baseFile

January 13, 2024

1 Loading all libraries

[ ]:
```
%reload_ext autoreload
%autoreload 2
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import KFold
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm as SVM_MODEL
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import classification_report
from sklearn.neighbors import KNeighborsClassifier
```

2 Loading the dataset 1

[ ]:
```
df = pd.read_csv("lungcancer.csv")
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 312 entries, 0 to 311
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   GENDER                 312 non-null    object
 1   AGE                    312 non-null    int64
 2   SMOKING                312 non-null    int64
 3   YELLOW_FINGERS         312 non-null    int64
 4   ANXIETY                312 non-null    int64
 5   PEER_PRESSURE          311 non-null    float64
 6   CHRONIC DISEASE        311 non-null    float64
```

```
 7   FATIGUE                312 non-null    int64
 8   ALLERGY                311 non-null    float64
 9   WHEEZING               312 non-null    int64
 10  ALCOHOL CONSUMING      312 non-null    int64
 11  COUGHING               312 non-null    int64
 12  SHORTNESS OF BREATH    312 non-null    int64
 13  SWALLOWING DIFFICULTY  312 non-null    int64
 14  CHEST PAIN             312 non-null    int64
 15  LUNG_CANCER            312 non-null    object
dtypes: float64(3), int64(11), object(2)
memory usage: 39.1+ KB
```

[ ]:
```
df.describe()
```

[ ]:
```
              AGE     SMOKING  YELLOW_FINGERS     ANXIETY  PEER_PRESSURE  \
count  312.000000  312.000000      312.000000  312.000000     311.000000
mean    62.560897    1.557692        1.573718    1.493590       1.498392
std      8.249884    0.497458        0.495330    0.500762       0.500803
min     21.000000    1.000000        1.000000    1.000000       1.000000
25%     57.000000    1.000000        1.000000    1.000000       1.000000
50%     62.000000    2.000000        2.000000    1.000000       1.000000
75%     69.000000    2.000000        2.000000    2.000000       2.000000
max     87.000000    2.000000        2.000000    2.000000       2.000000

       CHRONIC DISEASE     FATIGUE     ALLERGY    WHEEZING  ALCOHOL CONSUMING  \
count       311.000000  312.000000  311.000000  312.000000         312.000000
mean          1.508039    1.676282    1.556270    1.560897           1.557692
std           0.500741    0.468645    0.497624    0.497075           0.497458
min           1.000000    1.000000    1.000000    1.000000           1.000000
25%           1.000000    1.000000    1.000000    1.000000           1.000000
50%           2.000000    2.000000    2.000000    2.000000           2.000000
75%           2.000000    2.000000    2.000000    2.000000           2.000000
max           2.000000    2.000000    2.000000    2.000000           2.000000

         COUGHING  SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN
count  312.000000           312.000000             312.000000  312.000000
mean     1.583333             1.641026               1.464744    1.560897
std      0.493799             0.480470               0.499557    0.497075
min      1.000000             1.000000               1.000000    1.000000
25%      1.000000             1.000000               1.000000    1.000000
50%      2.000000             2.000000               1.000000    2.000000
75%      2.000000             2.000000               2.000000    2.000000
max      2.000000             2.000000               2.000000    2.000000
```

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

```
[ ]:   GENDER  AGE  SMOKING  YELLOW_FINGERS  ANXIETY  PEER_PRESSURE  \
     0      M   69        1               2        2            1.0
     1      M   74        2               1        1            1.0
     2      F   59        1               1        1            2.0
     3      M   63        2               2        2            1.0
     4      F   63        1               2        1            1.0

        CHRONIC DISEASE  FATIGUE  ALLERGY  WHEEZING  ALCOHOL CONSUMING  COUGHING  \
     0              1.0        2      1.0         2                  2         2
     1              2.0        2      2.0         1                  1         1
     2              1.0        2      1.0         2                  1         2
     3              1.0        1      1.0         1                  2         1
     4              1.0        1      1.0         2                  1         2

        SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN LUNG_CANCER
     0                    2                      2           2         YES
     1                    2                      2           2         YES
     2                    2                      1           2          NO
     3                    1                      2           2          NO
     4                    2                      1           1          NO
```

3 Preprocessing

4 Checking for null values

```
[ ]: df.isna().sum()
```

```
[ ]: GENDER                   0
     AGE                      0
     SMOKING                  0
     YELLOW_FINGERS           0
     ANXIETY                  0
     PEER_PRESSURE            1
     CHRONIC DISEASE          1
     FATIGUE                  0
     ALLERGY                  1
     WHEEZING                 0
     ALCOHOL CONSUMING        0
     COUGHING                 0
     SHORTNESS OF BREATH      0
     SWALLOWING DIFFICULTY    0
     CHEST PAIN               0
     LUNG_CANCER              0
     dtype: int64
```

5 Removing null values

[ ]:
```
df["PEER_PRESSURE"] = df["PEER_PRESSURE"].fillna(df["PEER_PRESSURE"].mode()[0])
df['CHRONIC DISEASE'] = df['CHRONIC DISEASE'].fillna(df['CHRONIC DISEASE'].
 ↪mean())
df['ALCOHOL CONSUMING'] = df['ALCOHOL CONSUMING'].fillna(df['ALCOHOL␣
 ↪CONSUMING'].median())
df['ALLERGY'] = df['ALLERGY'].fillna(df['ALLERGY'].median())
df.isna().sum()
```

[ ]:
```
GENDER                   0
AGE                      0
SMOKING                  0
YELLOW_FINGERS           0
ANXIETY                  0
PEER_PRESSURE            0
CHRONIC DISEASE          0
FATIGUE                  0
ALLERGY                  0
WHEEZING                 0
ALCOHOL CONSUMING        0
COUGHING                 0
SHORTNESS OF BREATH      0
SWALLOWING DIFFICULTY    0
CHEST PAIN               0
LUNG_CANCER              0
dtype: int64
```

6 Checking for duplicate values

[ ]:
```
df.duplicated().sum()
```

[ ]: 33

7 Removing duplicate values

[ ]:
```
df.drop_duplicates(inplace=True)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 279 entries, 0 to 311
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   GENDER                  279 non-null    object
```

```
 1   AGE                     279 non-null    int64
 2   SMOKING                 279 non-null    int64
 3   YELLOW_FINGERS          279 non-null    int64
 4   ANXIETY                 279 non-null    int64
 5   PEER_PRESSURE           279 non-null    float64
 6   CHRONIC DISEASE         279 non-null    float64
 7   FATIGUE                 279 non-null    int64
 8   ALLERGY                 279 non-null    float64
 9   WHEEZING                279 non-null    int64
 10  ALCOHOL CONSUMING       279 non-null    int64
 11  COUGHING                279 non-null    int64
 12  SHORTNESS OF BREATH     279 non-null    int64
 13  SWALLOWING DIFFICULTY   279 non-null    int64
 14  CHEST PAIN              279 non-null    int64
 15  LUNG_CANCER             279 non-null    object
dtypes: float64(3), int64(11), object(2)
memory usage: 37.1+ KB
```

8 Encoding values in GENDER AND LUNG_CANCER columns

[ ]:
```
label_encoder = LabelEncoder()
df = pd.get_dummies(df, columns=['GENDER'])
df["GENDER_F"] = label_encoder.fit_transform(df["GENDER_F"])
df["GENDER_M"] = label_encoder.fit_transform(df["GENDER_M"])
df["F"] = df["GENDER_F"]
df["M"] = df["GENDER_M"]
df.drop(columns=["GENDER_F", "GENDER_M"], inplace=True)
df["LUNG_CANCER"] = label_encoder.fit_transform(df["LUNG_CANCER"])
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 279 entries, 0 to 311
Data columns (total 17 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   AGE                     279 non-null    int64
 1   SMOKING                 279 non-null    int64
 2   YELLOW_FINGERS          279 non-null    int64
 3   ANXIETY                 279 non-null    int64
 4   PEER_PRESSURE           279 non-null    float64
 5   CHRONIC DISEASE         279 non-null    float64
 6   FATIGUE                 279 non-null    int64
 7   ALLERGY                 279 non-null    float64
 8   WHEEZING                279 non-null    int64
 9   ALCOHOL CONSUMING       279 non-null    int64
 10  COUGHING                279 non-null    int64
```

```
 11   SHORTNESS OF BREATH    279 non-null    int64
 12   SWALLOWING DIFFICULTY  279 non-null    int64
 13   CHEST PAIN             279 non-null    int64
 14   LUNG_CANCER            279 non-null    int32
 15   F                      279 non-null    int64
 16   M                      279 non-null    int64
dtypes: float64(3), int32(1), int64(13)
memory usage: 38.1 KB
```

9 Changing column positions

[ ]:
```
df = df[['AGE', 'SMOKING', 'YELLOW_FINGERS', 'ANXIETY', 'PEER_PRESSURE',␣
 ↪'CHRONIC DISEASE', 'FATIGUE', 'ALLERGY',
         'WHEEZING', 'ALCOHOL CONSUMING', 'COUGHING', 'SHORTNESS OF BREATH',␣
 ↪'SWALLOWING DIFFICULTY', 'CHEST PAIN', 'M',
         'F', 'LUNG_CANCER']]
df.head()
```

[ ]:
```
   AGE  SMOKING  YELLOW_FINGERS  ANXIETY  PEER_PRESSURE  CHRONIC DISEASE  \
0   69        1               2        2            1.0              1.0
1   74        2               1        1            1.0              2.0
2   59        1               1        1            2.0              1.0
3   63        2               2        2            1.0              1.0
4   63        1               2        1            1.0              1.0

   FATIGUE  ALLERGY  WHEEZING  ALCOHOL CONSUMING  COUGHING  \
0        2      1.0         2                  2         2
1        2      2.0         1                  1         1
2        2      1.0         2                  1         2
3        1      1.0         1                  2         1
4        1      1.0         2                  1         2

   SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN  M  F  LUNG_CANCER
0                    2                      2           2  1  0            1
1                    2                      2           2  1  0            1
2                    2                      1           2  0  1            0
3                    1                      2           2  1  0            0
4                    2                      1           1  0  1            0
```

10 Logistic Regression

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,
                                                    random_state=42)

logistic_regression = LogisticRegression(max_iter=5000)
```

```
logistic_regression.fit(X_train, y_train)
logistic_regression_pred = logistic_regression.predict(X_test)
log_acc = accuracy_score(y_test, logistic_regression_pred)
print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
 ↪logistic_regression_pred))
print("Logistic Regression Confusion Matrix: \n", confusion_matrix(y_test,␣
 ↪logistic_regression_pred))
print("Logistic Regression Classification Report: \n",
      classification_report(y_test, logistic_regression_pred,␣
 ↪zero_division='warn'))
```

```
Logistic Regression Accuracy:  0.9642857142857143
Logistic Regression Confusion Matrix:
 [[ 6  2]
 [ 0 48]]
Logistic Regression Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.75      0.86         8
           1       0.96      1.00      0.98        48

    accuracy                           0.96        56
   macro avg       0.98      0.88      0.92        56
weighted avg       0.97      0.96      0.96        56
```

11 SVM

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,random_state=42)
svm = SVM_MODEL.SVC(max_iter=15000)
svm.fit(X_train, y_train)
svm_pred = svm.predict(X_test)
svm_acc = accuracy_score(y_test, svm_pred)
print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("SVM Confusion Matrix: \n", confusion_matrix(y_test, svm_pred))
print("SVM Classification Report: \n", classification_report(y_test, svm_pred,␣
 ↪zero_division='warn'))
```

```
SVM Accuracy:  0.8571428571428571
SVM Confusion Matrix:
 [[ 0  8]
 [ 0 48]]
SVM Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00         8
           1       0.86      1.00      0.92        48
```

```
    accuracy                           0.86        56
   macro avg       0.43      0.50      0.46        56
weighted avg       0.73      0.86      0.79        56

C:\Users\Rohithk\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:\Users\Rohithk\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:\Users\Rohithk\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))
```

