Predicting Crime Against Women in India:

A Comparative Analysis of Logistic Regression and Decision Tree Model

Prince Mandal = 70
Shiven Kumar = 34
Sargam Raina = 45
Kannan Jain = 19
Hadi Abdul Ansari = 05

Dataset Overview

PREPROCESS THE DATA

```
import pandas as pd

# Load the dataset
df = pd.read_csv(r"C:/Users/ahadi/OneDrive/Desktop/CrimesOnWomenData.csv")

# Display the first few rows of the dataframe to understand the structure
print(df.head())
```

```
   Unnamed: 0                State  Year  Rape   K&A   DD   AoW   AoM    DV  WT
0           0       ANDHRA PRADESH  2001   871   765  420  3544  2271  5791   7
1           1    ARUNACHAL PRADESH  2001    33    55    0    78     3    11   0
2           2                ASSAM  2001   817  1070   59   850     4  1248   0
3           3                BIHAR  2001   888   518  859   562    21  1558  83
4           4         CHHATTISGARH  2001   959   171   70  1763   161   840   0
```

```
print(f"Dataset shape: {df.shape}")
```

```
Dataset shape: (736, 10)
```

Exploratory Data Analysis (EDA)

```
print("Missing values in each column:")
print(df.isnull().sum())
```

```
Missing values in each column:
Unnamed: 0    0
State         0
Year          0
Rape          0
K&A           0
DD            0
AoW           0
AoM           0
DV            0
WT            0
dtype: int64
```

```
print("Statistical summary:")
print(df.describe())
```

```
Statistical summary:
       Unnamed: 0         Year         Rape          K&A          DD
count  736.000000   736.000000   736.000000   736.000000   736.000000
mean   367.500000  2011.149457   727.855978  1134.542120   215.692935
std    212.609188     6.053453   977.024945  1993.536828   424.927334
min      0.000000  2001.000000     0.000000     0.000000     0.000000
25%    183.750000  2006.000000    35.000000    24.750000     1.000000
```

```
print("Columns in the dataset:")
print(df.columns)
```

```
Columns in the dataset:
Index(['Unnamed: 0', 'State', 'Year', 'Rape', 'K&A', 'DD', 'AoW', 'AoM', 'DV',
       'WT'],
      dtype='object')
```

```
df.rename(columns={
    'K&A': 'Kidnapping_Abduction',
    'DD': 'Dowry_Deaths',
    'AoW': 'Assault_on_Women',
    'AoM': 'Assault_on_Men',
    'DV': 'Domestic_Violence',
    'WT': 'Trafficking'
}, inplace=True)

# Check updated column names
print(df.columns)
```

```
Index(['Unnamed: 0', 'State', 'Year', 'Rape', 'Kidnapping_Abduction',
       'Dowry_Deaths', 'Assault_on_Women', 'Assault_on_Men',
       'Domestic_Violence', 'Trafficking'],
      dtype='object')
```

State Wise Crime

```
statewise_crimes = df.groupby('State').sum()
print(statewise_crimes)
```

```
                  Unnamed: 0   Year   Rape  Kidnapping_Abduction  \
State
A & N ISLANDS           1810  20055     84                    58
A & N Islands           6039  22176    340                   305
ANDHRA PRADESH          1530  20055  10696                 11921
ARUNACHAL PRADESH       1540  20055    412                   440
ASSAM                   1550  20055  12762                 16368
...                      ...    ...    ...                   ...
UTTARAKHAND             1790  20055   1101                  1795
Uttar Pradesh           6006  22176  30641                101701
Uttarakhand             6017  22176   5106                 18524
WEST BENGAL             1800  20055  16378                 13894
West Bengal             6028  22176  13108                 37848

                  Dowry_Deaths  Assault_on_Women  Assault_on_Men  \
State
A & N ISLANDS                4               182              36
A & N Islands                9               376              99
ANDHRA PRADESH            5112             42334           28759
ARUNACHAL PRADESH            1               666              16
ASSAM                     1015             10587              99
...                        ...               ...             ...
UTTARAKHAND                752              1290            1374
Uttar Pradesh            21357             76654           20024
Uttarakhand               1568              7870            1217
WEST BENGAL               4069             17163             798
West Bengal               4006             33851            4952
```

```
                  Domestic_Violence  Trafficking
State
A & N ISLANDS                   111            0
A & N Islands                   254           10
ANDHRA PRADESH                92242           17
ARUNACHAL PRADESH               123            0
ASSAM                         27735            4
...                             ...          ...
UTTARAKHAND                    3467            1
Uttar Pradesh                100227          330
Uttarakhand                   43784          187
WEST BENGAL                   91031          102
West Bengal                  171204          838

[70 rows x 9 columns]
```

