]   y=LabelEncoder().fit_transform(y)
      print(y)
```

Output:

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]

Step 7:

```
[ ]   from sklearn.model_selection import train_test_split
```

Step 8:

```
[ ]   X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20)
```

Step 9:

```
[ ]   from sklearn.naive_bayes import GaussianNB
      classifier = GaussianNB()
      classifier.fit(X_train,y_train)
```

Output:

```
▾ GaussianNB
GaussianNB()
```

Step 10:

```
[ ]   from sklearn.metrics import accuracy_score
```

Step 11:

```
[ ]   print("Accuracy is:",accuracy_score(classifier.predict(X_test),(y_test)))
```

Output:

Accuracy is: 0.6666666666666666

EX.NO :

DATE :

IMPLEMENT LINEAR REGRESSION

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression
     from sklearn.metrics import mean_squared_error, r2_score
```

Step 2:

```
[ ]  data=pd.read_csv("Linear_Regression_Advertising.csv")
     print("the First 5 values of data is :\n")
     data.head()
```

Output:

the First 5 values of data is :

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

Step 3:

```
[ ]    X =data[['TV', 'Radio', 'Newspaper']]
       y = data['Sales']
       X.head()
```

Output:

	TV	Radio	Newspaper
0	230.1	37.8	69.2
1	44.5	39.3	45.1
2	17.2	45.9	69.3
3	151.5	41.3	58.5
4	180.8	10.8	58.4

Step 4:

```
[ ]    y.head()
```

Output:

```
0    22.1
1    10.4
2     9.3
3    18.5
4    12.9
Name: Sales, dtype: float64
```

Step 5:

```
[ ]    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
       model = LinearRegression()
       model.fit(X_train, y_train)
```

Output:

```
▾ LinearRegression
LinearRegression()
```

Step 6:

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

Step 7:

```
[ ]  mse = mean_squared_error(y_test, y_pred)
     r2 = r2_score(y_test, y_pred)
     print(f'Mean Squared Error: {mse}')
     print(f'R^2 Score: {r2}')
```

Output :

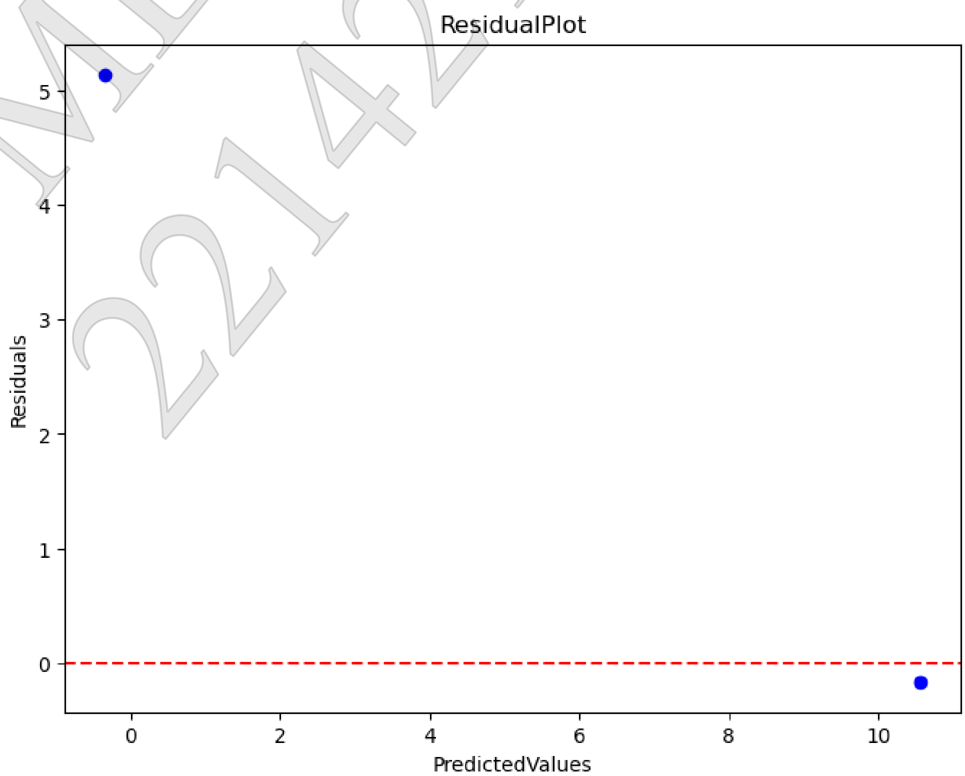
Mean Squared Error: 13.201451790963432

R^2 Score: -0.6838586468065599

Step 8:

```
[ ]  residuals=y_test-y_pred
     plt.figure(figsize=(8,6))
     plt.scatter(y_pred,residuals,color='blue')
     plt.title('ResidualPlot')
     plt.xlabel('PredictedValues')
     plt.ylabel('Residuals')
     plt.axhline(y=0,color='r', linestyle='--')
     plt.show()
```