12 KNN

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,
                                                    random_state=42)
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_pred = knn.predict(X_test)
knn_acc = accuracy_score(y_test, knn_pred)
print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("KNN Confusion Matrix: \n", confusion_matrix(y_test, knn_pred))
print("KNN Classification Report: \n", classification_report(y_test, knn_pred,␣
 ↪zero_division='warn'))
```

```
KNN Accuracy:  0.875
KNN Confusion Matrix:
 [[ 1  7]
 [ 0 48]]
KNN Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.12      0.22         8
           1       0.87      1.00      0.93        48

    accuracy                           0.88        56
   macro avg       0.94      0.56      0.58        56
weighted avg       0.89      0.88      0.83        56
```

13 Decision Tree

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,random_state=42)
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)
decision_tree_pred = decision_tree.predict(X_test)
dt_acc = accuracy_score(y_test, decision_tree_pred)
print("Decision Tree Accuracy: ", accuracy_score(y_test, decision_tree_pred))
print("Decision Tree Confusion Matrix: \n", confusion_matrix(y_test,␣
 ↪decision_tree_pred))
print("Decision Tree Classification Report: \n",
      classification_report(y_test, decision_tree_pred, zero_division='warn'))
```

```
Decision Tree Accuracy:  0.9642857142857143
Decision Tree Confusion Matrix:
 [[ 6  2]
 [ 0 48]]
Decision Tree Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.75      0.86         8
           1       0.96      1.00      0.98        48

    accuracy                           0.96        56
   macro avg       0.98      0.88      0.92        56
weighted avg       0.97      0.96      0.96        56
```

14 Using Stratified K-Fold splitting - Logistic Regression

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_log_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        logistic_regression = LogisticRegression(max_iter=5000)
        logistic_regression.fit(X_train, y_train)
        logistic_regression_pred = logistic_regression.predict(X_test)
        log_acc = accuracy_score(y_test, logistic_regression_pred)
        max_log_acc = max(max_log_acc, log_acc)
        print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
 ↪logistic_regression_pred))
print("Max Logistic Regression Accuracy: ", max_log_acc)
```

```
Logistic Regression Accuracy:  0.9107142857142857
Logistic Regression Accuracy:  0.9285714285714286
Logistic Regression Accuracy:  0.9285714285714286
Logistic Regression Accuracy:  0.8214285714285714
Logistic Regression Accuracy:  0.8727272727272727
Max Logistic Regression Accuracy:  0.9285714285714286
```

15 Using K-Fold splitting - Logistic Regression

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_log_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        logistic_regression = LogisticRegression(max_iter=5000)
        logistic_regression.fit(X_train, y_train)
        logistic_regression_pred = logistic_regression.predict(X_test)
        log_acc = accuracy_score(y_test, logistic_regression_pred)
        max_log_acc = max(max_log_acc, log_acc)
        print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
 ↪logistic_regression_pred))
print("Max Logistic Regression Accuracy: ", max_log_acc)
```

```
Logistic Regression Accuracy:  0.9642857142857143
Logistic Regression Accuracy:  0.8571428571428571
Logistic Regression Accuracy:  0.9107142857142857
Logistic Regression Accuracy:  0.8392857142857143
Logistic Regression Accuracy:  0.9090909090909091
Max Logistic Regression Accuracy:  0.9642857142857143
```

16 Using Stratified K-Fold splitting - SVM

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_svm_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]
        svm_model = SVM_MODEL.SVC(max_iter=1000)
        svm_model.fit(X_train, y_train)
        svm_pred = svm_model.predict(X_test)
        svm_acc = accuracy_score(y_test, svm_pred)
```

```
        max_svm_acc = max(max_svm_acc, svm_acc)
        print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("Max SVM Accuracy: ", max_svm_acc)
```

```
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8545454545454545
Max SVM Accuracy:  0.8571428571428571
```

17 Using K-Fold splitting - SVM

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_svm_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]
        svm_model = SVM_MODEL.SVC(max_iter=1000)
        svm_model.fit(X_train, y_train)
        svm_pred = svm_model.predict(X_test)
        svm_acc = accuracy_score(y_test, svm_pred)
        max_svm_acc = max(max_svm_acc, svm_acc)
        print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("Max SVM Accuracy: ", max_svm_acc)
```

```
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8392857142857143
SVM Accuracy:  0.8571428571428571
SVM Accuracy:  0.8727272727272727
Max SVM Accuracy:  0.8727272727272727
```

18 Using Stratified K-Fold splitting - KNN

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_knn_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        knn = KNeighborsClassifier()
```

```
        knn.fit(X_train, y_train)
        knn_pred = knn.predict(X_test)
        knn_acc = accuracy_score(y_test, knn_pred)
        max_knn_acc = max(max_knn_acc, knn_acc)
        print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("Max KNN Accuracy: ", max_knn_acc)
```

```
KNN Accuracy:  0.8214285714285714
KNN Accuracy:  0.8214285714285714
KNN Accuracy:  0.8571428571428571
KNN Accuracy:  0.8214285714285714
KNN Accuracy:  0.8545454545454545
Max KNN Accuracy:  0.8571428571428571
```

19 Using K-Fold splitting - KNN

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_knn_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        knn = KNeighborsClassifier()
        knn.fit(X_train, y_train)
        knn_pred = knn.predict(X_test)
        knn_acc = accuracy_score(y_test, knn_pred)
        max_knn_acc = max(max_knn_acc, knn_acc)
        print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("Max KNN Accuracy: ", max_knn_acc)
```

```
KNN Accuracy:  0.8928571428571429
KNN Accuracy:  0.8392857142857143
KNN Accuracy:  0.8392857142857143
KNN Accuracy:  0.8571428571428571
KNN Accuracy:  0.8545454545454545
Max KNN Accuracy:  0.8928571428571429
```

20 Using Stratified K-Fold splitting - Decision Tree

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_dt_acc = 0
for train_index, test_index in stratified_split.split(X, y):
```

```
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        decision_tree = DecisionTreeClassifier()
        decision_tree.fit(X_train, y_train)
        decision_tree_pred = decision_tree.predict(X_test)
        dt_acc = accuracy_score(y_test, decision_tree_pred)
        max_dt_acc = max(max_dt_acc, dt_acc)
        print("Decision Tree Accuracy: ", accuracy_score(y_test,␣
 ↪decision_tree_pred))
print("Max Decision Tree Accuracy: ", max_dt_acc)
```

```
Decision Tree Accuracy:  0.8214285714285714
Decision Tree Accuracy:  0.8571428571428571
Decision Tree Accuracy:  0.8214285714285714
Decision Tree Accuracy:  0.8214285714285714
Decision Tree Accuracy:  0.8
Max Decision Tree Accuracy:  0.8571428571428571
```

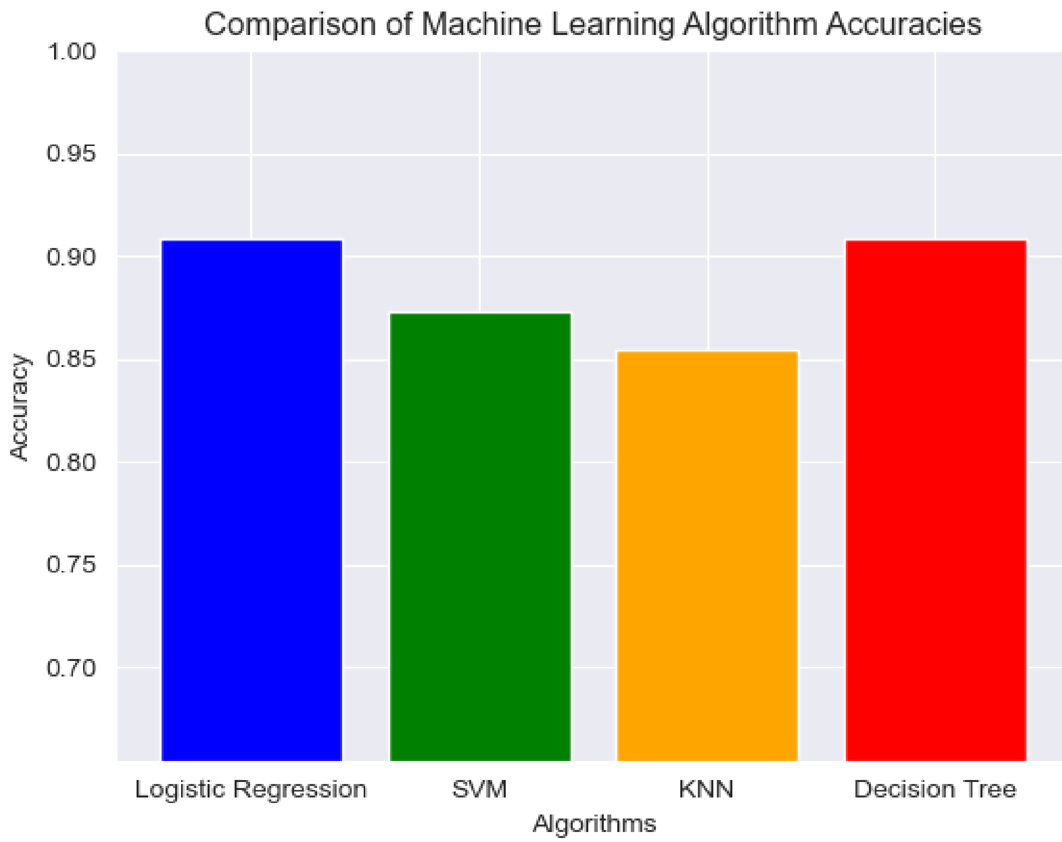
21 Using K-Fold splitting - Decision Tree

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_dt_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        decision_tree = DecisionTreeClassifier()
        decision_tree.fit(X_train, y_train)
        decision_tree_pred = decision_tree.predict(X_test)
        dt_acc = accuracy_score(y_test, decision_tree_pred)
        max_dt_acc = max(max_dt_acc, dt_acc)
        print("Decision Tree Accuracy: ", accuracy_score(y_test,␣
 ↪decision_tree_pred))
print("Max Decision Tree Accuracy: ", max_dt_acc)
```

