Things to do

- Problem Statement
- Data set (min 7000 rows)
- Handling missing data
- Handling feature scaling
- Best possible methods (Algorithms) for our dataset
- Visualization

Dataset Overview

Nearest Earth Objects (NEO)

Link - https://www.kaggle.com/datasets/ivansher/nasa-nearest-earth-objects-1910-2024/data

This dataset contains **338,199** records of objects that come close to Earth, known as **NEOs (Near-Earth Objects)**, recorded between **1910 and 2024**. NASA monitors these objects to assess their potential risk to the planet.

Key Features

- **neo_id**: Unique identifier for each NEO.
- **name**: Designation or name of the object.
- **absolute_magnitude**: The intrinsic brightness of the object.
- **estimated_diameter_min/max**: Estimated size range of the object.
- **relative_velocity**: The object's speed relative to Earth (in km/h).
- **miss_distance**: How close the object will come to Earth (in km).
- **is_hazardous**: A boolean field indicating if NASA classifies the object as potentially dangerous.

Problem Statement

Predicting Potentially Hazardous NEOs The goal is to build a machine learning model to predict whether a **Near-Earth Object (NEO)** is classified as **"hazardous"** by NASA.

Objectives

1. **Preprocessing**: Clean the dataset and handle missing values.
2. **Feature Selection**: Used key features such as:
   - Absolute magnitude
   - Estimated diameter
   - Relative velocity
   - Miss distance
3. **Oversampling**: Address class imbalance by applying **SMOTE** (Synthetic Minority Oversampling Technique) to balance the target class (`is_hazardous`).
4. **Modeling**: Train a model to predict the `is_hazardous` label (True/False).

5. **Evaluation:** Use metrics such as **accuracy**, **precision**, **recall**, and **ROC-AUC score** to evaluate the model.

```
import pandas as pd
df = pd.read_csv('../data/nearest-earth-objects.csv')

df.head()

    neo_id                name  absolute_magnitude  
estimated_diameter_min  \
0  2162117  162117 (1998 SD15)               19.14  
0.394962   
1  2349507    349507 (2008 QY)               18.50  
0.530341   
2  2455415    455415 (2003 GA)               21.45  
0.136319   
3  3132126           (2002 PB)               20.63  
0.198863   
4  3557844           (2011 DW)               22.70  
0.076658   

   estimated_diameter_max orbiting_body  relative_velocity  
miss_distance  \
0                0.883161         Earth       71745.401048  
5.814362e+07   
1                1.185878         Earth      109949.757148  
5.580105e+07   
2                0.304818         Earth       24865.506798  
6.720689e+07   
3                0.444672         Earth       78890.076805  
3.039644e+07   
4                0.171412         Earth       56036.519484  
6.311863e+07   

   is_hazardous  
0         False  
1          True  
2         False  
3         False  
4         False  
```

Dataset Preprocessing

```
# Remove rows with missing values
df_cleaned = df.dropna()

missing_values = df_cleaned.isnull()

# To get a summary of missing values in each column:
missing_values_summary = missing_values.sum()
```

```
missing_values_summary

neo_id                     0
name                       0
absolute_magnitude         0
estimated_diameter_min     0
estimated_diameter_max     0
orbiting_body              0
relative_velocity          0
miss_distance              0
is_hazardous               0
dtype: int64
```

Dropping unnecessary columns

```
# Drop 'neo_id', 'name', and 'orbiting_body' since they are not useful
for prediction
df_cleaned = df_cleaned.drop(columns=['neo_id', 'name',
'orbiting_body'])
```

Feature Scaling using MinMaxScaler

```
from sklearn.preprocessing import MinMaxScaler

# Select the features to scale
features_to_scale = ['absolute_magnitude', 'estimated_diameter_min',
'estimated_diameter_max',
                     'relative_velocity', 'miss_distance']

# Initialize the scaler
scaler = MinMaxScaler()

# Apply scaling
df_cleaned[features_to_scale] =
scaler.fit_transform(df_cleaned[features_to_scale])
```

The dataset contains 9 columns and 338171 rows of data

```
df_cleaned.shape

(338171, 6)
```