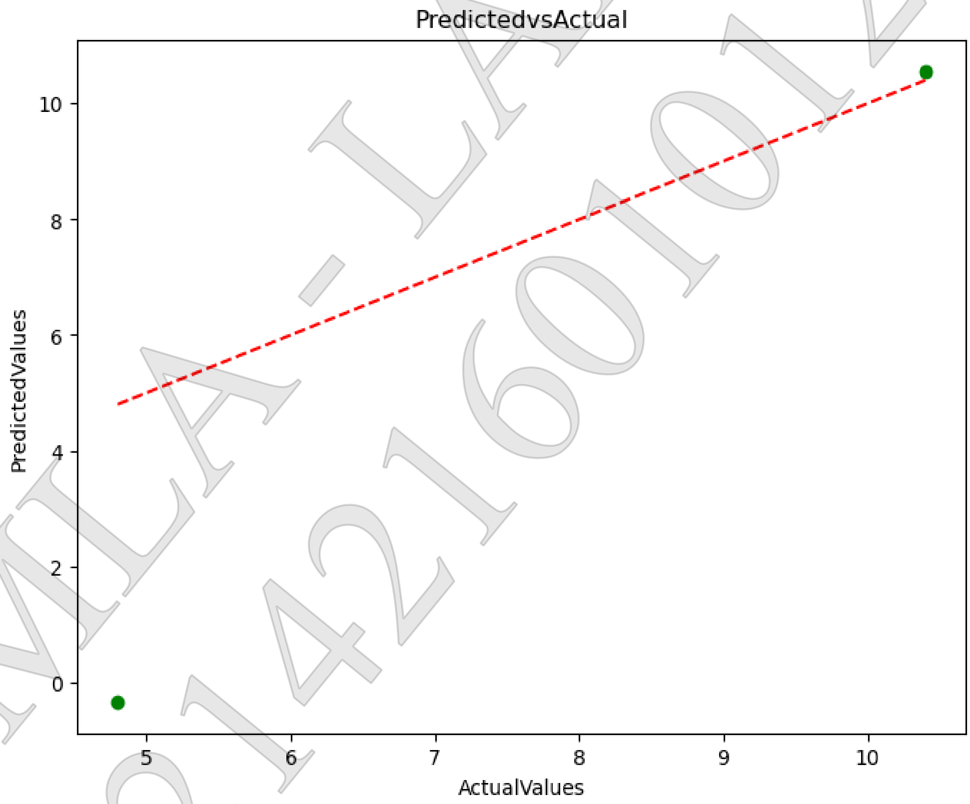
Output:



Step 9:

```
[ ]   plt.figure(figsize=(8,6))
      plt.scatter(y_test,y_pred,color='green')
      plt.title('PredictedvsActual')
      plt.xlabel('ActualValues')
      plt.ylabel('PredictedValues')
      plt.plot([min(y_test),max(y_test)], [min(y_test),max(y_test)],color='red',
linestyle='--')
      plt.show()
```

Output:



EX.NO :

DATE :

IMPLEMENT SUPPORT VECTOR MACHINE (SVM) ALGORITHM

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     import numpy as np
     from sklearn.model_selection import train_test_split,cross_val_score
     from sklearn.preprocessing import StandardScaler, LabelEncoder
     from sklearn.metrics import confusion_matrix, accuracy_score, precision_score,
     recall_score, f1_score
     from sklearn.svm import SVC
```

Step 2:

```
[ ]  data=pd.read_csv("SVM_PurchasePrediction.csv")
     print("the First 5 values of data is :\n")
     data.head()
```

Output:

the First 5 values of data is :

	Age	Income	Gender	Purchase
0	25	50000	Male	0
1	45	64000	Female	1
2	35	58000	Female	0
3	50	72000	Male	1
4	23	48000	Male	0

Step 3:

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

Step 4:

```
[ ]    data.fillna(method='ffill',inplace=True)
```

Step 5:

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

Step 6:

```
[ ]    sc=StandardScaler()
       X_scaled=sc.fit_transform(X)
```

Step 7:

```
[ ]    classifiers={
         'Linear SVM': SVC(kernel='linear',random_state=0),
         'Polynomial SVM': SVC(kernel='poly',degree=3,random_state=0),
         'RBF SVM': SVC(kernel='rbf',random_state=0)
       }
```

Step 8:

```
[ ]    for clf_name,clf in classifiers.items():
         scores=cross_val_score(clf,X_scaled,y,cv=5,scoring='accuracy')
         print(f"{clf_name} Cross-validation Accuracy : {scores.mean():.2f}(+/-
       {scores.std()*2:.2f})")
```

Output:

Linear SVM Cross-validation Accuracy : 0.80(+/-0.33)
Polynomial SVM Cross-validation Accuracy : 0.80(+/-0.53)
RBF SVM Cross-validation Accuracy : 0.80(+/-0.53)

Step 9:

```
[ ]    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
       classifier=SVC(kernel='linear',random_state=0)
       classifier.fit(X_train, y_train)
```

Output:

```
SVC
SVC(kernel='linear', random_state=0)
```

Step 10:

```
[ ]  y_pred=classifier.predict(X_test)
```

Step 11:

```
[ ]  cm=confusion_matrix(y_test,y_pred)
     accuracy=accuracy_score(y_test,y_pred)
     precision=precision_score(y_test,y_pred)
     recall=recall_score(y_test,y_pred)
     f1=f1_score(y_test,y_pred)
```

Step 12:

```
[ ]  print(f"Confusion Matrix :\n",cm)
     print(f"Accuracy :{accuracy:.2f}")
     print(f"Precision :{precision:.2f}")
     print(f"Recall :{recall:.2f}")
     print(f"F1 Performance score :{f1:.2f}")
```

Output :

```
Confusion Matrix :
 [[4]]
Accuracy :1.00
Precision :1.00
Recall :1.00
F1 Performance score :1.00
```

EX.NO :

DATE :

IMPLEMENT DECISION TREE CLASSIFIER

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.metrics import
     confusion_matrix,accuracy_score,precision_score,recall_score,f1_score
```

Step 2:

```
[ ]  data=pd.read_csv("DecisionTree_TargetIncome.csv")
     print("the First 5 values of data is :\n")
     data.head()
```

Output:

the First 5 values of data is :

	Age	Income	Gender	TargetVariable
0	25	50000	Male	0
1	45	64000	Female	1
2	35	58000	Female	0
3	50	72000	Male	1
4	23	48000	Male	0

Step 3:

```
[ ]  data=pd.get_dummies(data, columns=['Gender'],drop_first=True)
```

Step 4:

```
[ ]    print(data.columns)
```

Step 5:

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

Step 6:

```
[ ]    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
       classifier=DecisionTreeClassifier(random_state=0)
       classifier.fit(X_train, y_train)
```

Output:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=0)
```

Step 7:

```
[ ]    y_pred=classifier.predict(X_test)
```

Step 8:

```
[ ]    cm=confusion_matrix(y_test,y_pred)
       accuracy=accuracy_score(y_test,y_pred)
       precision=precision_score(y_test,y_pred)
       recall=recall_score(y_test,y_pred)
       f1=f1_score(y_test,y_pred)
```

Step 9:

```
[ ]    print(f"Confusion Matrix :\n",cm)
       print(f"Accuracy :{accuracy:.2f}")
       print(f"Precision :{precision:.2f}")
       print(f"Recall :{recall:.2f}")
       print(f"F1 score :{f1:.2f}")
```

Output :

Confusion Matrix :

[[0 0]

[1 3]]

Accuracy :0.75

Precision :1.00

Recall :0.75

F1 score :0.86

EX.NO :

DATE :

IMPLEMENT RANDOM FOREST ALGORITHM

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     from sklearn.model_selection import train_test_split
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.metrics import accuracy_score,classification_report
     import warnings
     warnings.filterwarnings('ignore')
```

Step 2:

```
[ ]  titanic_data=pd.read_csv('RandomForest_TitanicSurvival.csv')
     titanic_data.head()
```

Output:

	Passenger Id	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25	-	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7.925	-	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05	-	S

Step 3:

```
[ ]    titanic_data=titanic_data.dropna(subset=['Survived'])
```

Step 4:

```
[ ]    X=titanic_data[['Pclass','Sex','Age','SibSp','Parch','Fare']]
       y=titanic_data['Survived']
```

Step 5:

```
[ ]    X.loc[:,'Sex']=X['Sex'].map({'female':0,'male':1})
       X.loc[:,'Age']=X['Age'].fillna(X['Age'].median())
```

Step 6:

```
[ ]    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
       rf_classifier=RandomForestClassifier(n_estimators=100,random_state=42)
       rf_classifier.fit(X_train, y_train)
```

Output:

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Step 7:

```
[ ]    y_pred=rf_classifier.predict(X_test)
```

Step 8:

```
[ ]    accuracy=accuracy_score(y_test,y_pred)
       classification_rep=classification_report(y_test,y_pred)
```

Step 9:

```
[ ]    print(f"Accurancy :{accuracy:.2f}")
       print(f"Classification Report :\n",classification_rep)
```

Output :

Accurancy :0.80

Classification Report :

	precision	recall	f1-score	support
0	0.82	0.85	0.83	105
1	0.77	0.73	0.75	74
accuracy			0.80	179
macro avg	0.79	0.79	0.79	179
weighted avg	0.80	0.80	0.80	179

EX.NO :

DATE :

IMPLEMENT K-MEANS CLUSTERING ALGORITHM

SOURCE CODE :

Step 1:

```
[ ]   import pandas as pd
      import numpy as np
      from sklearn.cluster import KMeans
      import matplotlib.pyplot as plt
```

Step 2:

```
[ ]   data=pd.read_csv("KMeans_FeatureClusters.csv")
      print("the First 5 values of data is :\n")
      data.head()
```

Output:

the First 5 values of data is :

	Feature1	**Feature2**
0	2.3	3.4
1	1.5	1.8
2	7.6	6.5
3	2.1	4.2
4	8.0	7.0

Step 3:

```
[ ]    kmeans=KMeans(n_clusters=2,random_state=0)
       kmeans.fit(df)
```

Output:

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1382: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

```
▾ KMeans
KMeans(n_clusters=2, random_state=0)
```

Step 4:

```
[ ]    df['cluster']=kmeans.labels_
```

Step 5:

```
[ ]    print(df.head())
```

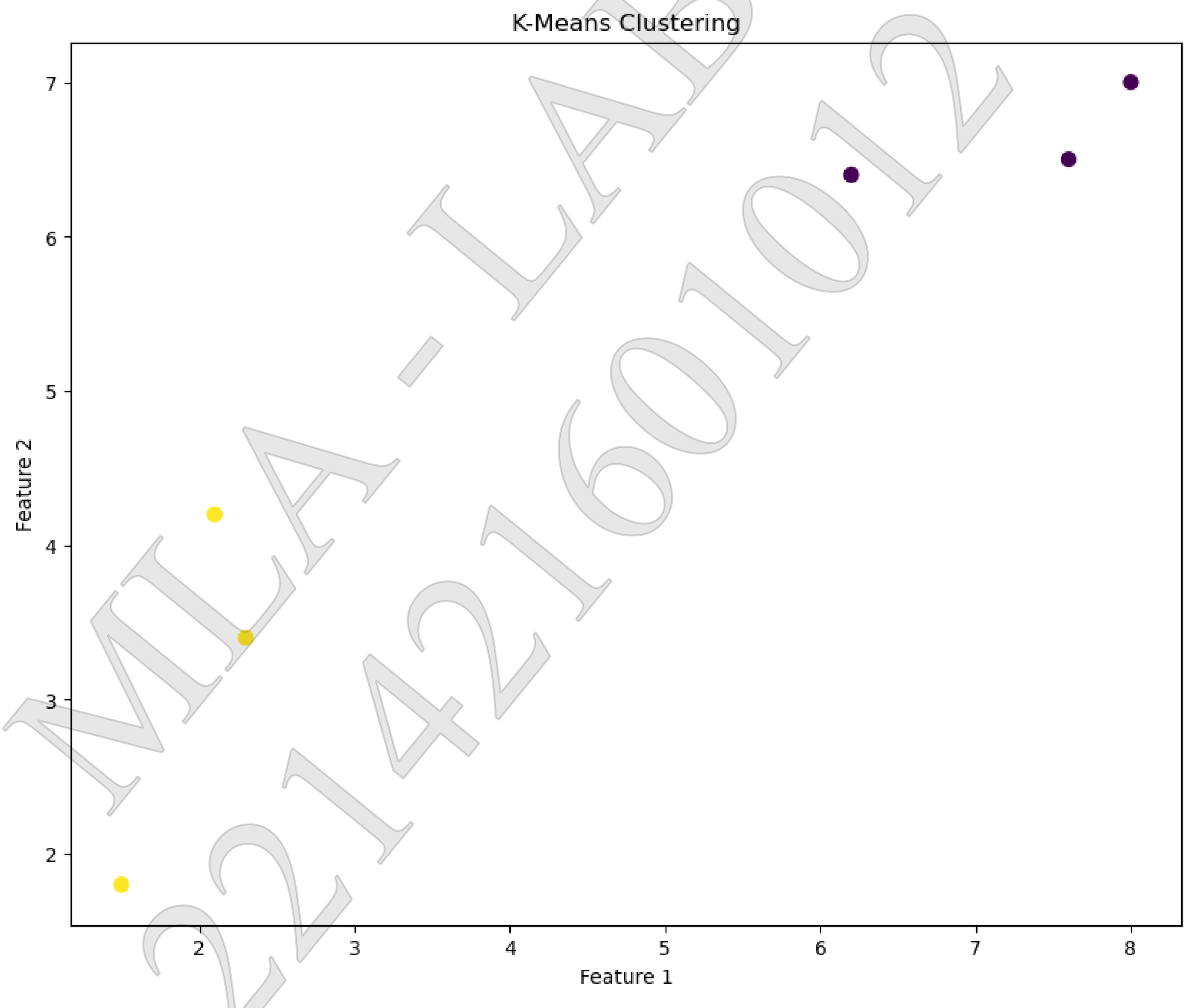
Output:

	Feature1	**Feature2**	**Cluster**
0	2.3	3.4	1
1	1.5	1.8	1
2	7.6	6.5	0
3	2.1	4.2	1
4	8.0	7.0	0

Step 6:

```
[ ]     plt.figure(figsize=(10,8))
        plt.scatter(df['Feature1'],df['Feature2'],c=df['cluster'],cmap='viridis',s=50)
        plt.title('K-Means Clustering')
        plt.xlabel('Feature 1')
        plt.ylabel('Feature 2')
        plt.show()
```

Output:



EX.NO :

DATE :

IMPLEMENT PRINCIPAL COMPONENT ANALYSIS (PCA)

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     import numpy as np
     from sklearn.decomposition import PCA
     from sklearn.preprocessing import StandardScaler
     import matplotlib.pyplot as plt
     import seaborn as sns
```

Step 2:

```
[ ]  data=pd.read_csv("PCA_CustomerSegmentation.csv")
     print("the First 5 values of data is :\n")
     data.head()
```

Output:

the First 5 values of data is :

	Age	Annual Income	Spending Score	Number of Purchases	Cluster
0	22	35000	45	15	3
1	28	45000	50	18	2
2	33	60000	55	22	1
3	38	70000	60	25	4
4	45	80000	65	30	2

Step 3:

```
[ ]    Features=['Age','Annual Income','Spending Score','Number of Purchases']
       X=df[Features]
```

Step 4:

```
[ ]    Scaler=StandardScaler()
       X_scaled=Scaler.fit_transform(X)
```

Step 5:

```
[ ]    pca=PCA(n_components=2)
       X_pca=pca.fit_transform(X_scaled)
```

Step 6:

```
[ ]    df_pca=pd.DataFrame(data=X_pca,columns=['pc1','pc2'])
       df_pca['Cluster']=df['Cluster']
```

Step 7:

```
[ ]    plt.figure(figsize=(10,6))
       sns.scatterplot(x='pc1',y='pc2',hue='Cluster',data=df_pca,palette='viridis')
       plt.title('PCA Result - Customer Segmentation')
       plt.xlabel('principal component 1')
       plt.ylabel('principal component 2')
       plt.show()
```

Output :

Step 8:

```
[ ]   explained_variance=pca.explained_variance_ratio_
      print(f'Explained Variance by each Component: {explained_variance}')
      print(f'Total Explained Variance : {np.sum(explained_variance)}')
```

Output :

Explained Variance by each Component: [0.87276806 0.1144451]

Total Explained Variance : 0.9872131621734076

EX.NO :

DATE :

IMPLEMENT K-NEAREST NEIGHBORS (KNN) ALGORITHM

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     import plotly.graph_objects as go
     import plotly.offline as pyoff
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
```

Step 2:

```
[ ]  data=pd.read_csv("KNN_CellClassification.csv")
     data.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 698 entries, 0 to 697
Data columns (total 11 columns):
 #  Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0  1000025  698 non-null    int64
 1  5        698 non-null    int64
 2  1        698 non-null    int64
 3  1.1      698 non-null    int64
 4  1.2      698 non-null    int64
 5  2        698 non-null    int64
 6  1.3      698 non-null    object
 7  3        698 non-null    int64
 8  1.4      698 non-null    int64
 9  1.5      698 non-null    int64
 10  2.1     698 non-null    int64
dtypes: int64(10), object(1)
memory usage: 60.1+ KB
```

Step 3:

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

Output:

	1000025	5	1	1.1	1.2	2	1.3	3	1.4	1.5	2.1
0	1002945	5	4	4	5	7	10	3	2	1	2
1	1015425	3	1	1	1	2	2	3	1	1	2
2	1016277	6	8	8	1	3	4	3	7	1	2
3	1017023	4	1	1	3	2	1	3	1	1	2
4	1017122	8	10	10	8	7	10	9	7	1	4