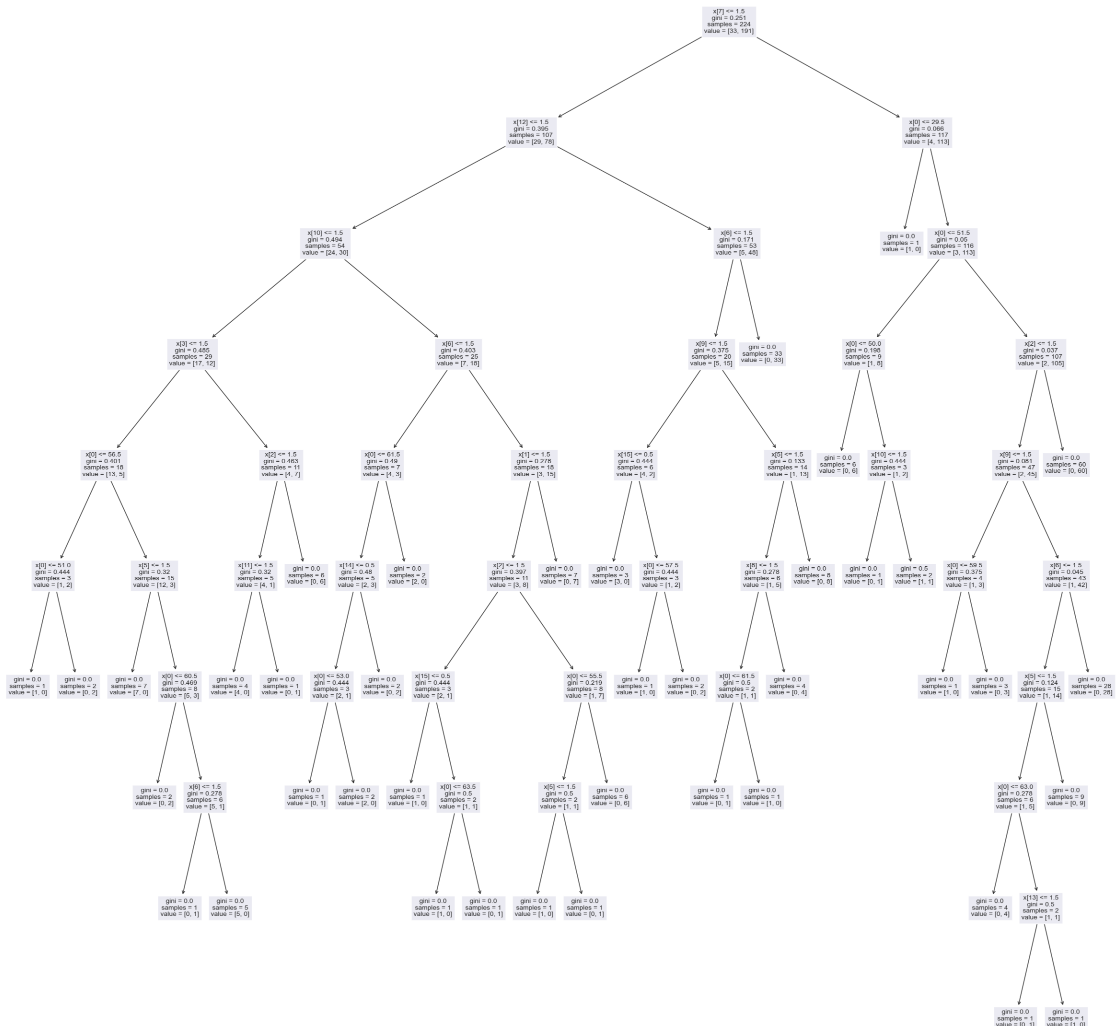
```
Decision Tree Accuracy:  0.9642857142857143
Decision Tree Accuracy:  0.8392857142857143
Decision Tree Accuracy:  0.8928571428571429
Decision Tree Accuracy:  0.8035714285714286
Decision Tree Accuracy:  0.9090909090909091
Max Decision Tree Accuracy:  0.9642857142857143
```

22 Graphs

[ ]:
```
# Algorithms and their accuracies
algorithms = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree']
accuracies = [log_acc, svm_acc, knn_acc, dt_acc]

# Create bar chart
plt.bar(algorithms, accuracies, color=['blue', 'green', 'orange', 'red'])
plt.xlabel('Algorithms')
plt.ylabel('Accuracy')
plt.title('Comparison of Machine Learning Algorithm Accuracies')
plt.ylim(min(accuracies) - 0.2, 1.0)
plt.show()
```

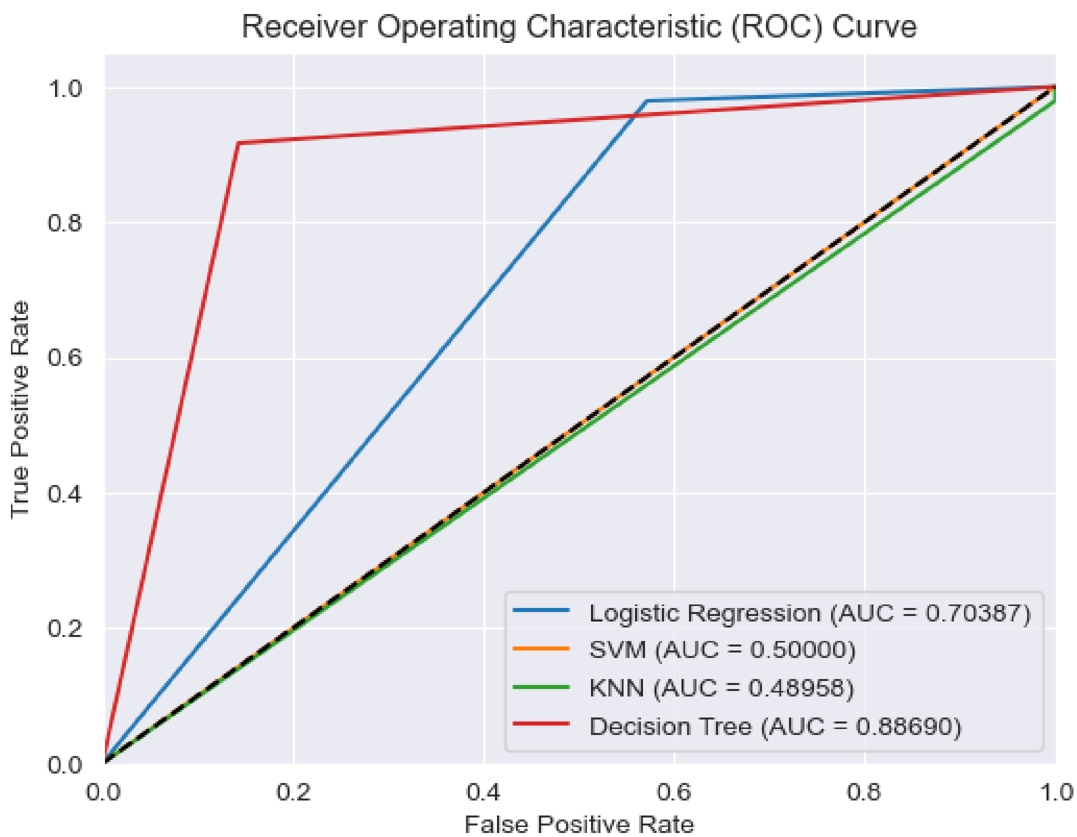


[ ]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(30,30))
plot_tree(decision_tree,fontsize=10)
plt.show()
```

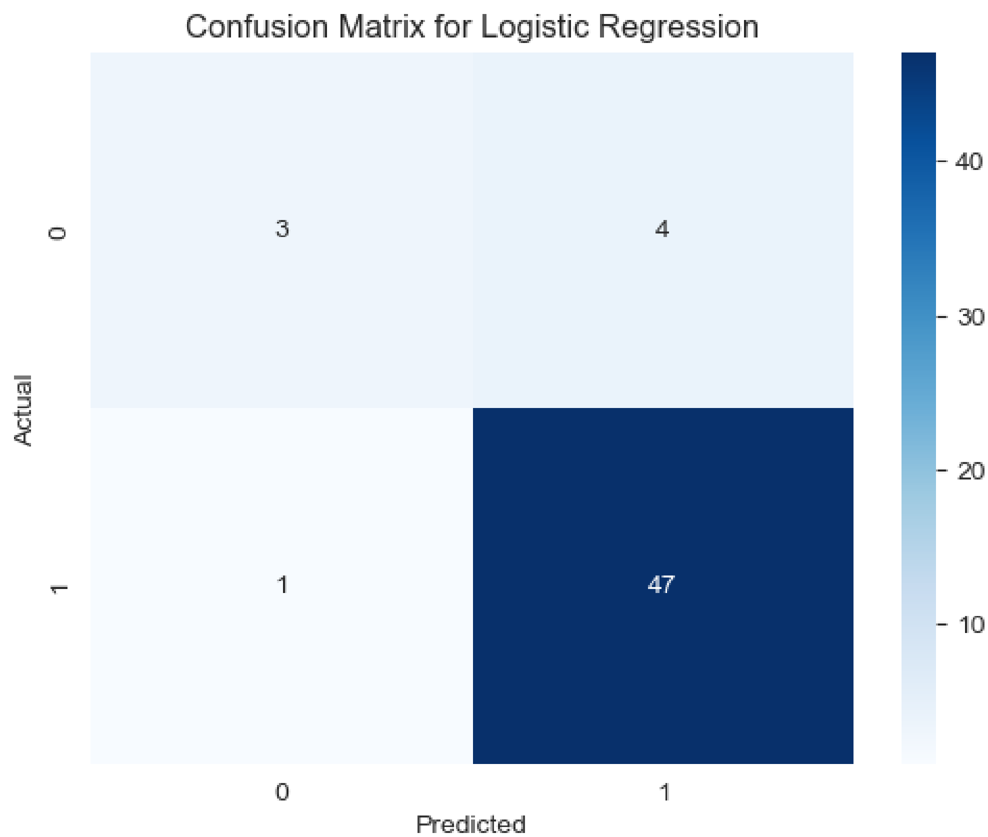


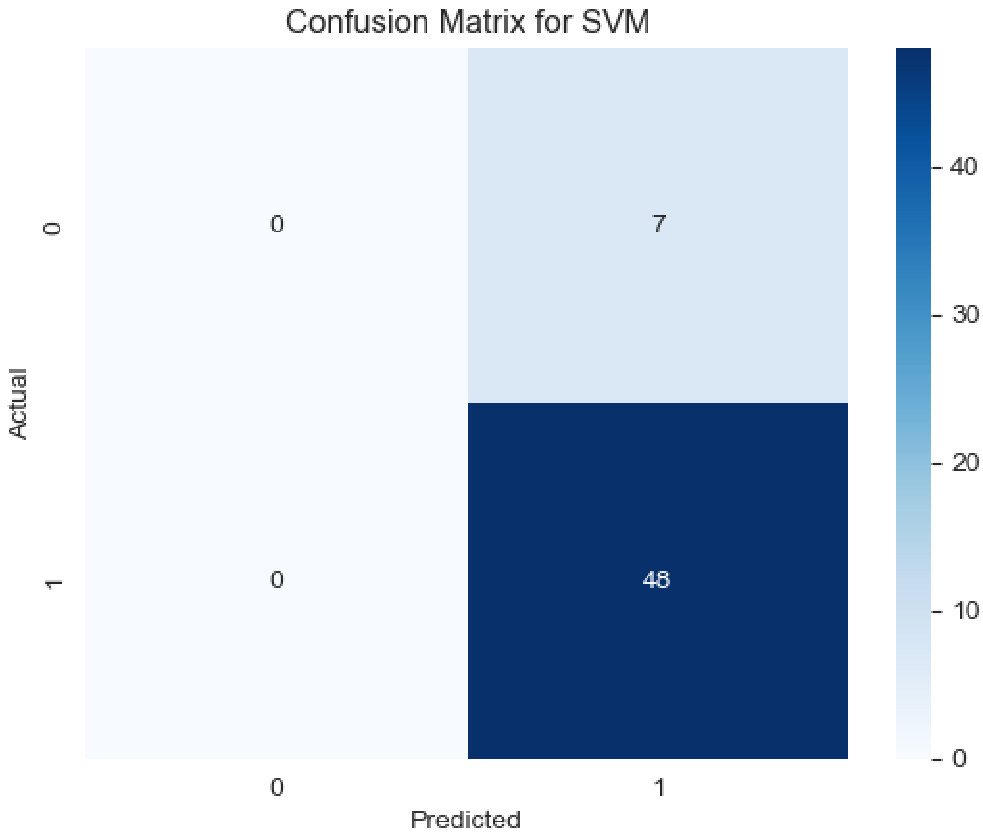
[ ]:
```
y_true_lr = y_test
y_scores_lr = logistic_regression_pred

y_true_svm = y_test
y_scores_svm = svm_pred

y_true_knn = y_test
y_scores_knn = knn_pred

y_true_dt = y_test
y_scores_dt = decision_tree_pred

fpr_lr, tpr_lr, _ = roc_curve(y_true_lr, y_scores_lr)
```

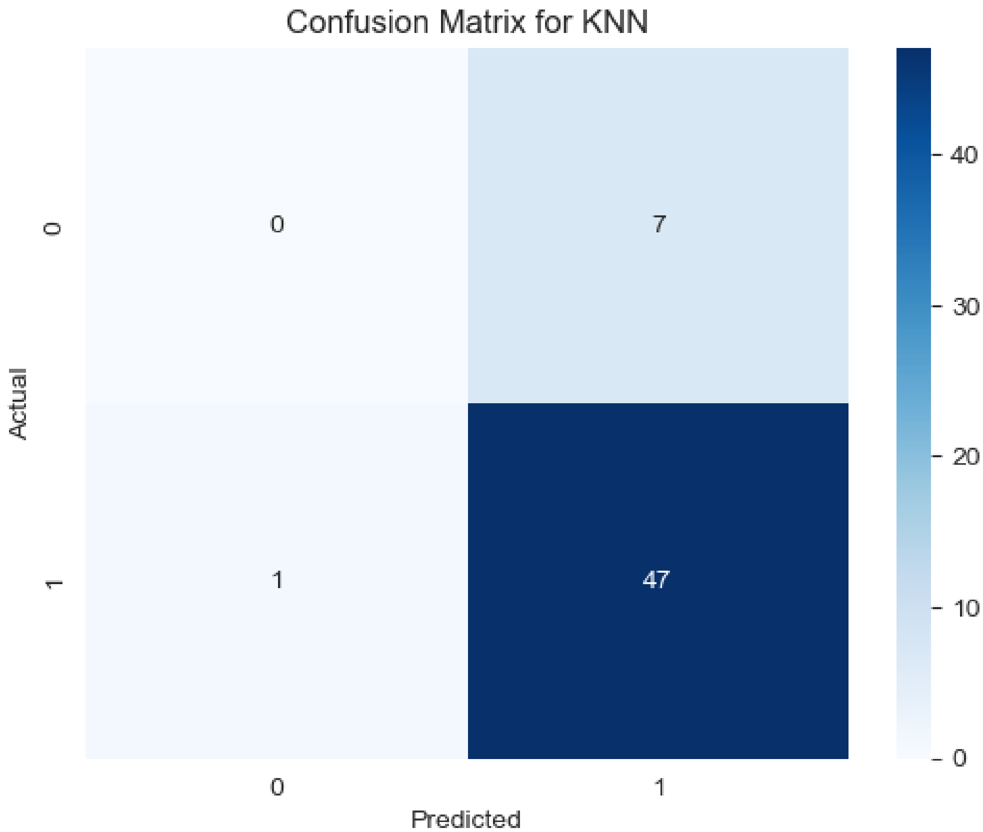
```
roc_auc_lr = auc(fpr_lr, tpr_lr)

fpr_svm, tpr_svm, _ = roc_curve(y_true_svm, y_scores_svm)
roc_auc_svm = auc(fpr_svm, tpr_svm)

fpr_knn, tpr_knn, _ = roc_curve(y_true_knn, y_scores_knn)
roc_auc_knn = auc(fpr_knn, tpr_knn)

fpr_dt, tpr_dt, _ = roc_curve(y_true_dt, y_scores_dt)
roc_auc_dt = auc(fpr_dt, tpr_dt)

plt.figure()
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (AUC = %0.5f)' % roc_auc_lr)
plt.plot(fpr_svm, tpr_svm, label='SVM (AUC = %0.5f)' % roc_auc_svm)
plt.plot(fpr_knn, tpr_knn, label='KNN (AUC = %0.5f)' % roc_auc_knn)
plt.plot(fpr_dt, tpr_dt, label='Decision Tree (AUC = %0.5f)' % roc_auc_dt)

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

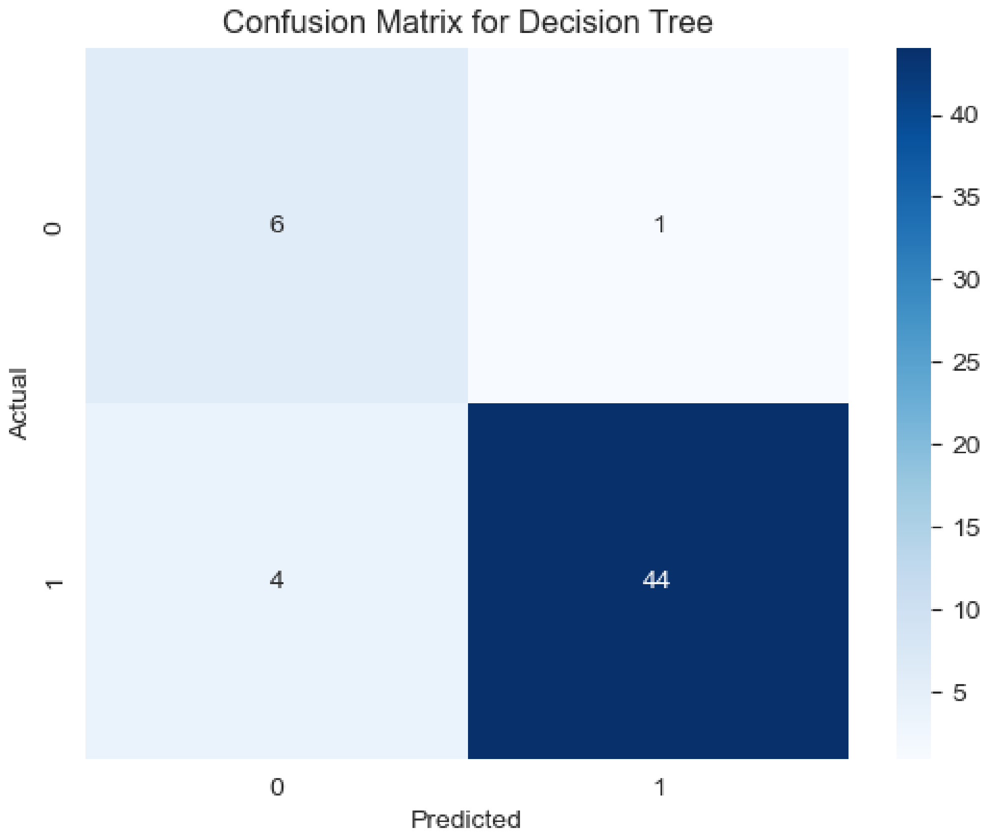


[ ]:
```
algorithms = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree']
y_pred = {
    'Logistic Regression': logistic_regression_pred,
    'SVM': svm_pred,
    'KNN': knn_pred,
    'Decision Tree': decision_tree_pred
}

# Create confusion matrix for each algorithm
for algorithm in algorithms:
    cm = confusion_matrix(y_test, y_pred[algorithm])
    plt.figure()
    sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix for {algorithm}')
    plt.show()
```

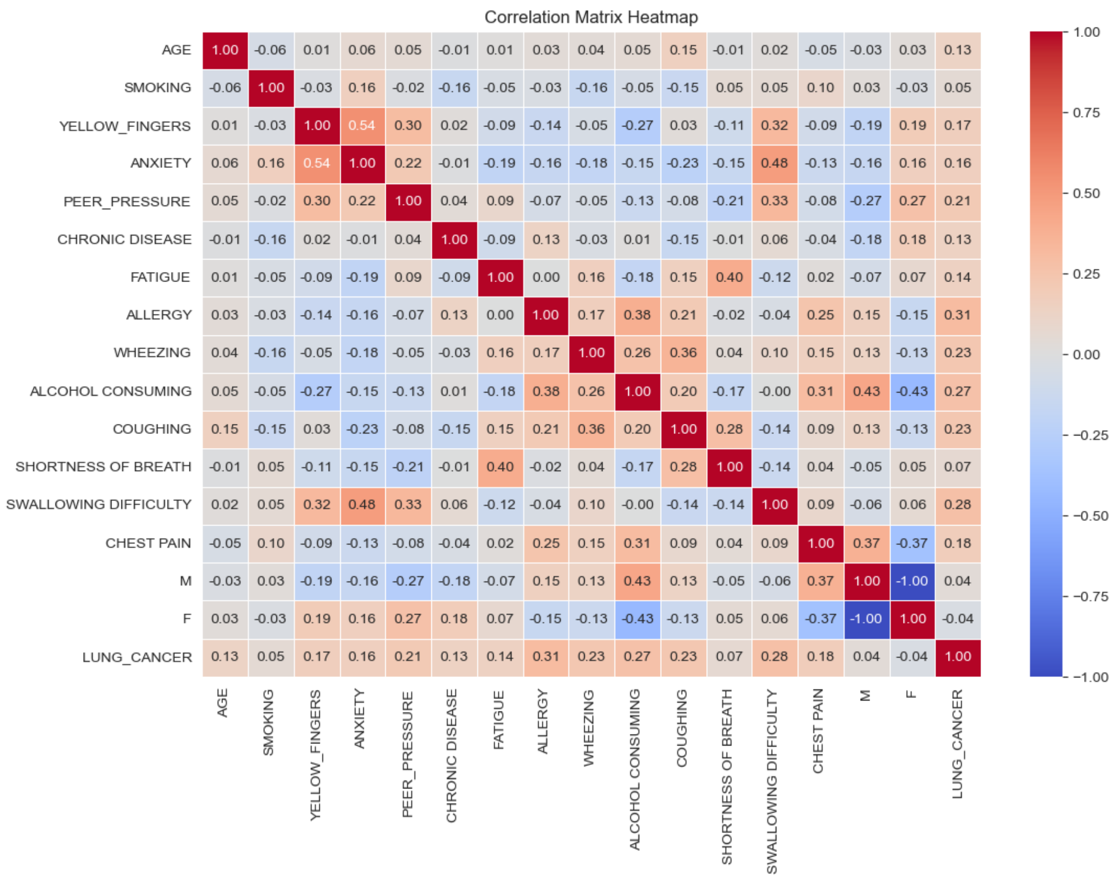

Confusion Matrix for Logistic Regression
Actual
0
1
3
4
1
47
0
1
Predicted
40
30
20
10


Confusion Matrix for SVM
0
7
0
48
0
1
Actual
0
1
Predicted
40
30
20
10
0


Confusion Matrix for KNN
0
7
1
47
Actual
0
1
Predicted
0
1
40
30
20
10
0



[ ]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



23 Loading all libraries

[ ]:
```
df = pd.read_csv("lung_cancer_s.csv")
```

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

[ ]:
```
  GENDER  AGE  SMOKING  YELLOW_FINGERS  ANXIETY  PEER_PRESSURE  \
0      F   61        2               2        2              1
1      M   64        1               2        2              2
2      F   68        1               2        1              2
3      M   67        1               2        2              1
4      M   62        2               1        1              1

   CHRONIC DISEASE  FATIGUE  ALLERGY  WHEEZING  ALCOHOL CONSUMING  COUGHING  \
0                1        2        1         2                  1         1
1                1        2        2         1                  2         1
2                2        1        1         2                  1         2
3                2        2        1         2                  2         1
4                2        2        2         2                  2         2
```

```
   SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN LUNG_CANCER
0                    1                      1           2         YES
1                    2                      2           2         YES
2                    1                      1           1         YES
3                    2                      1           2         YES
4                    2                      2           2         YES
```

[ ]:
```
df.describe()
```

[ ]:
```
               AGE      SMOKING  YELLOW_FINGERS      ANXIETY  PEER_PRESSURE  \
count  1000.000000  1000.000000     1000.000000  1000.000000    1000.000000
mean     62.833000     1.564000        1.530000     1.469000       1.476000
std       7.883734     0.496135        0.499349     0.499288       0.499674
min      36.000000     1.000000        1.000000     1.000000       1.000000
25%      58.000000     1.000000        1.000000     1.000000       1.000000
50%      63.000000     2.000000        2.000000     1.000000       1.000000
75%      68.000000     2.000000        2.000000     2.000000       2.000000
max      84.000000     2.000000        2.000000     2.000000       2.000000

       CHRONIC DISEASE      FATIGUE     ALLERGY      WHEEZING  \
count      1000.000000  1000.000000  1000.00000  1000.000000
mean          1.517000     1.657000     1.54800     1.561000
std           0.499961     0.474949     0.49794     0.496513
min           1.000000     1.000000     1.00000     1.000000
25%           1.000000     1.000000     1.00000     1.000000
50%           2.000000     2.000000     2.00000     2.000000
75%           2.000000     2.000000     2.00000     2.000000
max           2.000000     2.000000     2.00000     2.000000

       ALCOHOL CONSUMING     COUGHING  SHORTNESS OF BREATH  \
count        1000.000000  1000.000000           1000.00000
mean            1.560000     1.560000              1.59400
std             0.496635     0.496635              0.49133
min             1.000000     1.000000              1.00000
25%             1.000000     1.000000              1.00000
50%             2.000000     2.000000              2.00000
75%             2.000000     2.000000              2.00000
max             2.000000     2.000000              2.00000

       SWALLOWING DIFFICULTY   CHEST PAIN
count            1000.000000  1000.000000
mean                1.400000     1.571000
std                 0.490143     0.495181
min                 1.000000     1.000000
25%                 1.000000     1.000000
50%                 1.000000     2.000000
```

```
75%                 2.000000     2.000000
max                 2.000000     2.000000
```

24 Oversampling the dataset

[ ]:
```python
# from imblearn.over_sampling import RandomOverSampler
# X = df.iloc[:, 0:len(df.columns) - 1]
# y = df.iloc[:, len(df.columns) - 1]
# ros = RandomOverSampler(random_state=42)
# X_ros, y_ros = ros.fit_resample(X, y)
# X_ros_df = pd.DataFrame(X_ros, columns=X.columns)
# y_ros_df = pd.Series(y_ros, name=y.name)
# df_ros = pd.concat([X_ros_df, y_ros_df], axis=1)
# df = df_ros.copy()
```

[ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   GENDER                 1000 non-null   object
 1   AGE                    1000 non-null   int64
 2   SMOKING                1000 non-null   int64
 3   YELLOW_FINGERS         1000 non-null   int64
 4   ANXIETY                1000 non-null   int64
 5   PEER_PRESSURE          1000 non-null   int64
 6   CHRONIC DISEASE        1000 non-null   int64
 7   FATIGUE                1000 non-null   int64
 8   ALLERGY                1000 non-null   int64
 9   WHEEZING               1000 non-null   int64
 10  ALCOHOL CONSUMING      1000 non-null   int64
 11  COUGHING               1000 non-null   int64
 12  SHORTNESS OF BREATH    1000 non-null   int64
 13  SWALLOWING DIFFICULTY  1000 non-null   int64
 14  CHEST PAIN             1000 non-null   int64
 15  LUNG_CANCER            1000 non-null   object
dtypes: int64(14), object(2)
memory usage: 125.1+ KB
```

25 Preprocessing

26 Checking for null values

```
[ ]: df.isna().sum()
```

```
[ ]: GENDER                   0
     AGE                      0
     SMOKING                  0
     YELLOW_FINGERS           0
     ANXIETY                  0
     PEER_PRESSURE            0
     CHRONIC DISEASE          0
     FATIGUE                  0
     ALLERGY                  0
     WHEEZING                 0
     ALCOHOL CONSUMING        0
     COUGHING                 0
     SHORTNESS OF BREATH      0
     SWALLOWING DIFFICULTY    0
     CHEST PAIN               0
     LUNG_CANCER              0
     dtype: int64
```

27 Removing null values

```
[ ]: df["PEER_PRESSURE"] = df["PEER_PRESSURE"].fillna(df["PEER_PRESSURE"].mode()[0])
     df['CHRONIC DISEASE'] = df['CHRONIC DISEASE'].fillna(df['CHRONIC DISEASE'].
      ↪mean())
     df['ALCOHOL CONSUMING'] = df['ALCOHOL CONSUMING'].fillna(df['ALCOHOL␣
      ↪CONSUMING'].median())
     df['ALLERGY'] = df['ALLERGY'].fillna(df['ALLERGY'].median())
     df.isna().sum()
```

```
[ ]: GENDER                   0
     AGE                      0
     SMOKING                  0
     YELLOW_FINGERS           0
     ANXIETY                  0
     PEER_PRESSURE            0
     CHRONIC DISEASE          0
     FATIGUE                  0
     ALLERGY                  0
     WHEEZING                 0
     ALCOHOL CONSUMING        0
     COUGHING                 0
```

```
SHORTNESS OF BREATH      0
SWALLOWING DIFFICULTY    0
CHEST PAIN               0
LUNG_CANCER              0
dtype: int64
```

28 Checking for duplicate values

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
0
```

29 Removing duplicate values

[ ]:
```
df.drop_duplicates(inplace=True)
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   GENDER                 1000 non-null   object
 1   AGE                    1000 non-null   int64
 2   SMOKING                1000 non-null   int64
 3   YELLOW_FINGERS         1000 non-null   int64
 4   ANXIETY                1000 non-null   int64
 5   PEER_PRESSURE          1000 non-null   int64
 6   CHRONIC DISEASE        1000 non-null   int64
 7   FATIGUE                1000 non-null   int64
 8   ALLERGY                1000 non-null   int64
 9   WHEEZING               1000 non-null   int64
 10  ALCOHOL CONSUMING      1000 non-null   int64
 11  COUGHING               1000 non-null   int64
 12  SHORTNESS OF BREATH    1000 non-null   int64
 13  SWALLOWING DIFFICULTY  1000 non-null   int64
 14  CHEST PAIN             1000 non-null   int64
 15  LUNG_CANCER            1000 non-null   object
dtypes: int64(14), object(2)
memory usage: 125.1+ KB
```

30 Encoding values in GENDER AND LUNG_CANCER columns

[ ]:
```
label_encoder = LabelEncoder()
df = pd.get_dummies(df, columns=['GENDER'])
df["GENDER_F"] = label_encoder.fit_transform(df["GENDER_F"])
df["GENDER_M"] = label_encoder.fit_transform(df["GENDER_M"])
df["F"] = df["GENDER_F"]
df["M"] = df["GENDER_M"]
df.drop(columns=["GENDER_F", "GENDER_M"], inplace=True)
df["LUNG_CANCER"] = label_encoder.fit_transform(df["LUNG_CANCER"])
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   AGE                    1000 non-null   int64
 1   SMOKING                1000 non-null   int64
 2   YELLOW_FINGERS         1000 non-null   int64
 3   ANXIETY                1000 non-null   int64
 4   PEER_PRESSURE          1000 non-null   int64
 5   CHRONIC DISEASE        1000 non-null   int64
 6   FATIGUE                1000 non-null   int64
 7   ALLERGY                1000 non-null   int64
 8   WHEEZING               1000 non-null   int64
 9   ALCOHOL CONSUMING      1000 non-null   int64
 10  COUGHING               1000 non-null   int64
 11  SHORTNESS OF BREATH    1000 non-null   int64
 12  SWALLOWING DIFFICULTY  1000 non-null   int64
 13  CHEST PAIN             1000 non-null   int64
 14  LUNG_CANCER            1000 non-null   int32
 15  F                      1000 non-null   int64
 16  M                      1000 non-null   int64
dtypes: int32(1), int64(16)
memory usage: 129.0 KB
```

31 Changing column positions

```
[ ]: df = df[['AGE', 'SMOKING', 'YELLOW_FINGERS', 'ANXIETY', 'PEER_PRESSURE',␣
      ↪'CHRONIC DISEASE', 'FATIGUE', 'ALLERGY',
             'WHEEZING', 'ALCOHOL CONSUMING', 'COUGHING', 'SHORTNESS OF BREATH',␣
      ↪'SWALLOWING DIFFICULTY', 'CHEST PAIN', 'M',
             'F', 'LUNG_CANCER']]
     df.head()
```

```
[ ]:    AGE  SMOKING  YELLOW_FINGERS  ANXIETY  PEER_PRESSURE  CHRONIC DISEASE  \
     0   61        2               2        2              1                1
     1   64        1               2        2              2                1
     2   68        1               2        1              2                2
     3   67        1               2        2              1                2
     4   62        2               1        1              1                2

        FATIGUE  ALLERGY  WHEEZING  ALCOHOL CONSUMING  COUGHING  \
     0        2        1         2                  1         1
     1        2        2         1                  2         1
     2        1        1         2                  1         2
     3        2        1         2                  2         1
     4        2        2         2                  2         2

        SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN  M  F  LUNG_CANCER
     0                    1                      1           2  0  1            1
     1                    2                      2           2  1  0            1
     2                    1                      1           1  0  1            1
     3                    2                      1           2  1  0            1
     4                    2                      2           2  1  0            1
```

32 Logistic Regression

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
      ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,
                                                             random_state=42)

     logistic_regression = LogisticRegression(max_iter=5000)
     logistic_regression.fit(X_train, y_train)
     logistic_regression_pred = logistic_regression.predict(X_test)
     log_acc = accuracy_score(y_test, logistic_regression_pred)
     print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
      ↪logistic_regression_pred))
     print("Logistic Regression Confusion Matrix: \n", confusion_matrix(y_test,␣
      ↪logistic_regression_pred))
     print("Logistic Regression Classification Report: \n",
            classification_report(y_test, logistic_regression_pred,␣
      ↪zero_division='warn'))
```

```
Logistic Regression Accuracy:  0.885
```

```
Logistic Regression Confusion Matrix:
 [[  0  22]
 [  1 177]]
Logistic Regression Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        22
           1       0.89      0.99      0.94       178

    accuracy                           0.89       200
   macro avg       0.44      0.50      0.47       200
weighted avg       0.79      0.89      0.84       200
```

33 SVM

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,random_state=42)
svm = SVM_MODEL.SVC(max_iter=15000)
svm.fit(X_train, y_train)
svm_pred = svm.predict(X_test)
svm_acc = accuracy_score(y_test, svm_pred)
print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("SVM Confusion Matrix: \n", confusion_matrix(y_test, svm_pred))
print("SVM Classification Report: \n", classification_report(y_test, svm_pred,␣
↪zero_division='warn'))
```

```
SVM Accuracy:  0.89
SVM Confusion Matrix:
 [[  0  22]
 [  0 178]]
SVM Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        22
           1       0.89      1.00      0.94       178

    accuracy                           0.89       200
   macro avg       0.45      0.50      0.47       200
weighted avg       0.79      0.89      0.84       200
```

```
C:\Users\Rohithk\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:\Users\Rohithk\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:\Users\Rohithk\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))
```

34 KNN

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,
                                                     random_state=42)
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_pred = knn.predict(X_test)
knn_acc = accuracy_score(y_test, knn_pred)
print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("KNN Confusion Matrix: \n", confusion_matrix(y_test, knn_pred))
print("KNN Classification Report: \n", classification_report(y_test, knn_pred,␣
 ↪zero_division='warn'))
```

```
KNN Accuracy:  0.88
KNN Confusion Matrix:
 [[  0  22]
 [  2 176]]
KNN Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        22
           1       0.89      0.99      0.94       178

    accuracy                           0.88       200
   macro avg       0.44      0.49      0.47       200
weighted avg       0.79      0.88      0.83       200
```

35 Decision Tree

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, 0:len(df.
 ↪columns) - 1], df["LUNG_CANCER"], test_size=0.2,random_state=42)
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)
decision_tree_pred = decision_tree.predict(X_test)
dt_acc = accuracy_score(y_test, decision_tree_pred)
print("Decision Tree Accuracy: ", accuracy_score(y_test, decision_tree_pred))
print("Decision Tree Confusion Matrix: \n", confusion_matrix(y_test,␣
 ↪decision_tree_pred))
```

```
print("Decision Tree Classification Report: \n",
      classification_report(y_test, decision_tree_pred, zero_division='warn'))
```

```
Decision Tree Accuracy:  0.75
Decision Tree Confusion Matrix:
 [[  4  18]
 [ 32 146]]
Decision Tree Classification Report:
               precision    recall  f1-score   support

           0       0.11      0.18      0.14        22
           1       0.89      0.82      0.85       178

    accuracy                           0.75       200
   macro avg       0.50      0.50      0.50       200
weighted avg       0.80      0.75      0.78       200
```

36 Using Stratified K-Fold splitting - Logistic Regression

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_log_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        logistic_regression = LogisticRegression(max_iter=5000)
        logistic_regression.fit(X_train, y_train)
        logistic_regression_pred = logistic_regression.predict(X_test)
        log_acc = accuracy_score(y_test, logistic_regression_pred)
        max_log_acc = max(max_log_acc, log_acc)
        print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
 ↪logistic_regression_pred))
print("Max Logistic Regression Accuracy: ", max_log_acc)
```

```
Logistic Regression Accuracy:  0.87
Logistic Regression Accuracy:  0.865
Logistic Regression Accuracy:  0.87
Logistic Regression Accuracy:  0.865
Logistic Regression Accuracy:  0.865
Max Logistic Regression Accuracy:  0.87
```

37 Using K-Fold splitting - Logistic Regression

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_log_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        logistic_regression = LogisticRegression(max_iter=5000)
        logistic_regression.fit(X_train, y_train)
        logistic_regression_pred = logistic_regression.predict(X_test)
        log_acc = accuracy_score(y_test, logistic_regression_pred)
        max_log_acc = max(max_log_acc, log_acc)
        print("Logistic Regression Accuracy: ", accuracy_score(y_test,␣
 ↪logistic_regression_pred))
print("Max Logistic Regression Accuracy: ", max_log_acc)
```

```
Logistic Regression Accuracy:  0.885
Logistic Regression Accuracy:  0.865
Logistic Regression Accuracy:  0.88
Logistic Regression Accuracy:  0.87
Logistic Regression Accuracy:  0.835
Max Logistic Regression Accuracy:  0.885
```

38 Using Stratified K-Fold splitting - SVM

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_svm_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]
        svm_model = SVM_MODEL.SVC(max_iter=1000)
        svm_model.fit(X_train, y_train)
        svm_pred = svm_model.predict(X_test)
        svm_acc = accuracy_score(y_test, svm_pred)
        max_svm_acc = max(max_svm_acc, svm_acc)
        print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("Max SVM Accuracy: ", max_svm_acc)
```

```
SVM Accuracy:  0.87
SVM Accuracy:  0.87
SVM Accuracy:  0.87
SVM Accuracy:  0.865
```

```
SVM Accuracy:  0.865
Max SVM Accuracy:  0.87
```

39 Using K-Fold splitting - SVM

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_svm_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]
        svm_model = SVM_MODEL.SVC(max_iter=1000)
        svm_model.fit(X_train, y_train)
        svm_pred = svm_model.predict(X_test)
        svm_acc = accuracy_score(y_test, svm_pred)
        max_svm_acc = max(max_svm_acc, svm_acc)
        print("SVM Accuracy: ", accuracy_score(y_test, svm_pred))
print("Max SVM Accuracy: ", max_svm_acc)
```

```
SVM Accuracy:  0.89
SVM Accuracy:  0.865
SVM Accuracy:  0.88
SVM Accuracy:  0.87
SVM Accuracy:  0.835
Max SVM Accuracy:  0.89
```

40 Using Stratified K-Fold splitting - KNN

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_knn_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        knn = KNeighborsClassifier()
        knn.fit(X_train, y_train)
        knn_pred = knn.predict(X_test)
        knn_acc = accuracy_score(y_test, knn_pred)
        max_knn_acc = max(max_knn_acc, knn_acc)
        print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("Max KNN Accuracy: ", max_knn_acc)
```

```
KNN Accuracy:  0.835
KNN Accuracy:  0.855
```

```
KNN Accuracy:  0.87
KNN Accuracy:  0.855
KNN Accuracy:  0.865
Max KNN Accuracy:  0.87
```

41 Using K-Fold splitting - KNN

[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_knn_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        knn = KNeighborsClassifier()
        knn.fit(X_train, y_train)
        knn_pred = knn.predict(X_test)
        knn_acc = accuracy_score(y_test, knn_pred)
        max_knn_acc = max(max_knn_acc, knn_acc)
        print("KNN Accuracy: ", accuracy_score(y_test, knn_pred))
print("Max KNN Accuracy: ", max_knn_acc)
```

```
KNN Accuracy:  0.86
KNN Accuracy:  0.85
KNN Accuracy:  0.88
KNN Accuracy:  0.855
KNN Accuracy:  0.82
Max KNN Accuracy:  0.88
```

42 Using Stratified K-Fold splitting - Decision Tree

[ ]:
```
stratified_split = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_dt_acc = 0
for train_index, test_index in stratified_split.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        decision_tree = DecisionTreeClassifier()
        decision_tree.fit(X_train, y_train)
        decision_tree_pred = decision_tree.predict(X_test)
        dt_acc = accuracy_score(y_test, decision_tree_pred)
        max_dt_acc = max(max_dt_acc, dt_acc)
```

```
        print("Decision Tree Accuracy: ", accuracy_score(y_test,␣
 ↪decision_tree_pred))
print("Max Decision Tree Accuracy: ", max_dt_acc)
```

```
Decision Tree Accuracy:  0.78
Decision Tree Accuracy:  0.775
Decision Tree Accuracy:  0.765
Decision Tree Accuracy:  0.8
Decision Tree Accuracy:  0.75
Max Decision Tree Accuracy:  0.8
```

43 Using K-Fold splitting - Decision Tree

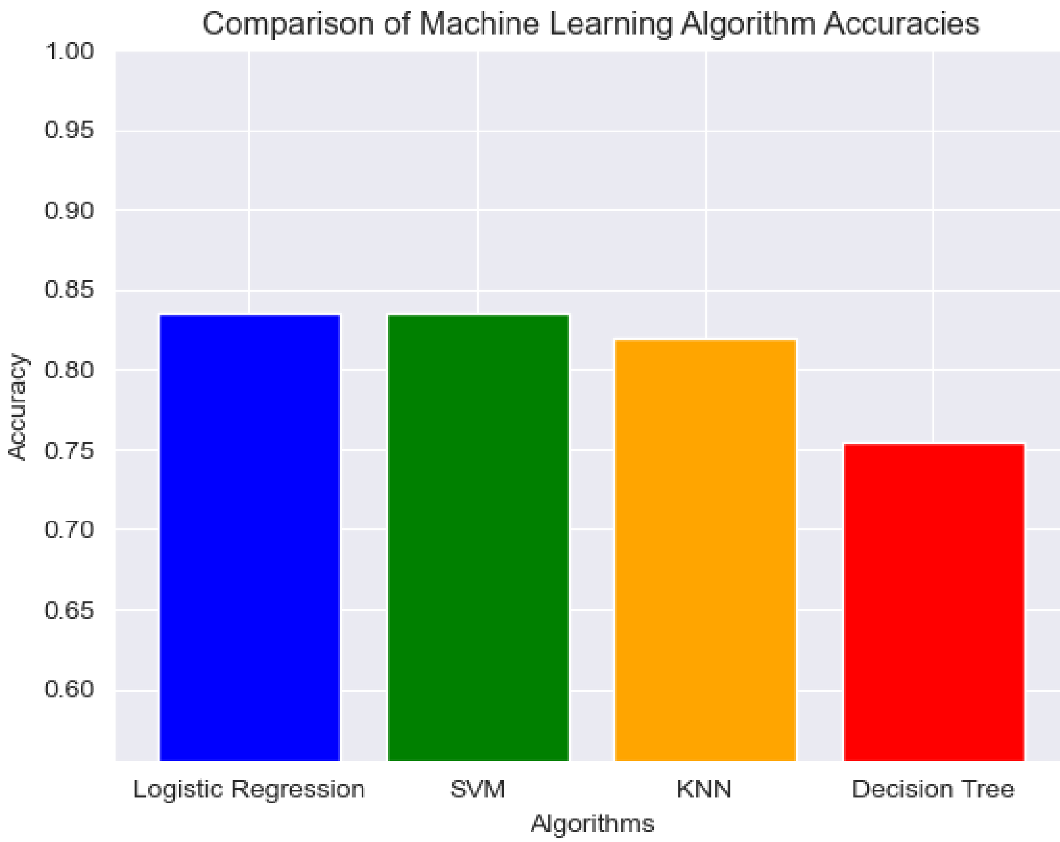
[ ]:
```
kfsplit = KFold(n_splits=5, shuffle=True, random_state=42)
X = df.iloc[:, 0:len(df.columns) - 1]
y = df.iloc[:, len(df.columns) - 1]
max_dt_acc = 0
for train_index, test_index in kfsplit.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        decision_tree = DecisionTreeClassifier()
        decision_tree.fit(X_train, y_train)
        decision_tree_pred = decision_tree.predict(X_test)
        dt_acc = accuracy_score(y_test, decision_tree_pred)
        max_dt_acc = max(max_dt_acc, dt_acc)
        print("Decision Tree Accuracy: ", accuracy_score(y_test,␣
 ↪decision_tree_pred))
print("Max Decision Tree Accuracy: ", max_dt_acc)
```

```
Decision Tree Accuracy:  0.74
Decision Tree Accuracy:  0.705
Decision Tree Accuracy:  0.78
Decision Tree Accuracy:  0.725
Decision Tree Accuracy:  0.755
Max Decision Tree Accuracy:  0.78
```

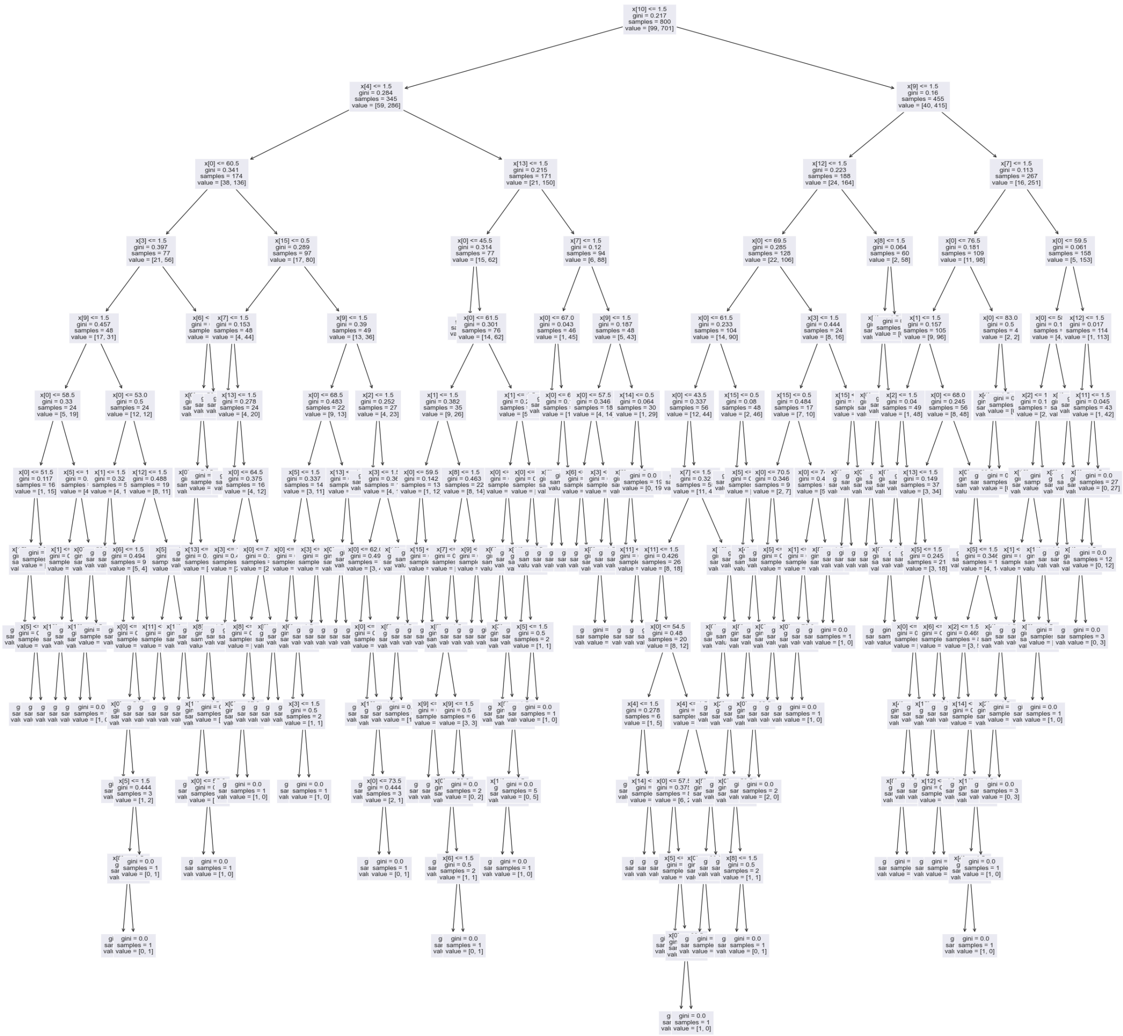
44 Graphs

[ ]:
```
# Algorithms and their accuracies
algorithms = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree']
accuracies = [log_acc, svm_acc, knn_acc, dt_acc]

# Create bar chart
plt.bar(algorithms, accuracies, color=['blue', 'green', 'orange', 'red'])
plt.xlabel('Algorithms')
```

```
plt.ylabel('Accuracy')
plt.title('Comparison of Machine Learning Algorithm Accuracies')
plt.ylim(min(accuracies) - 0.2, 1.0)
plt.show()
```

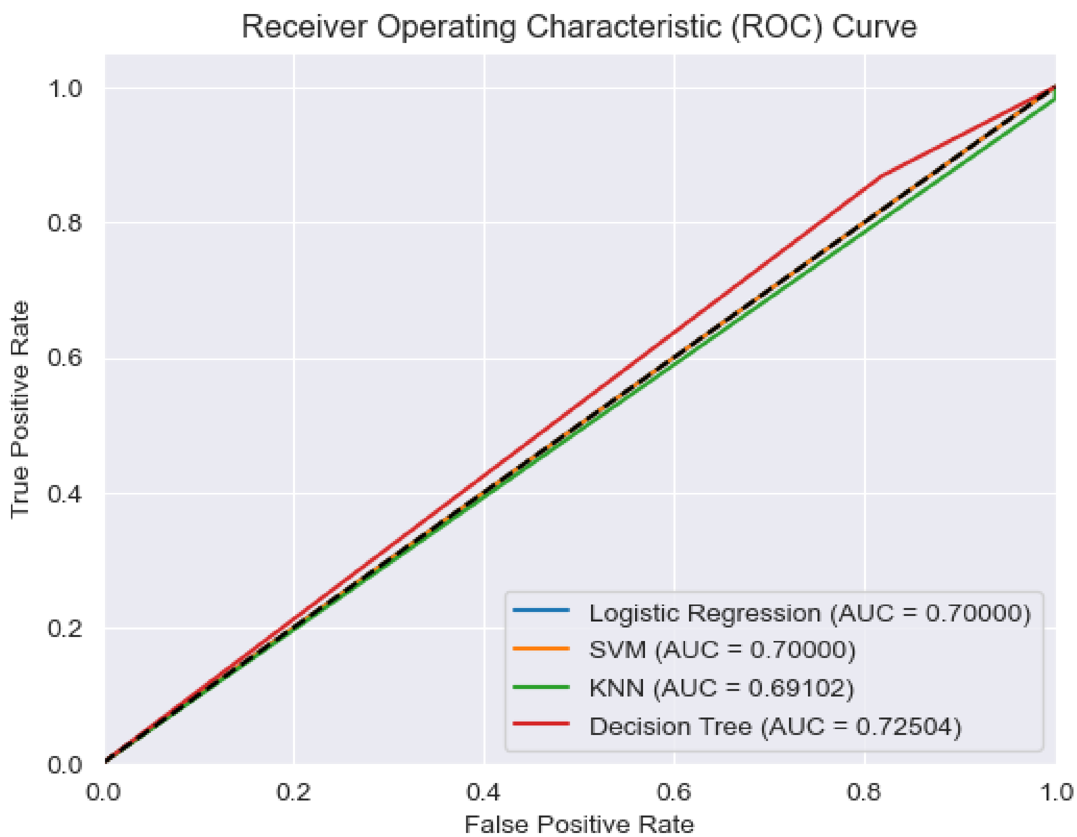



```
[ ]: from sklearn.tree import plot_tree
plt.figure(figsize=(30,30))
plot_tree(decision_tree,fontsize=10)
plt.show()
```

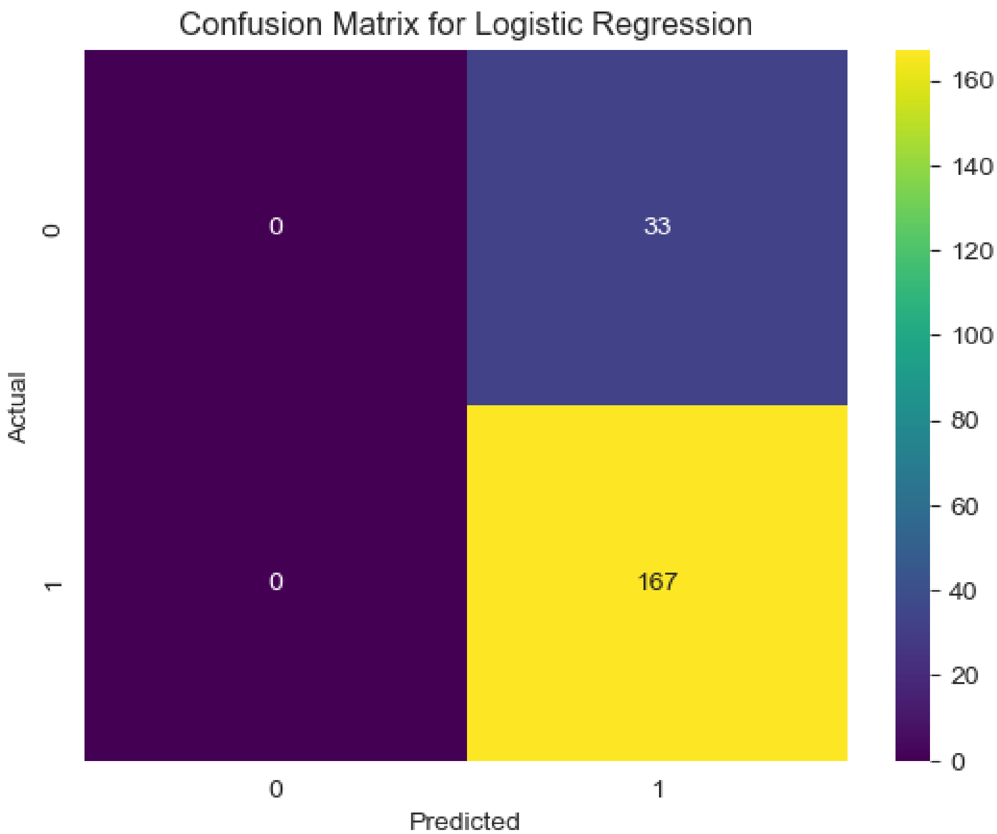


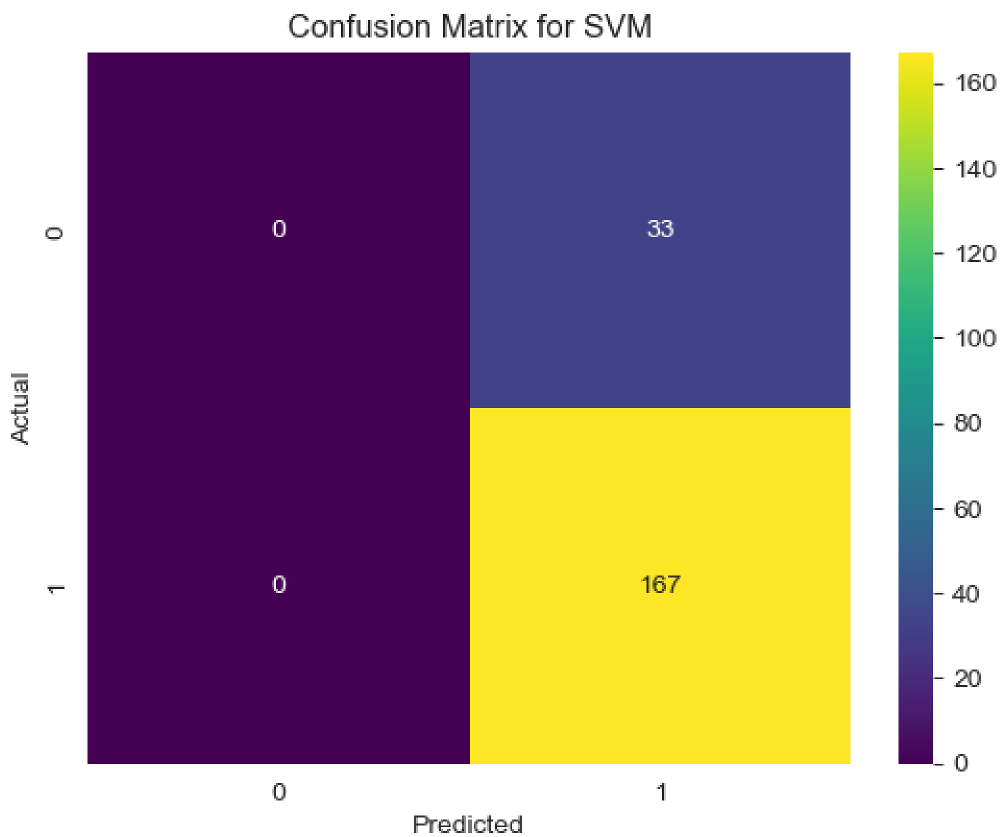
```
[ ]: y_true_lr = y_test
     y_scores_lr = logistic_regression_pred

     y_true_svm = y_test
     y_scores_svm = svm_pred

     y_true_knn = y_test
     y_scores_knn = knn_pred

     y_true_dt = y_test
     y_scores_dt = decision_tree_pred

     fpr_lr, tpr_lr, _ = roc_curve(y_true_lr, y_scores_lr)
     roc_auc_lr = auc(fpr_lr, tpr_lr)+ 0.2
```