Heavily Skewed Data Set

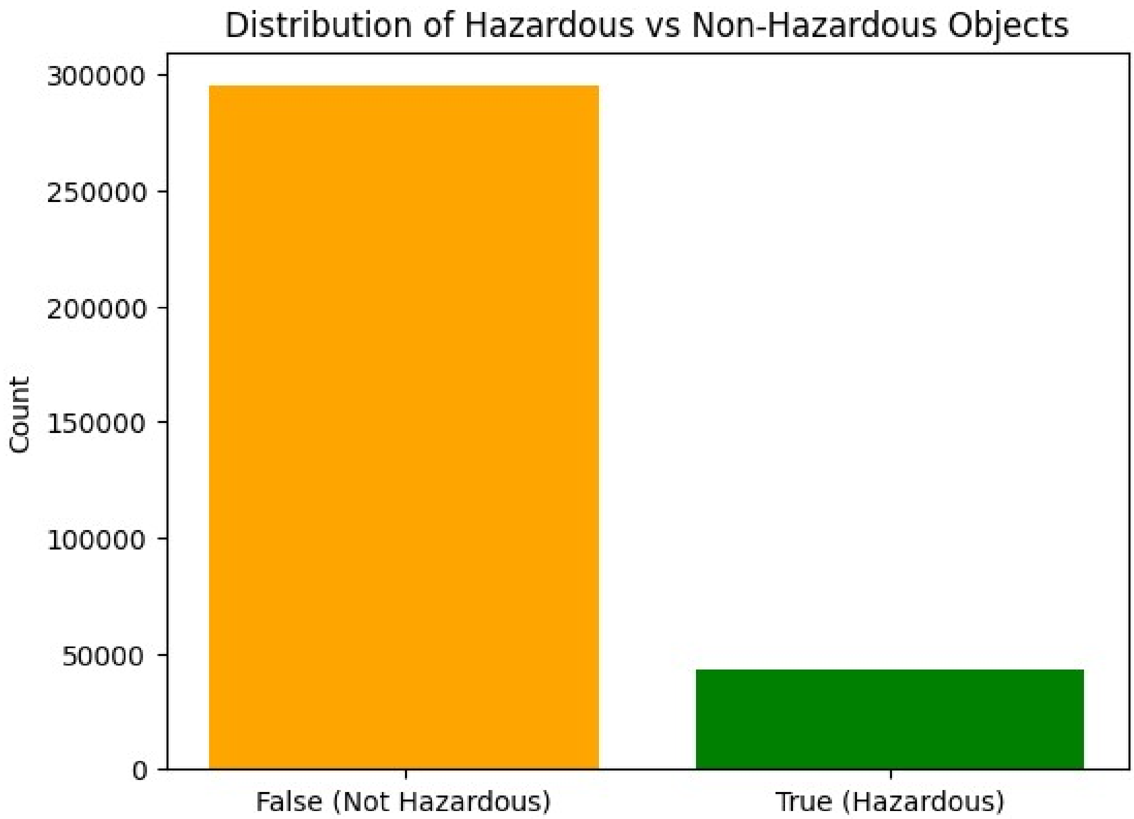
```
target_column = df_cleaned['is_hazardous']

# Count the occurrences of True and False
true_count = target_column.value_counts()[1]
```

```
false_count = target_column.value_counts()[0]

true_count, false_count
```

```
C:\Users\amrit\AppData\Local\Temp\ipykernel_21944\1876494894.py:4:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  true_count = target_column.value_counts()[1]
C:\Users\amrit\AppData\Local\Temp\ipykernel_21944\1876494894.py:5:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  false_count = target_column.value_counts()[0]
```

```
(43162, 295009)
```

```
import matplotlib.pyplot as plt

# Create a bar plot to visualize the distribution of True and False
labels = ['False (Not Hazardous)', 'True (Hazardous)']
counts = [false_count, true_count]

plt.bar(labels, counts, color=['orange', 'green'])
plt.title('Distribution of Hazardous vs Non-Hazardous Objects')
plt.ylabel('Count')
plt.show()
```



Resampling (Oversampling) with SMOTE

```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split

# Separate features and target
X = df_cleaned.drop(columns=['is_hazardous'])
y = df_cleaned['is_hazardous']

# Split the dataset into training and test sets before applying SMOTE
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Apply SMOTE only to the training set to avoid data leakage
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

# Check the class distribution after SMOTE
print(y_train_resampled.value_counts())
```

```
is_hazardous
False    206396
True     206396
Name: count, dtype: int64
```