Yearly Crime

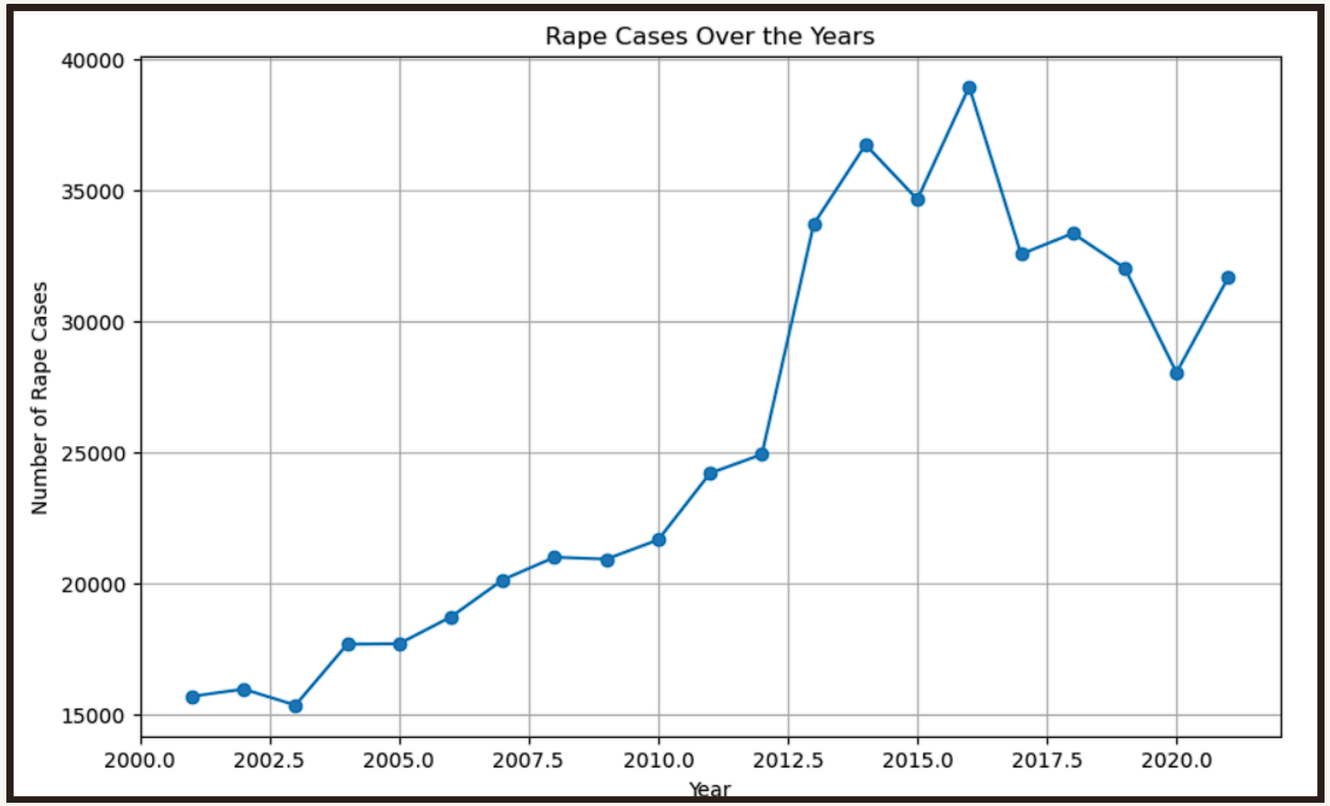
```
yearwise_crimes = df.groupby('Year').sum()
print(yearwise_crimes)
```

```
      Unnamed: 0                                              State   Rape
Year
2001         561  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  15694
2002        1717  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  15970
2003        2873  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  15357
2004        4029  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  17682
2005        5185  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  17701
2006        6341  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  18725
2007        7497  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  20139
2008        8653  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  21001
2009        9809  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  20928
2010       10965  ANDHRA PRADESHARUNACHAL PRADESHASSAMBIHARCHHAT...  21665
2011       12870  Andhra PradeshArunachal PradeshAssamBiharChhat...  24206
2012       14166  Andhra PradeshArunachal PradeshAssamBiharChhat...  24923
2013       15462  Andhra PradeshArunachal PradeshAssamBiharChhat...  33707
2014       16758  Andhra PradeshArunachal PradeshAssamBiharChhat...  36735
2015       18054  Andhra PradeshArunachal PradeshAssamBiharChhat...  34651
2016       19350  Andhra PradeshArunachal PradeshAssamBiharChhat...  38947
2017       20646  Andhra PradeshArunachal PradeshAssamBiharChhat...  32559
2018       21942  Andhra PradeshArunachal PradeshAssamBiharChhat...  33356
2019       23238  Andhra PradeshArunachal PradeshAssamBiharChhat...  32033
2020       24534  Andhra PradeshArunachal PradeshAssamBiharChhat...  28046
2021       25830  Andhra PradeshArunachal PradeshAssamBiharChhat...  31677

      Kidnapping_Abduction  Dowry_Deaths  Assault_on_Women  Assault_on_Men
Year
2001                 13681          6738             33622            9656
2002                 13613          6687             33497           10027
2003                 12499          6078             32450           12220
```