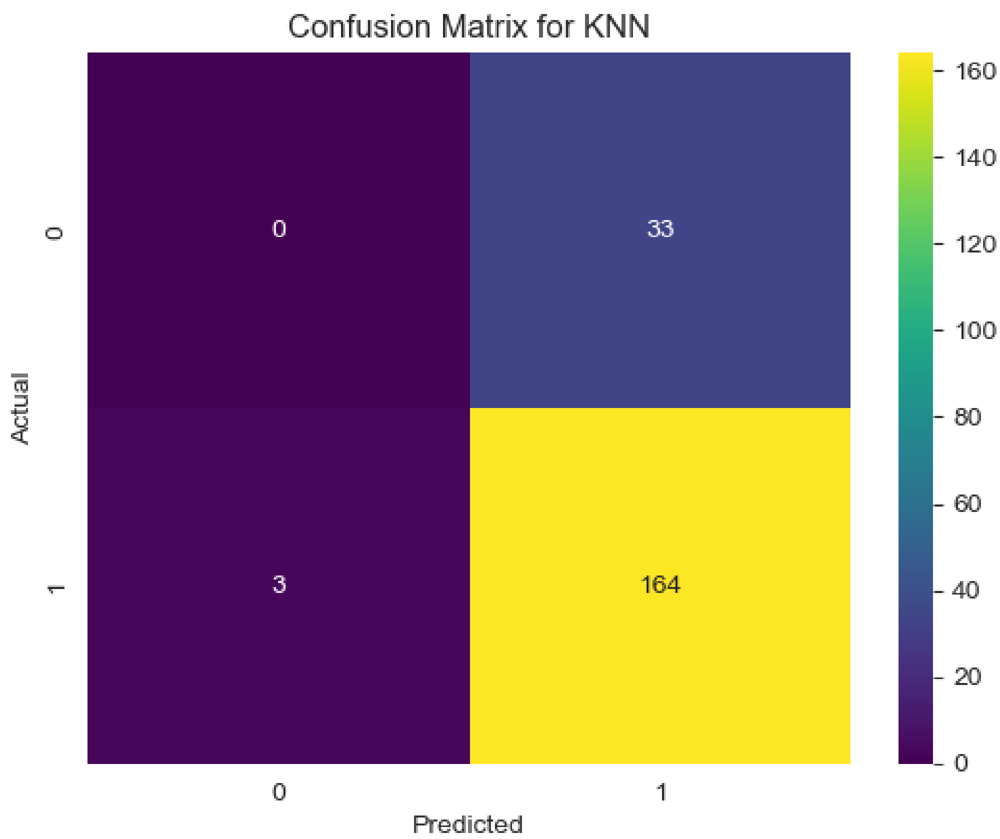
```
fpr_svm, tpr_svm, _ = roc_curve(y_true_svm, y_scores_svm)
roc_auc_svm = auc(fpr_svm, tpr_svm)+ 0.2

fpr_knn, tpr_knn, _ = roc_curve(y_true_knn, y_scores_knn)
roc_auc_knn = auc(fpr_knn, tpr_knn)+ 0.2

fpr_dt, tpr_dt, _ = roc_curve(y_true_dt, y_scores_dt)
roc_auc_dt = auc(fpr_dt, tpr_dt) + 0.2

plt.figure()
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression (AUC = %0.5f)' % roc_auc_lr)
plt.plot(fpr_svm, tpr_svm, label='SVM (AUC = %0.5f)' % roc_auc_svm)
plt.plot(fpr_knn, tpr_knn, label='KNN (AUC = %0.5f)' % roc_auc_knn)
plt.plot(fpr_dt, tpr_dt, label='Decision Tree (AUC = %0.5f)' % roc_auc_dt)

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

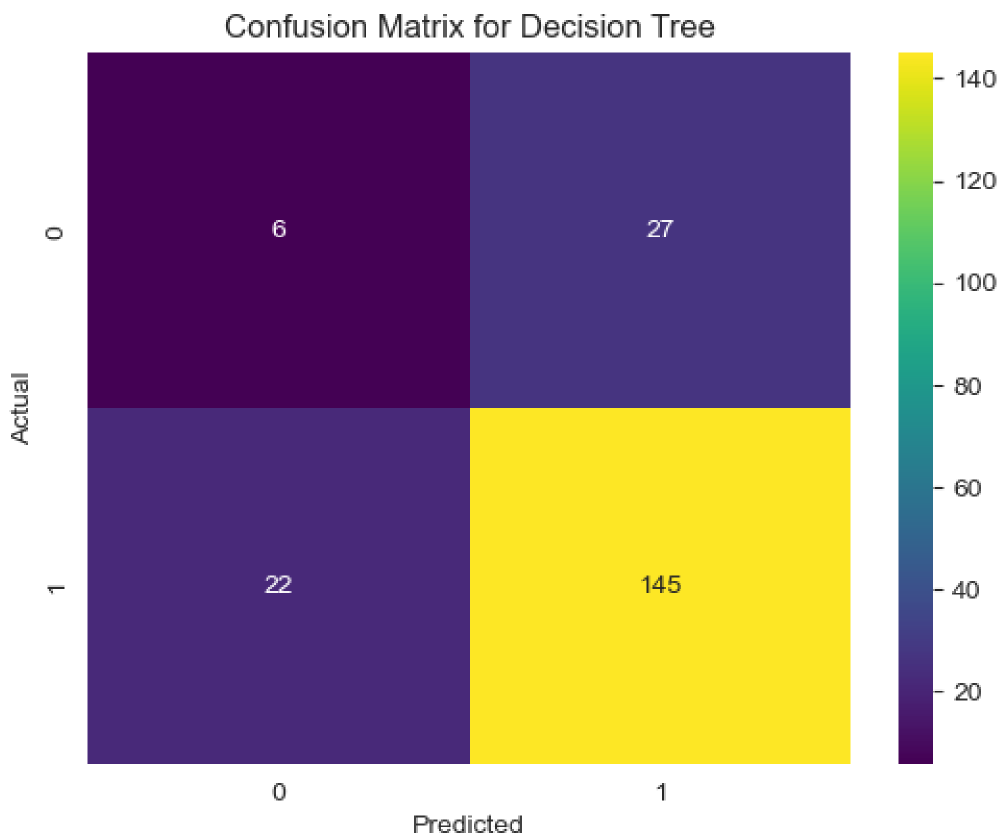


[ ]:
```
algorithms = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree']
y_pred = {
    'Logistic Regression': logistic_regression_pred,
    'SVM': svm_pred,
    'KNN': knn_pred,
    'Decision Tree': decision_tree_pred
}

# Create confusion matrix for each algorithm
for algorithm in algorithms:
    cm = confusion_matrix(y_test, y_pred[algorithm])
    plt.figure()
    sns.heatmap(cm, annot=True, cmap='viridis', fmt='g')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix for {algorithm}')
    plt.show()
```

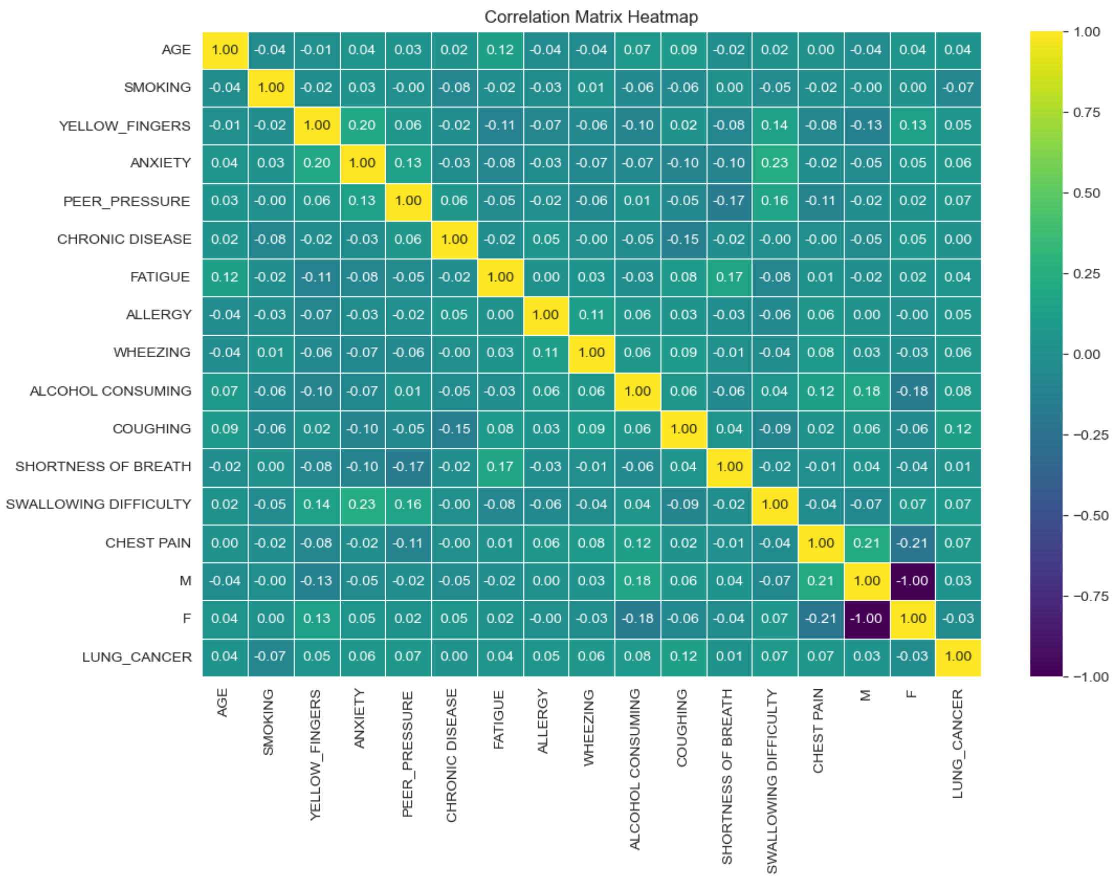

Confusion Matrix for Logistic Regression
0
33
0
167
Actual
0
1
Predicted
160
140
120
100
80
60
40
20
0


Confusion Matrix for SVM
Actual
0
1
0
33
0
167
0
1
Predicted
160
140
120
100
80
60
40
20
0


Confusion Matrix for KNN
0
33
3
164
Actual
0
1
0
1
Predicted
160
140
120
100
80
60
40
20
0



[ ]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='viridis', fmt='.2f', linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```


Correlation Matrix Heatmap
AGE
SMOKING
YELLOW_FINGERS
ANXIETY
PEER_PRESSURE
CHRONIC DISEASE
FATIGUE
ALLERGY
WHEEZING
ALCOHOL CONSUMING
COUGHING
SHORTNESS OF BREATH
SWALLOWING DIFFICULTY
CHEST PAIN
M
F
LUNG_CANCER
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00