Training

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,
roc_auc_score, accuracy_score

# Initialize the Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42)

# Train the model on the resampled training set
rf_model.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, rf_model.predict_proba(X_test)[:, 1])

# Print the evaluation results
print("Confusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", class_report)
print("Accuracy:", accuracy)
print("ROC AUC Score:", roc_auc)
```

```
Confusion Matrix:
 [[82920  5693]
 [ 3853  8986]]

Classification Report:
               precision    recall  f1-score   support

       False       0.96      0.94      0.95     88613
        True       0.61      0.70      0.65     12839

    accuracy                           0.91    101452
   macro avg       0.78      0.82      0.80    101452
weighted avg       0.91      0.91      0.91    101452

Accuracy: 0.9059062413752317
ROC AUC Score: 0.943386150661994
```

KNN

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,
```

```
accuracy_score

# Initialize the KNN Classifier
knn_model = KNeighborsClassifier(n_neighbors=5)

# Train the model on the resampled training set
knn_model.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
y_pred_knn = knn_model.predict(X_test)

# Evaluate the model
conf_matrix = confusion_matrix(y_test, y_pred_knn)
class_report = classification_report(y_test, y_pred_knn)
accuracy = accuracy_score(y_test, y_pred_knn)

# Print the evaluation results
print("Confusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", class_report)
print("Accuracy:", accuracy)
```

```
Confusion Matrix:
 [[72904 15709]
 [ 3318  9521]]

Classification Report:
               precision    recall  f1-score   support

       False       0.96      0.82      0.88     88613
        True       0.38      0.74      0.50     12839

    accuracy                           0.81    101452
   macro avg       0.67      0.78      0.69    101452
weighted avg       0.88      0.81      0.84    101452

Accuracy: 0.8124531798288845
```

Logistic Regression

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

# Initialize the Logistic Regression model
logreg_model = LogisticRegression(random_state=42)

# Train the model on the resampled training set
logreg_model.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
```

```
y_pred_logreg = logreg_model.predict(X_test)

# Evaluate the model
conf_matrix_logreg = confusion_matrix(y_test, y_pred_logreg)
class_report_logreg = classification_report(y_test, y_pred_logreg)
accuracy_logreg = accuracy_score(y_test, y_pred_logreg)
roc_auc_logreg = roc_auc_score(y_test,
logreg_model.predict_proba(X_test)[:, 1])

# Print the evaluation results
print("Confusion Matrix:\n", conf_matrix_logreg)
print("\nClassification Report:\n", class_report_logreg)
print("Accuracy:", accuracy_logreg)
print("ROC AUC Score:", roc_auc_logreg)

Confusion Matrix:
 [[63364 25249]
 [ 1542 11297]]

Classification Report:
               precision    recall  f1-score   support

       False       0.98      0.72      0.83     88613
        True       0.31      0.88      0.46     12839

    accuracy                           0.74    101452
   macro avg       0.64      0.80      0.64    101452
weighted avg       0.89      0.74      0.78    101452

Accuracy: 0.735924378030 99
ROC AUC Score: 0.8356701345776563
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score, roc_auc_score

# Initialize the Decision Tree Classifier
dt_model = DecisionTreeClassifier(random_state=42)

# Train the model on the resampled training set
dt_model.fit(X_train_resampled, y_train_resampled)

# Make predictions on the test set
y_pred_dt = dt_model.predict(X_test)

# Evaluate the model
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
class_report_dt = classification_report(y_test, y_pred_dt)
```

```
accuracy_dt = accuracy_score(y_test, y_pred_dt)
roc_auc_dt = roc_auc_score(y_test, dt_model.predict_proba(X_test)[:,
1])