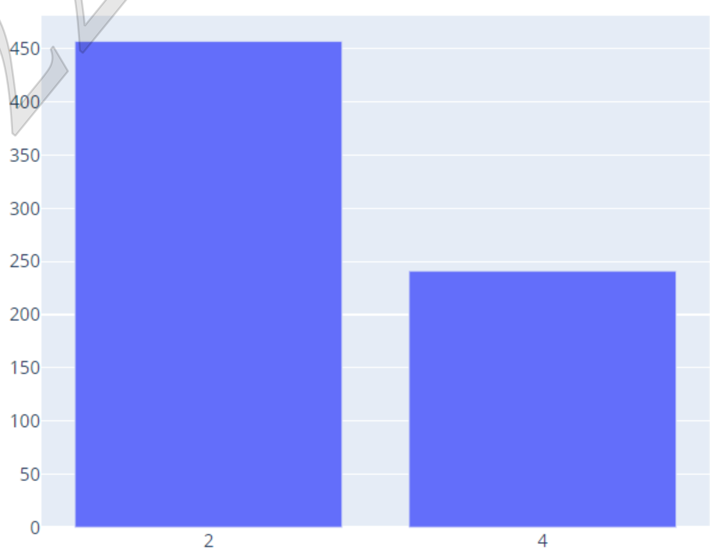
Step 4:

```
[ ]    data.columns=['Id','Clump Thickness','uniformity of cell size','uniformity of cell shape','Marginal Adhesion','Single Epithelial cell size','Bare Nuclei','Bland Chromatin','Normal Nucleoli','Mitoses','Class']
```

Step 5:

```
[ ]    target_balance=data['Class'].value_counts().reset_index()
       target_balance.columns=['Class','Count']
       target_class=go.Bar(
          name="Target Balance",
          x=target_balance['Class'].astype(str),
          y=target_balance['Count']
          )
       fig=go.Figure(target_class)
       pyoff.iplot(fig)
```

Output:



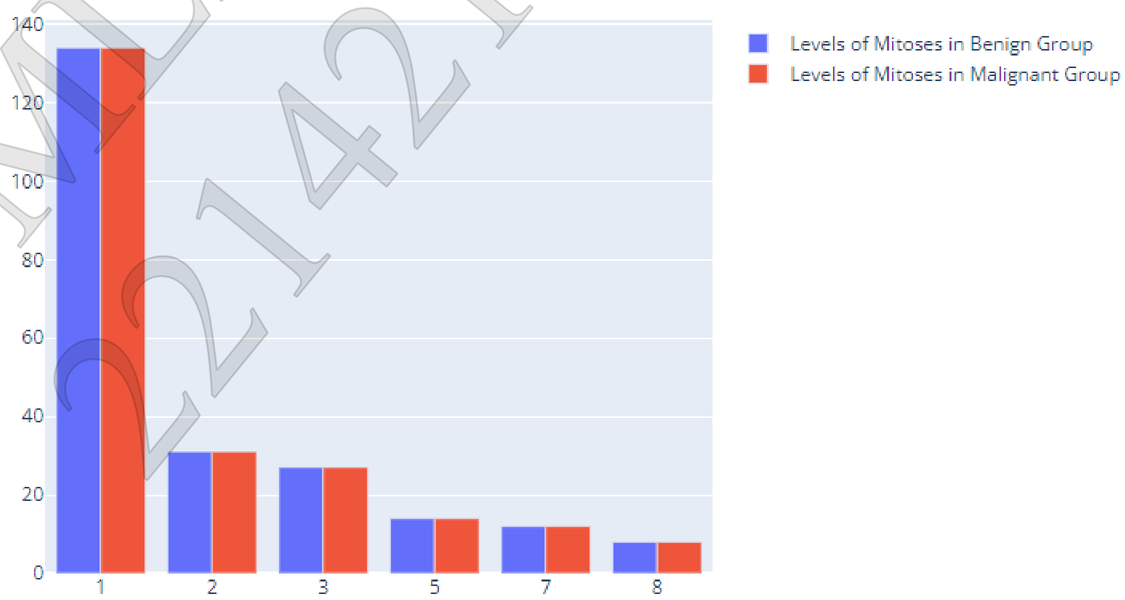
Step 6:

```
[ ]    beg_class_pat=data.loc[data['Class']==2]
       mal_class_pat=data.loc[data['Class']==4]
       Mith_10_beg=beg_class_pat['Mitoses'].value_counts().reset_index()
       Mith_10_beg.columns=['Mitoses','Count']
       Mith_10_mal=mal_class_pat['Mitoses'].value_counts().reset_index()
       Mith_10_mal.columns=['Mitoses','Count']
```

Step 7:

```
[ ]    fig=go.Figure(data=[
         go.Bar(name='Levels of Mitoses in Benign
       Group',x=Mith_10_beg['Mitoses'].astype(str),y=Mith_10_mal['Count']),
         go.Bar(name='Levels of Mitoses in Malignant
       Group',x=Mith_10_beg['Mitoses'].astype(str),y=Mith_10_mal['Count'])])
       fig.update_layout(barmode='group')
       fig.show()
```

Output:



Step 8:

```
[ ]    x=data.drop(columns=['Id','Class'])
       y=data['Class']
```

Step 9:

```
print("Unique Values in 'Bara Nuclei':",x['Bare Nuclei'].unique())
```

Output :

Unique Values in 'Bara Nuclei': ['10' '2' '4' '1' '3' '9' '7' '?' '5' '8' '6']

Step 10:

```
x['Bare Nuclei']=pd.to_numeric(x['Bare Nuclei'],errors='coerce')
```

Step 11:

```
x=x.fillna(x.median())
```

Step 12:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=42)
```

Step 13:

```
scaler=StandardScaler()
x_train_scaled=scaler.fit_transform(x_train)
x_test_scaled=scaler.transform(x_test)
```

Step 14:

```
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train_scaled,y_train)
```

Output :

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

Step 15:

```
y_pred=knn.predict(x_test_scaled)
```

Step 16:

```
[ ]  print("Accuracy: ",accuracy_score(y_test,y_pred))
     print()
     print("Confusion Matrix: \n",confusion_matrix(y_test,y_pred))
     print("Classification Report: \n",classification_report(y_test,y_pred))
```

Output :

```
Accuracy:  0.9714285714285714


Confusion Matrix:
 [[131   4]
 [  2  73]]
Classification Report:
              precision    recall  f1-score   support