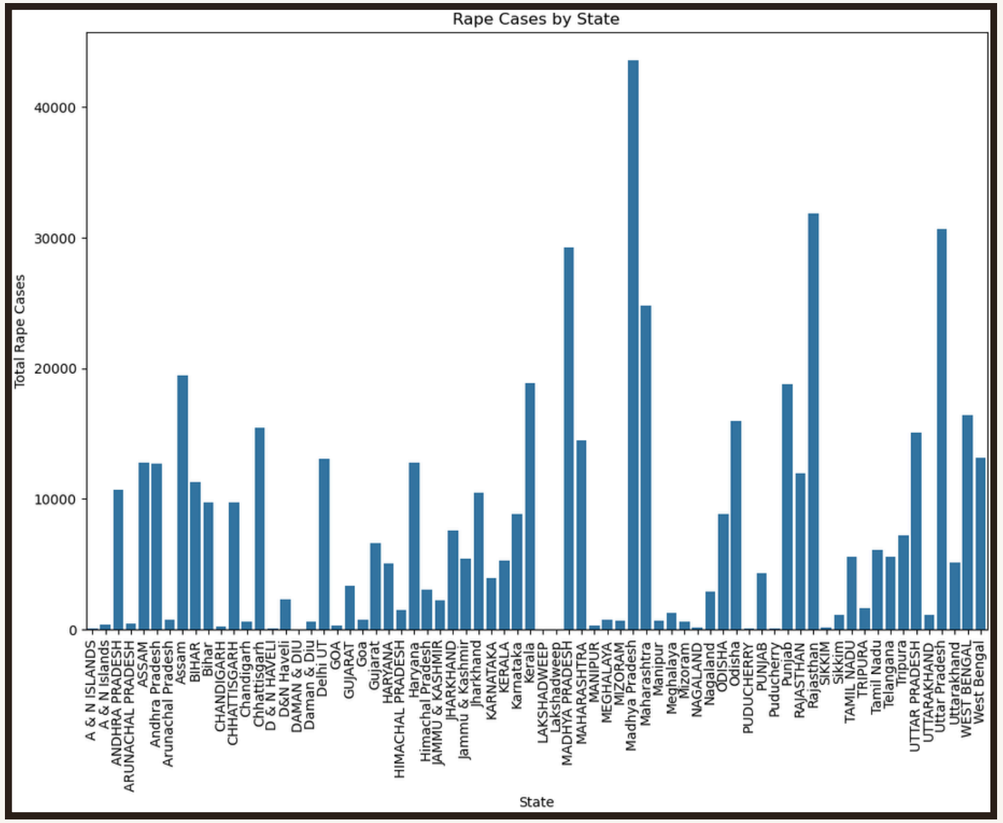
```
      Domestic_Violence  Trafficking
Year
2001              49032          114
2002              49102           76
2003              49492           46
2004              56867           89
2005              56995          148
2006              61400           67
2007              74143           61
2008              79957           67
```

Data Visualization

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
plt.plot(df.groupby('Year')['Rape'].sum(), marker='o')
plt.title('Rape Cases Over the Years')
plt.xlabel('Year')
plt.ylabel('Number of Rape Cases')
plt.grid(True)
plt.show()
```




```python
import seaborn as sns

plt.figure(figsize=(12,8))
sns.barplot(x=statewise_crimes.index, y=statewise_crimes['Rape'])
plt.xticks(rotation=90)
plt.title('Rape Cases by State')
plt.xlabel('State')
plt.ylabel('Total Rape Cases')
plt.show()
```



Modelling Approach

ACTUAL MODEL SELECTION AND DATA PREPROCESSING STARTS

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Encoding categorical variables (if any)
le = LabelEncoder()
df['State'] = le.fit_transform(df['State'])  # Example for categorical column

imputer = SimpleImputer(strategy='mean')
df_imputed = pd.DataFrame(imputer.fit_transform(df.select_dtypes(include=['float64', 'int64'])), columns=df.select_dtypes(includ

# Adding back non-numeric columns if they were removed
df_imputed[df.select_dtypes(exclude=['float64', 'int64']).columns] = df.select_dtypes(exclude=['float64', 'int64'])
# Define features and target
# For simplicity, let's say we want to predict if the rape cases exceed a certain threshold
df_imputed['High_Rape'] = df_imputed['Rape'] > df_imputed['Rape'].median()

# Features and target
X = df_imputed.drop(columns=['Rape', 'High_Rape'])
y = df_imputed['High_Rape']

# Split the data
```

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Handle missing values
imputer = SimpleImputer(strategy='mean')
numeric_columns = df.select_dtypes(include=['float64', 'int64']).columns
df[numeric_columns] = imputer.fit_transform(df[numeric_columns])

# Convert categorical columns using one-hot encoding
categorical_columns = df.select_dtypes(include=['object']).columns
df = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Define features and target
df['High_Rape'] = df['Rape'] > df['Rape'].median()
X = df.drop(columns=['Rape', 'High_Rape'])
y = df['High_Rape']
```

TRAIN THE MODEL

```
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression Model

APPLY LOGISTIC REGRESSION

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Initialize models
logistic_model = LogisticRegression()

# Train Logistic Regression model
logistic_model.fit(X_train, y_train)
y_pred_logistic = logistic_model.predict(X_test)

# Evaluate Logistic Regression
accuracy_logistic = accuracy_score(y_test, y_pred_logistic)
report_logistic = classification_report(y_test, y_pred_logistic)
conf_matrix_logistic = confusion_matrix(y_test, y_pred_logistic)

# Print evaluation metrics
print("Logistic Regression:")
print(f"Accuracy: {accuracy_logistic:.2f}")
print("Classification Report:")
print(report_logistic)
print("Confusion Matrix:")
print(conf_matrix_logistic)
```

Output

```
Logistic Regression:
Accuracy: 0.91
Classification Report:
              precision    recall  f1-score   support

       False       0.90      0.95      0.92       123
        True       0.93      0.87      0.90        98

    accuracy                           0.91       221
   macro avg       0.92      0.91      0.91       221
weighted avg       0.92      0.91      0.91       221

Confusion Matrix:
[[117   6]
 [ 13  85]]
```

Decision Tree Model

APPLY DECISION TREE ALGORITHM

```
from sklearn.tree import DecisionTreeClassifier

# Initialize models
decision_tree_model = DecisionTreeClassifier()

# Train Decision Tree model
decision_tree_model.fit(X_train, y_train)
y_pred_tree = decision_tree_model.predict(X_test)

# Evaluate Decision Tree
accuracy_tree = accuracy_score(y_test, y_pred_tree)
report_tree = classification_report(y_test, y_pred_tree)
conf_matrix_tree = confusion_matrix(y_test, y_pred_tree)

print("\nDecision Tree:")
print(f"Accuracy: {accuracy_tree:.2f}")
print("Classification Report:")
print(report_tree)
print("Confusion Matrix:")
print(conf_matrix_tree)
```

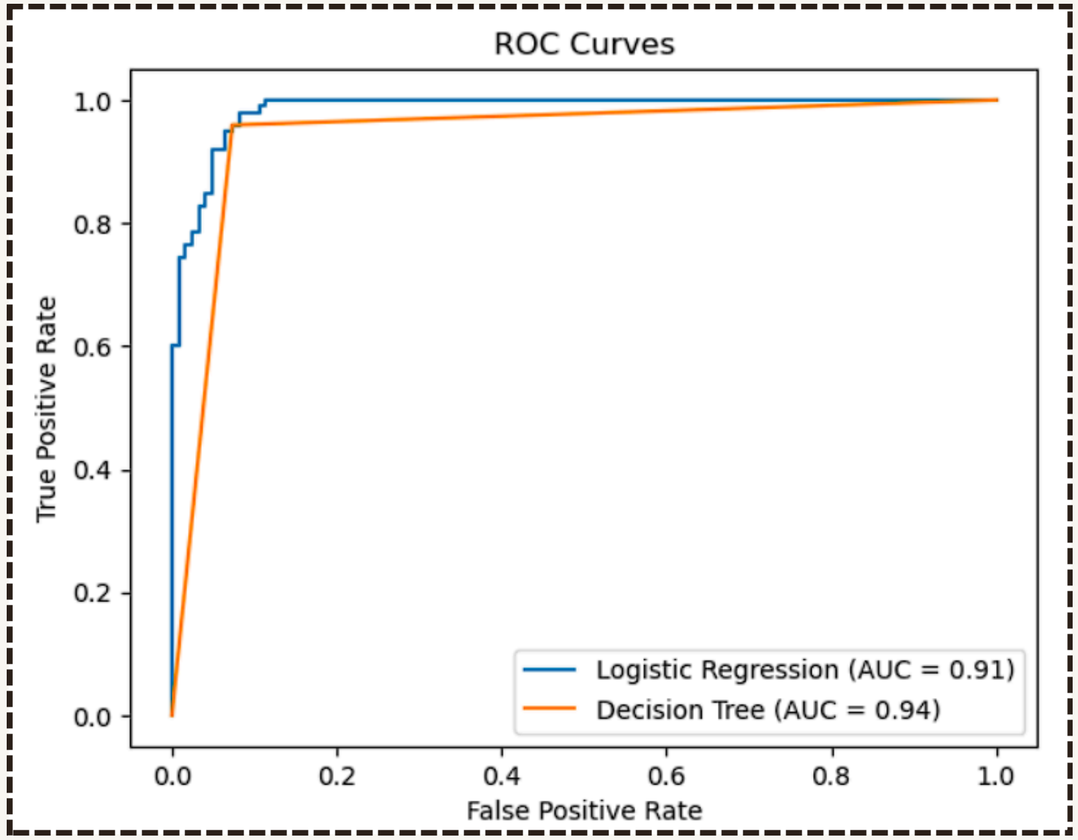
Output

```
Decision Tree:
Accuracy: 0.94
Classification Report:
              precision    recall  f1-score   support

       False       0.97      0.93      0.95       123
        True       0.91      0.96      0.94        98

    accuracy                           0.94       221
   macro avg       0.94      0.94      0.94       221
weighted avg       0.94      0.94      0.94       221

Confusion Matrix:
[[114   9]
 [  4  94]]
```

Model COMPARISON THROUGH ROC CURVE

COMAPRE THROUGH ROC CURVE

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, roc_auc_score

# ROC Curve for Logistic Regression
fpr_log, tpr_log, _ = roc_curve(y_test, logistic_model.predict_proba(X_test)[:,1])
plt.plot(fpr_log, tpr_log, label=f"Logistic Regression (AUC = {roc_auc_score(y_test, y_pred_logistic):.2f})"

# ROC Curve for Decision Tree
fpr_tree, tpr_tree, _ = roc_curve(y_test, decision_tree_model.predict_proba(X_test)[:,1])
plt.plot(fpr_tree, tpr_tree, label=f"Decision Tree (AUC = {roc_auc_score(y_test, y_pred_tree):.2f})")

# Plot settings
plt.title('ROC Curves')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

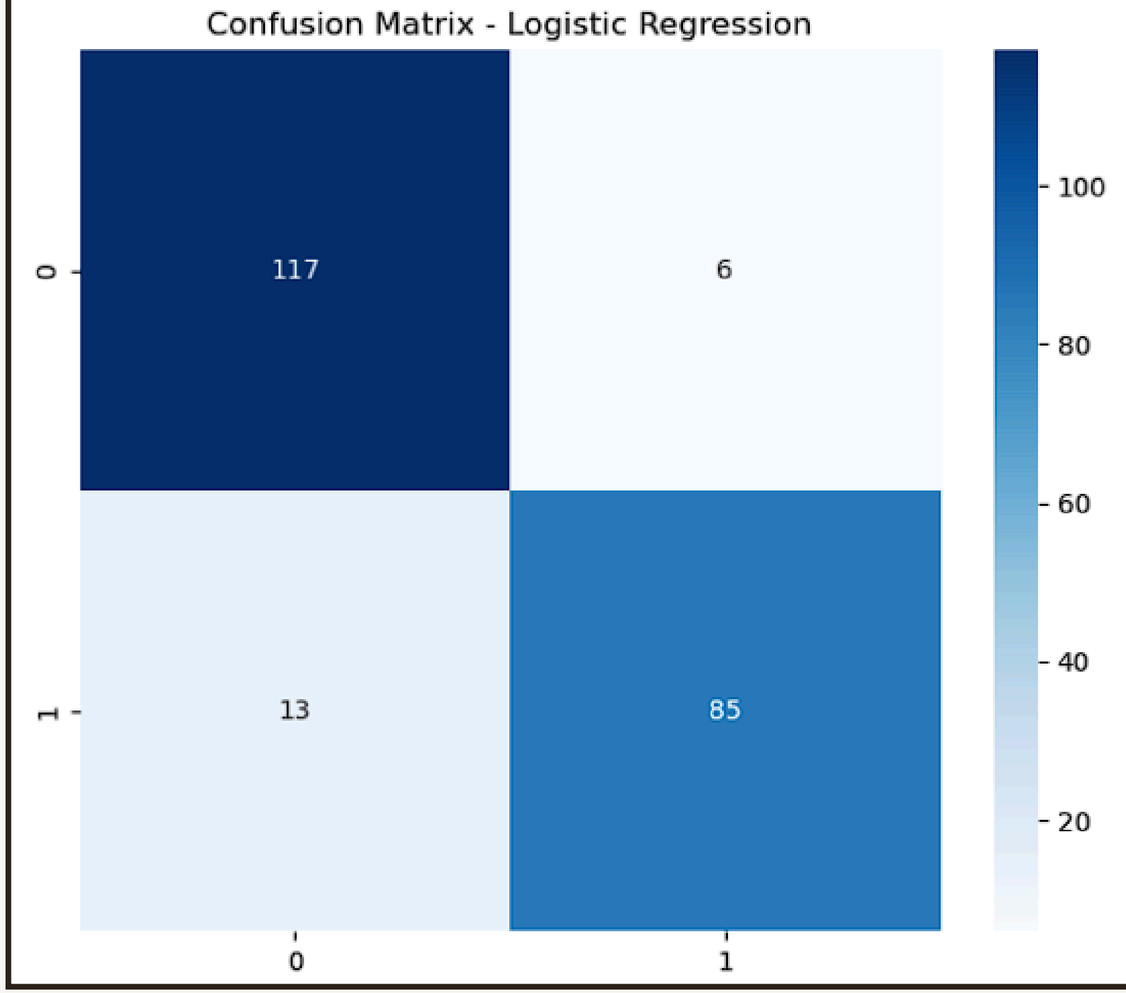


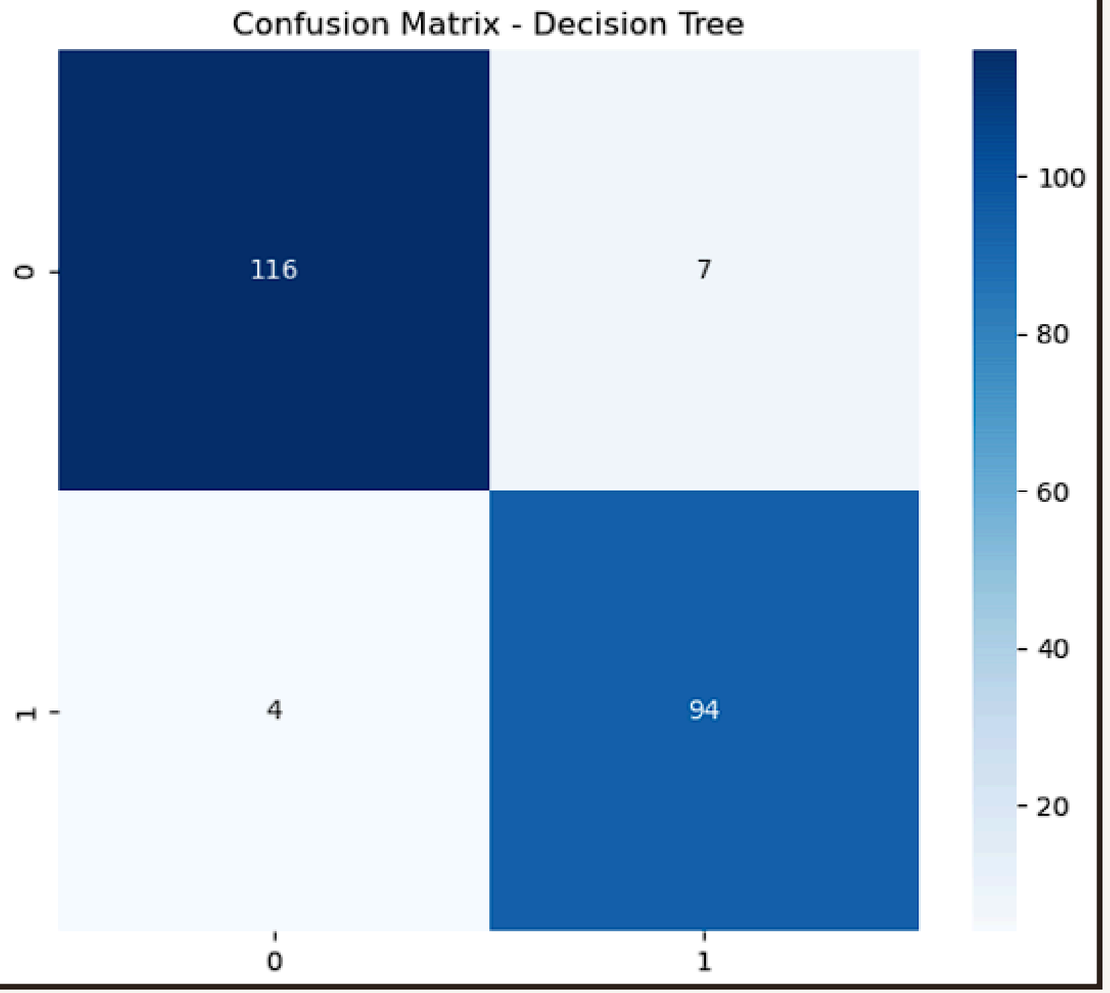
COMPARING THROUGH HEAT MAP

COMAPRING THROUGH HEATMAPS

```
# Make predictions
y_pred_lr = lr.predict(X_test)
y_pred_dt = dt.predict(X_test)

# Calculate accuracy
accuracy_lr = accuracy_score(y_test, y_pred_lr)
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print(f'Logistic Regression Accuracy: {accuracy_lr}')
print(f'Decision Tree Accuracy: {accuracy_dt}')

# Plot confusion matrices
fig, axes = plt.subplots(1, 2, figsize=(16, 6))
sns.heatmap(confusion_matrix(y_test, y_pred_lr), annot=True, fmt='d', cmap='Blues', ax=axes[0])
axes[0].set_title('Confusion Matrix - Logistic Regression')

sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt='d', cmap='Blues', ax=axes[1])
axes[1].set_title('Confusion Matrix - Decision Tree')

plt.show()

# Display classification reports
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))

print("Decision Tree Classification Report:")
print(classification_report(y_test, y_pred_dt))
```

Logistic Regression Accuracy: 0.9140271493212669
Decision Tree Accuracy: 0.9502262443438914





OVERALL CONCLUSION

Logistic Regression Classification Report:

	precision	recall	f1-score	support
False	0.90	0.95	0.92	123
True	0.93	0.87	0.90	98
accuracy			0.91	221
macro avg	0.92	0.91	0.91	221
weighted avg	0.92	0.91	0.91	221

Decision Tree Classification Report:

	precision	recall	f1-score	support
False	0.97	0.94	0.95	123
True	0.93	0.96	0.94	98
accuracy			0.95	221
macro avg	0.95	0.95	0.95	221
weighted avg	0.95	0.95	0.95	221

THEREFORE WE CAN CONCLUDE THAT THE MODEL IS BETTER FITTED FOR DECISION TREE CLASSIFIER WITH AN ACCURACY OF 95% AND FOR LOGISTIC REGRESSION 91%. THE MODEL IS A GOOD FIT.

THANKYOU!