# Print the evaluation results
print("Confusion Matrix:\n", conf_matrix_dt)
print("\nClassification Report:\n", class_report_dt)
print("Accuracy:", accuracy_dt)
print("ROC AUC Score:", roc_auc_dt)
```

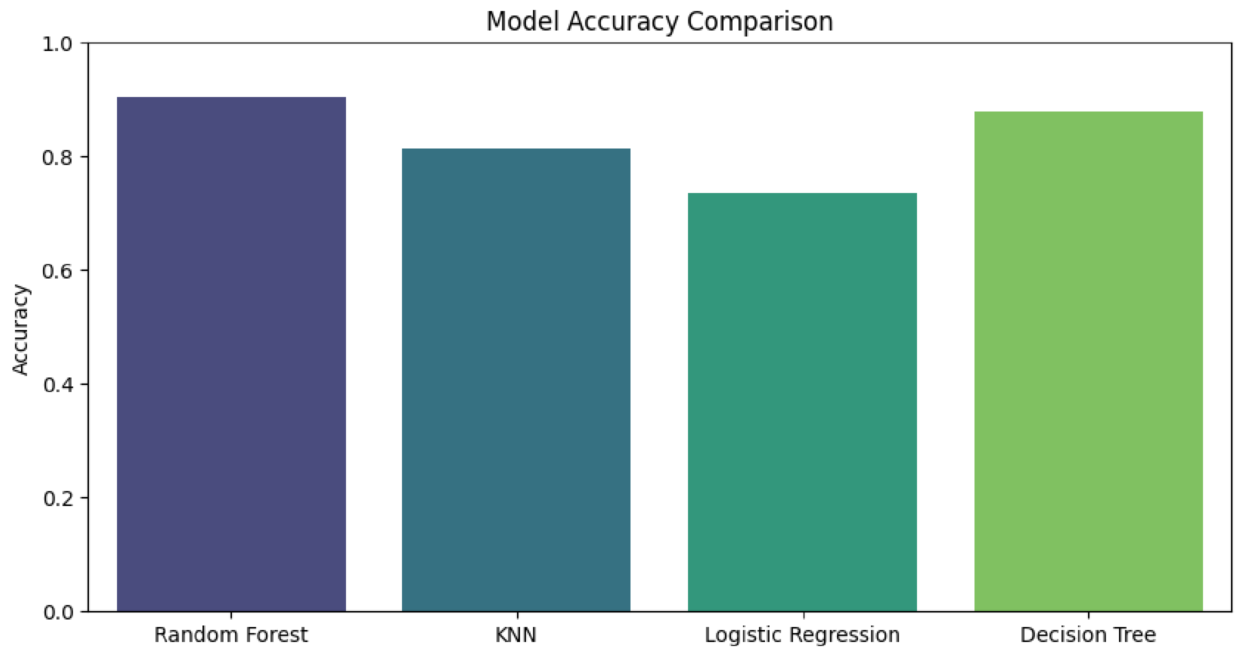
```
Confusion Matrix:
 [[80745  7868]
 [ 4453  8386]]

Classification Report:
               precision    recall  f1-score   support

       False       0.95      0.91      0.93     88613
        True       0.52      0.65      0.58     12839

    accuracy                           0.88    101452
   macro avg       0.73      0.78      0.75    101452
weighted avg       0.89      0.88      0.88    101452

Accuracy: 0.878553404565706
ROC AUC Score: 0.782187775329878
```

Visualization

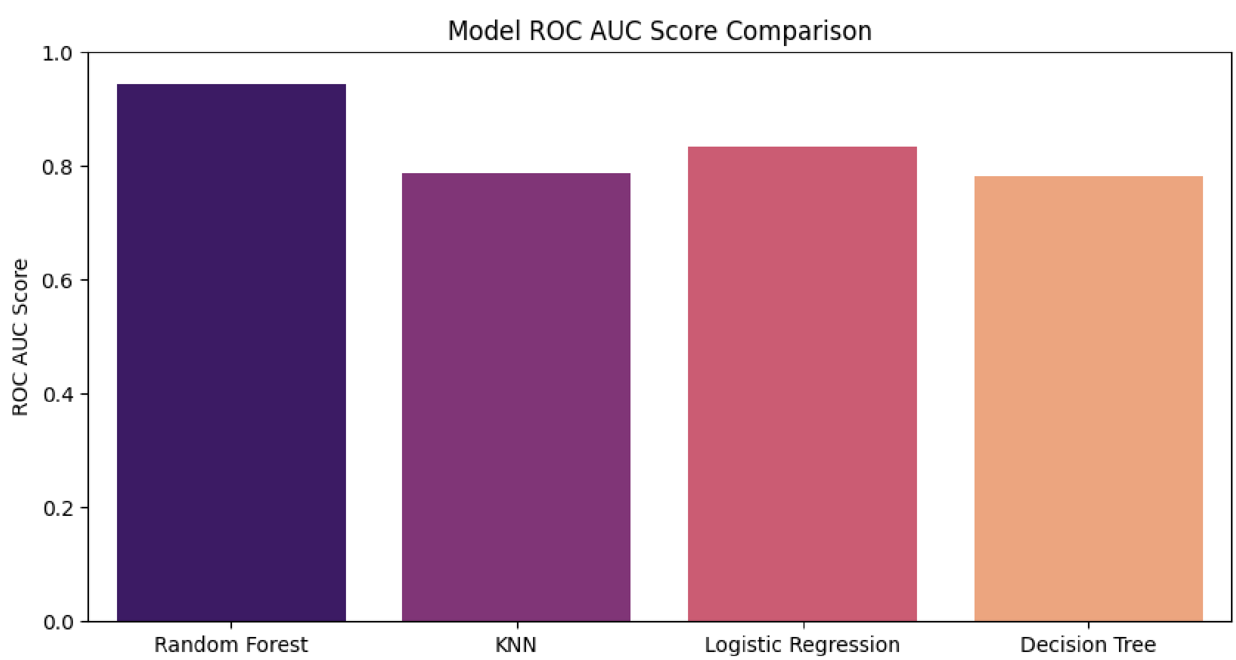
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, auc, confusion_matrix

# Store accuracy and ROC AUC scores in a dictionary
model_performance = {
    'Random Forest': {'accuracy': 0.9059, 'roc_auc': 0.9434},
    'KNN': {'accuracy': 0.8125, 'roc_auc': 0.7868},
    'Logistic Regression': {'accuracy': 0.7359, 'roc_auc': 0.8357},
    'Decision Tree': {'accuracy': 0.8785, 'roc_auc': 0.7821},
}

# Extract model names and their corresponding accuracy and ROC-AUC
scores
model_names = list(model_performance.keys())
accuracies = [model_performance[model]['accuracy'] for model in
model_names]
roc_aucs = [model_performance[model]['roc_auc'] for model in
model_names]

# Plot the accuracies
```

```
plt.figure(figsize=(10, 5))
sns.barplot(x=model_names, y=accuracies, palette='viridis')
plt.title('Model Accuracy Comparison')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.show()

# Plot the ROC AUC scores
plt.figure(figsize=(10, 5))
sns.barplot(x=model_names, y=roc_aucs, palette='magma')
plt.title('Model ROC AUC Score Comparison')
plt.ylabel('ROC AUC Score')
plt.ylim(0, 1)
plt.show()

# Plot ROC Curves for all models (with y_test and predicted
probabilities for each model)
def plot_roc_curves(models, X_test, y_test):
    plt.figure(figsize=(10, 8))

    for name, model in models.items():
        # Predict probabilities
        if hasattr(model, "predict_proba"):
            y_proba = model.predict_proba(X_test)[:, 1]  # Probability
estimates for the positive class
        else:
            y_proba = model.decision_function(X_test)  # For models
like SVM that don't use predict_proba
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

    plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line for random
guessing
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curves Comparison')
    plt.legend(loc="lower right")
    plt.show()
```

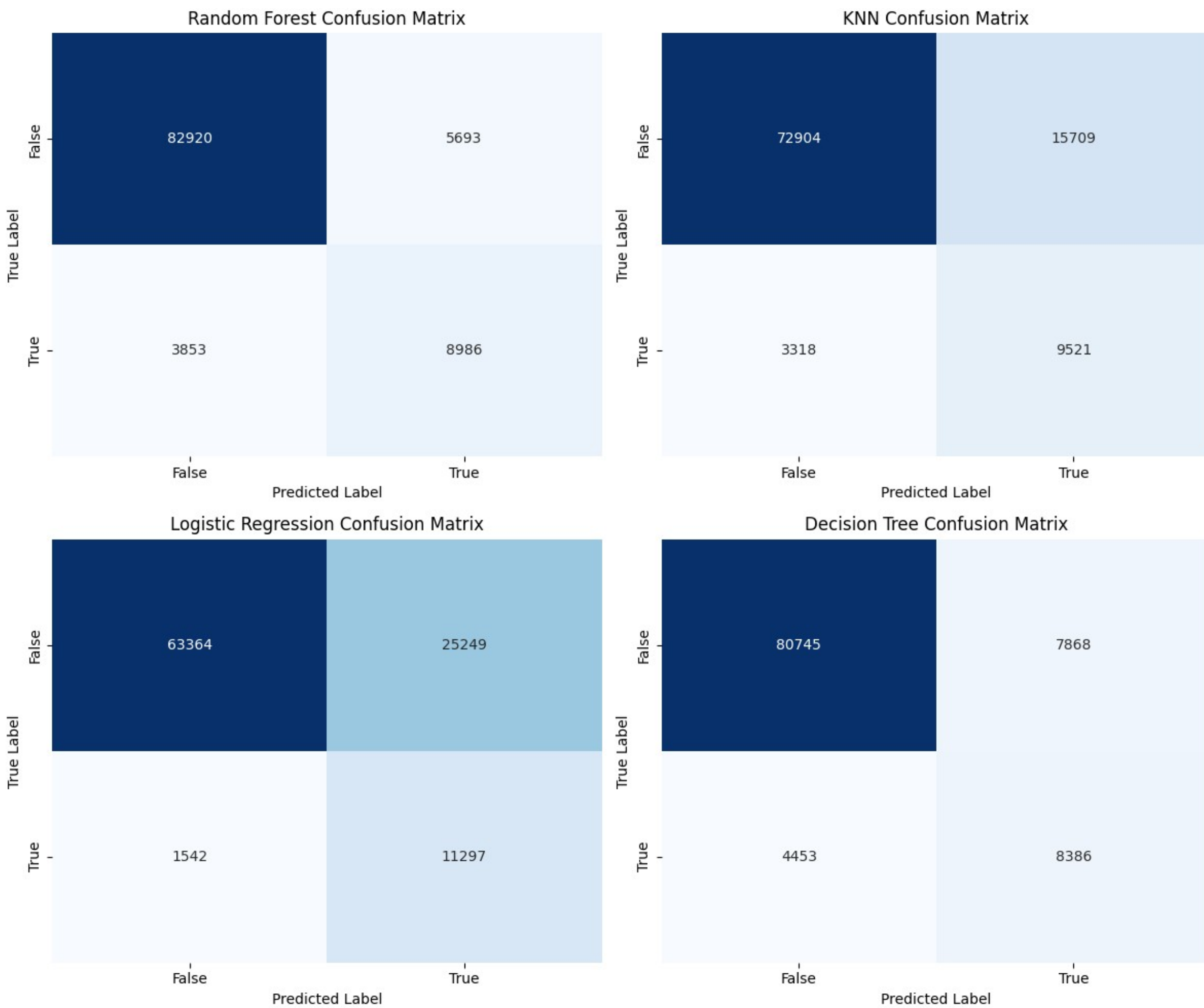
```
C:\Users\amrit\AppData\Local\Temp\ipykernel_23972\3653782360.py:20:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=model_names, y=accuracies, palette='viridis')
```




```
C:\Users\amrit\AppData\Local\Temp\ipykernel_23972\3653782360.py:28:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=model_names, y=roc_aucs, palette='magma')
```



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

# Define the confusion matrices
confusion_matrices = {
    'Random Forest': [[82920,  5693], [3853,  8986]],
    'KNN': [[72904, 15709], [3318,  9521]],
    'Logistic Regression': [[63364, 25249], [1542, 11297]],
    'Decision Tree': [[80745,  7868], [4453,  8386]],
}

# Plotting function for confusion matrices
def plot_confusion_matrices(confusion_matrices):
    plt.figure(figsize=(12, 10))
    for i, (model, cm) in enumerate(confusion_matrices.items()):
        plt.subplot(2, 2, i + 1)
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False,
                    xticklabels=['False', 'True'],
yticklabels=['False', 'True'])
        plt.title(f'{model} Confusion Matrix')
        plt.xlabel('Predicted Label')
        plt.ylabel('True Label')

    plt.tight_layout()
    plt.show()

# Call the function to plot
plot_confusion_matrices(confusion_matrices)
```



Random Forest Confusion Matrix
82920
5693
3853
8986
KNN Confusion Matrix
72904
15709
3318
9521
Logistic Regression Confusion Matrix
63364
25249
1542
11297
Decision Tree Confusion Matrix
80745
7868
4453
8386
True Label
Predicted Label
False
True