           2       0.98      0.97      0.98       135
           4       0.95      0.97      0.96        75

    accuracy                           0.97       210
   macro avg       0.97      0.97      0.97       210
weighted avg       0.97      0.97      0.97       210
```

EX.NO :

DATE :

DEMONSTRATE WEKA TOOL

SOURCE CODE :

Step 1:

```
[ ]   import pandas as pd
      from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import StandardScaler
      from sklearn.ensemble import RandomForestClassifier
      from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

Step 2:

```
[ ]   data=pd.read_csv("Weka_CustomerChurn.csv")
      print("the First 5 values of data is :\n")
      data.head()
```

Output:

the First 5 values of data is :

	Customer ID	Gender	Senior Citizen	Partner	Dependents	Tenure	Phone Service	Monthly Charges	Total Charges	Churn
0	1	Male	0	Yes	No	1	No	29.85	29.85	No
1	2	Female	1	No	No	34	Yes	56.95	1889.50	No
2	3	Female	0	Yes	Yes	2	Yes	53.85	108.15	Yes
3	4	Male	0	No	Yes	45	Yes	42.30	1840.75	No
4	5	Female	1	No	No	2	No	70.70	151.65	Yes

Step 3:

```
[ ]   X = data.drop(columns=['Churn'])
      y = data['Churn'].apply(lambda x: 1 if x == 'Yes' else 0)
```

Step 4:

```
[ ]   X = pd.get_dummies(X, drop_first=True)
```

Step 5:

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

Step 6:

```
[ ]   scaler = StandardScaler()
      X_train = scaler.fit_transform(X_train)
      X_test = scaler.transform(X_test)
```

Step 7:

```
[ ]   model = RandomForestClassifier(n_estimators=100, random_state=42)
```

Step 8:

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

Output:

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Step 9:

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

Step 10:

```
[ ]   accuracy = accuracy_score(y_test, y_pred)
      conf_matrix = confusion_matrix(y_test, y_pred)
      report = classification_report(y_test, y_pred)
```

Output :

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Step 11:

```
[ ]  print(f'Accuracy: {accuracy}')
     print('Confusion Matrix:')
     print(conf_matrix)
     print('Classification Report:')
     print(report)
```

Output :

```
Accuracy: 0.5
Confusion Matrix:
[[0 1]
 [0 1]]
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.50      1.00      0.67         1

    accuracy                           0.50         2
   macro avg       0.25      0.50      0.33         2
weighted avg       0.25      0.50      0.33         2
```

EX.NO :

DATE :

BUILD AN UNSUPERVISED MODEL USING [Scikit-Learn and PyTorch]

SOURCE CODE :

Step 1:

```
[ ]  import pandas as pd
     from sklearn.datasets import load_iris
     from sklearn.preprocessing import StandardScaler
```

Step 2:

```
[ ]  iris=load_iris()
     X=pd.DataFrame(iris.data,columns=iris.feature_names)
```

Step 3:

```
[ ]  Scaler=StandardScaler()
     X_Scaled=Scaler.fit_transform(X)
```

Step 4:

```
[ ]  from sklearn.cluster import KMeans
     from sklearn.metrics import silhouette_score
     kmeans=KMeans(n_clusters=3,random_state=42)
     kmeans_labels=kmeans.fit_predict(X_Scaled)
```

Output :

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the
value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1382:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there
are less chunks than available threads. You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```

Step 5:

```
[ ]   kmeans_silhouette=silhouette_score(X_Scaled, kmeans_labels)
      print(f'K-Means Silhouette Score: {kmeans_silhouette}')
```

Output :

K-Means Silhouette Score: 0.45994823920518635

Step 6:

```
[ ]   import torch
      import torch.nn as nn
      import torch.optim as optim
      from torch.utils.data import DataLoader, TensorDataset
      X_tensor=torch.tensor(X_Scaled, dtype=torch.float32)
```

Step 7:

```
[ ]   data_loader=DataLoader(TensorDataset(X_tensor),batch_size=16,shuffle=True)
```

Step 8:

```
[ ]   class Autoencoder(nn.Module):
        def __init__(self):
          super(Autoencoder, self).__init__()
          self.encoder=nn.Sequential(
            nn.Linear(4,2),
            nn.ReLU()
          )
          self.decoder=nn.Sequential(
            nn.Linear(2,4),
            nn.ReLU()
          )
        def forward(self,x):
          encoded=self.encoder(x)
          decoded=self.decoder(encoded)
          return decoded
```

Step 9:

```
[ ]  autoencoder=Autoencoder()
     criterion=nn.MSELoss()
     optimizer=optim.Adam(autoencoder.parameters(),lr=0.01)
```

Step 10:

```
[ ]  num_epochs=100
     for epoch in range(num_epochs):
        for data in data_loader:
            inputs, =data
            optimizer.zero_grad()
            outputs=autoencoder(inputs)
            loss=criterion(outputs, inputs)
            loss.backward()
            optimizer.step()
```

Step 11:

```
[ ]  with torch.no_grad():
        encoded_data=autoencoder.encoder(X_tensor).numpy()
```

Step 12:

```
[ ]  encoded_kmeans=KMeans(n_clusters=3,random_state=42)
     encoded_kmeans_labels=encoded_kmeans.fit_predict(encoded_data)
```

Output :

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1382: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

Step 13:

```
[ ]   encoded_silhouette = silhouette_score(X_Scaled, encoded_kmeans_labels)
      print(f'Autoencoder + kmeans silhouette score : {encoded_silhouette}')
```

Output :

Autoencoder + kmeans silhouette score : 0.302958422921628

EX.NO :

DATE :

IMPLEMENT LOGISTIC REGRESSION

SOURCE CODE :

Step 1:

```
[ ]     import pandas as pd
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler, LabelEncoder
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

Step 2:

```
[ ]     data=pd.read_csv("LogisticRegression_HeartDisease.csv")
        print("the First 5 values of data is :\n")
        data.head()
```

Output:

the First 5 values of data is :

	Age	CholesterolLevel	BloodPressure	SmokingStatus	HeartDisease
0	68	213.510222	119.336301	No	No
1	58	209.232228	109.821694	Yes	No
2	44	194.023226	154.003458	No	No
3	72	152.111973	162.855094	Yes	No
4	37	179.826361	121.379939	No	Yes

Step 3:

```
[ ]     label_encoder = LabelEncoder()
        data['SmokingStatus'] = label_encoder.fit_transform(data['SmokingStatus'])
        data['HeartDisease'] = label_encoder.fit_transform(data['HeartDisease'])
```

Step 4:

```
X = data[['Age', 'CholesterolLevel', 'BloodPressure', 'SmokingStatus']]
X.head()
```

Output:

	Age	CholesterolLevel	BloodPressure	SmokingStatus
0	68	213.510222	119.336301	0
1	58	209.232228	109.821694	1
2	44	194.023226	154.003458	0
3	72	152.111973	162.855094	1
4	37	179.826361	121.379939	0

Step 5:

```
y = data[['HeartDisease']]
y.head()
```

Output:

	HeartDisease
0	**0**
1	**0**
2	**0**
3	**0**
4	**1**

Step 6:

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

Step 7:

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

Step 8:

```
[ ]   model = LogisticRegression()
      model.fit(X_train, y_train)
```

Output:

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
▾ LogisticRegression
LogisticRegression()
```

Step 9:

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

Step 10:

```
[ ]   accuracy = accuracy_score(y_test, y_pred)
      conf_matrix = confusion_matrix(y_test, y_pred)
      class_report = classification_report(y_test, y_pred)
```

Step 11:

```
[ ]   print(f'Accuracy: {accuracy:.2f}')
      print('Confusion Matrix:')
      print(conf_matrix)
      print('Classification Report:')
      print(class_report)
```

Output:

```
Accuracy: 0.60
Confusion Matrix:
      [[7 3]
       [5 5]]
Classification Report:
              precision    recall  f1-score   support

           0       0.58      0.70      0.64        10
           1       0.62      0.50      0.56        10

    accuracy                           0.60        20
   macro avg       0.60      0.60      0.60        20
weighted avg       0.60      0.60      0.60        20
```

EX.NO :

DATE :

IMPLEMENT NEURAL NETWORK MODEL

SOURCE CODE :

Step 1:

```
[ ]   import numpy as np
      import pandas as pd
      from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import StandardScaler
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense
      from sklearn.metrics import classification_report, confusion_matrix
      import matplotlib.pyplot as plt
      import seaborn as sns
```

Step 2:

```
[ ]   df=pd.read_csv("NeuralNetwork_PredictiveMaintenance.csv")
      print("the First 5 values of data is :\n")
      df.head()
```

Output:

The First 5 values of data is :

	sensor_1	sensor_2	sensor_3	sensor_4	sensor_5	sensor_6	sensor_7	sensor_8	sensor_9	sensor_10	failure
0	0.374540	0.950714	0.731994	0.598658	0.156019	0.155995	0.058084	0.866176	0.601115	0.708073	0
1	0.020584	0.969910	0.832443	0.212339	0.181825	0.183405	0.304242	0.524756	0.431945	0.291229	1
2	0.611853	0.139494	0.292145	0.366362	0.456070	0.785176	0.199674	0.514234	0.592415	0.046450	1
3	0.607545	0.170524	0.065052	0.948886	0.965632	0.808397	0.304614	0.097672	0.684233	0.440152	1
4	0.122038	0.495177	0.034389	0.909320	0.258780	0.662522	0.311711	0.520068	0.546710	0.184854	0

Step 3:

```
[ ]   X = df.drop('failure', axis=1).values  # Features (sensor data)
      y = df['failure'].values  # Target (failure labels)
```

Step 4:

```
[ ]    scaler = StandardScaler()
       X_scaled = scaler.fit_transform(X)
```

Step 5:

```
[ ]    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.15,
       random_state=42)

       X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.15,
       random_state=42)
```

Step 6:

```
[ ]    model = Sequential()
       model.add(Dense(64, input_dim=X.shape[1], activation='relu'))
       model.add(Dense(32, activation='relu'))
       model.add(Dense(1, activation='sigmoid'))
```

Output:

```
C:\ProgramData \anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning:
Do not    pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Step 7:

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

Step 8:

```
[ ]    # Train the model with fewer epochs
       history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10,
       batch_size=32)

       # Evaluate the model on the test set
       test_loss, test_accuracy = model.evaluate(X_test, y_test)
       print(f"Test Loss: {test_loss}")
       print(f"Test Accuracy: {test_accuracy}")

       # Predict and generate classification report
       y_pred = (model.predict(X_test) > 0.5).astype("int32")
       print(classification_report(y_test, y_pred))
```

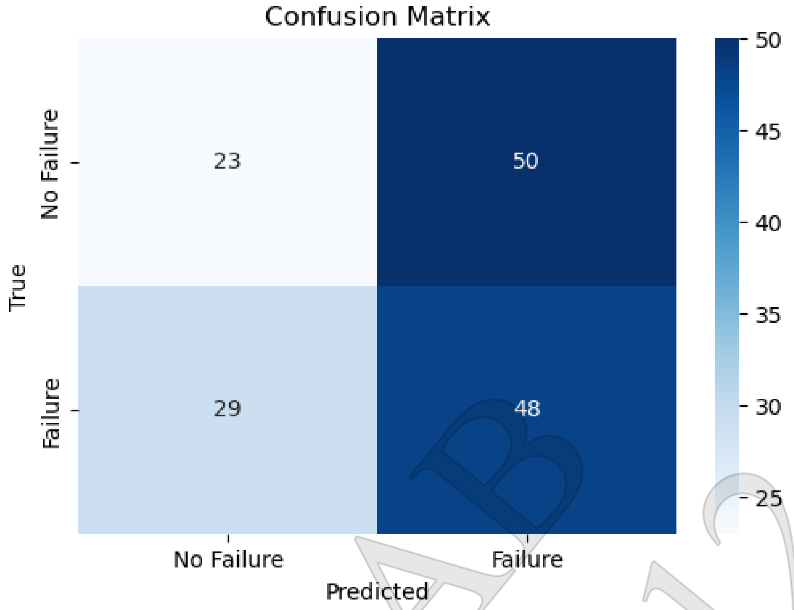
Output:

```
Epoch 1/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7976 - loss: 0.5117 - val_accuracy: 0.5156 - val_loss: 0.7832
Epoch 2/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7784 - loss: 0.5235 - val_accuracy: 0.5156 - val_loss: 0.7902
Epoch 3/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7891 - loss: 0.5068 - val_accuracy: 0.5000 - val_loss: 0.7948
Epoch 4/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7687 - loss: 0.5194 - val_accuracy: 0.4922 - val_loss: 0.8020
Epoch 5/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7619 - loss: 0.5247 - val_accuracy: 0.5312 - val_loss: 0.8121
Epoch 6/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7967 - loss: 0.5169 - val_accuracy: 0.5234 - val_loss: 0.8118
Epoch 7/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7831 - loss: 0.5106 - val_accuracy: 0.5000 - val_loss: 0.8141
Epoch 8/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7767 - loss: 0.5078 - val_accuracy: 0.5391 - val_loss: 0.8291
Epoch 9/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.7946 - loss: 0.4805 - val_accuracy: 0.4922 - val_loss: 0.8261
Epoch 10/10
23/23 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8199 - loss: 0.4780 - val_accuracy: 0.5156 - val_loss: 0.8287
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.4935 - loss: 0.7497
Test Loss: 0.7296823263168335
Test Accuracy: 0.5
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

              precision    recall  f1-score   support

           0       0.48      0.44      0.46        73
           1       0.51      0.56      0.53        77

    accuracy                           0.50       150
   macro avg       0.50      0.50      0.50       150
weighted avg       0.50      0.50      0.50       150
```

Step 9:

```
[ ]  # Confusion Matrix
     cm = confusion_matrix(y_test, y_pred)
     plt.figure(figsize=(6, 4))
     sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Failure', 'Failure'], yticklabels=['No Failure', 'Failure'])
     plt.title('Confusion Matrix')
     plt.xlabel('Predicted')
     plt.ylabel('True')
     plt.show()
```

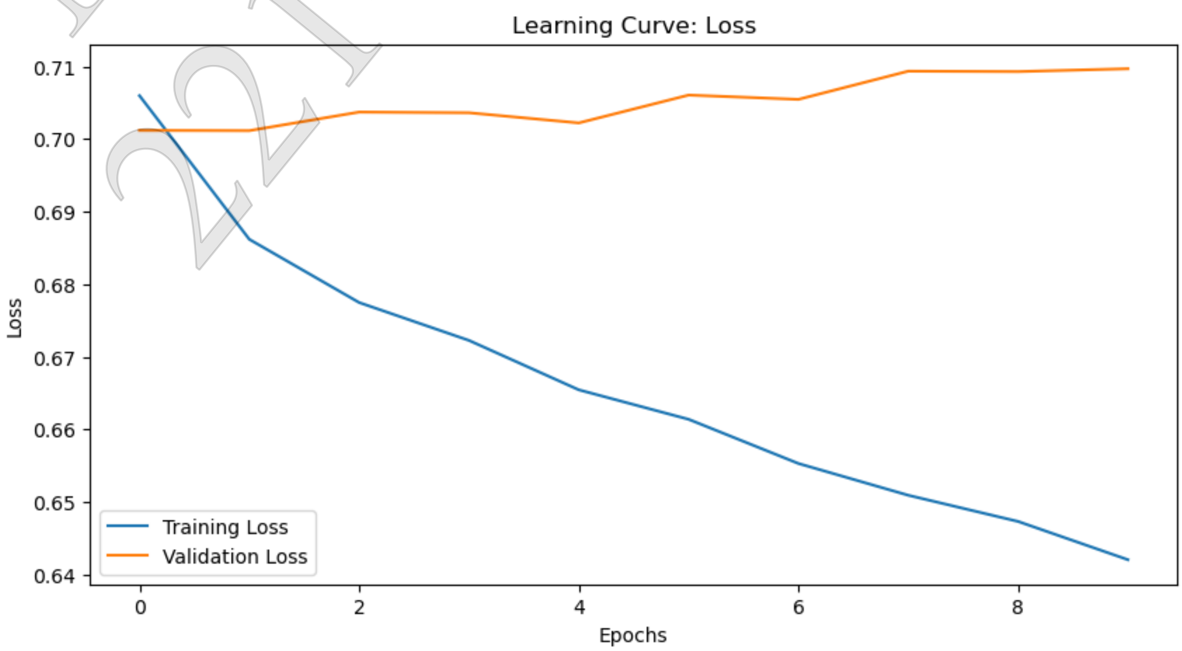
Output:



Step 10:

```
[ ]     # Plot learning curves for loss
        plt.figure(figsize=(10, 5))
        plt.plot(history.history['loss'], label='Training Loss')
        plt.plot(history.history['val_loss'], label='Validation Loss')
        plt.title('Learning Curve: Loss')
        plt.xlabel('Epochs')
        plt.ylabel('Loss')
        plt.legend()
        plt.show()
```

Output:



Step 11:

```
[ ]  # Plot learning curves for accuracy
     plt.figure(figsize=(10, 5))
     plt.plot(history.history['accuracy'], label='Training Accuracy')
     plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
     plt.title('Learning Curve: Accuracy')
     plt.xlabel('Epochs')
     plt.ylabel('Accuracy')
     plt.legend()
     plt.show()
```

Output: