Classification Task: Eco-Driving Score Prediction

Predicting driving sustainability style based on telematics data.

1. Exploratory Data Analysis and Data Understanding

Task 1.1: Data Overview

Dataset Description:

- **(a) Created by:** Automotive Sustainability Analytics (2024).
- **(b) Access:** The dataset was uploaded on kaggle.
- **(c) UNSDG Alignment: Goal 11** (Sustainable Cities) and **Goal 12** (Responsible Consumption).
- **(d) Attributes:** Indicators include acceleration, braking intensity, speed variance, and vehicle type.

Questions:

1. Can we distinguish between aggressive and sustainable driving based purely on sensor data?
2. How does speed variance contribute to low sustainability scores?

```
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, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
from sklearn.feature_selection import RFE

df = pd.read_csv('/content/drive/MyDrive/ConceptAndTechnologiesOfAI/FinalAssignment/eco_driving_score.csv')

# Binary condition for Eco-Friendly style
THRESHOLD = 70
df['Binary_Eco_Style'] = (df['eco_score'] >= THRESHOLD).astype(int)

print("Class Distribution:")
print(df['Binary_Eco_Style'].value_counts())
df.head()
```

```
Class Distribution:
Binary_Eco_Style
0    26306
1     3694
Name: count, dtype: int64
```

	rpm_variation	harsh_braking_count	idling_time	fuel_consumption	acceleration_smoothness	eco_score	Binary_Eco_Style
0	2147	5	14.2	7.87	0.97	42.1	0
1	1703	3	4.2	9.37	0.50	36.1	0
2	2253	0	5.5	8.85	0.78	49.8	0
3	2866	3	21.7	5.87	0.60	27.7	0
4	1636	2	3.1	6.71	0.99	79.4	1

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Task 1.2: Visualization

Plotting the class distribution to check for imbalance.

```
# Check for missing values and data types
print("Missing Values:")
print(df.isnull().sum())

# Check for duplicate entries
print(f"\nDuplicate rows: {df.duplicated().sum()}")

# Summary Statistics
print("\n Summary :")
display(df.describe())

class_counts = df['Binary_Eco_Style'].value_counts(normalize=True) * 100
print(f"\nClass Distribution:\n{class_counts}")
```

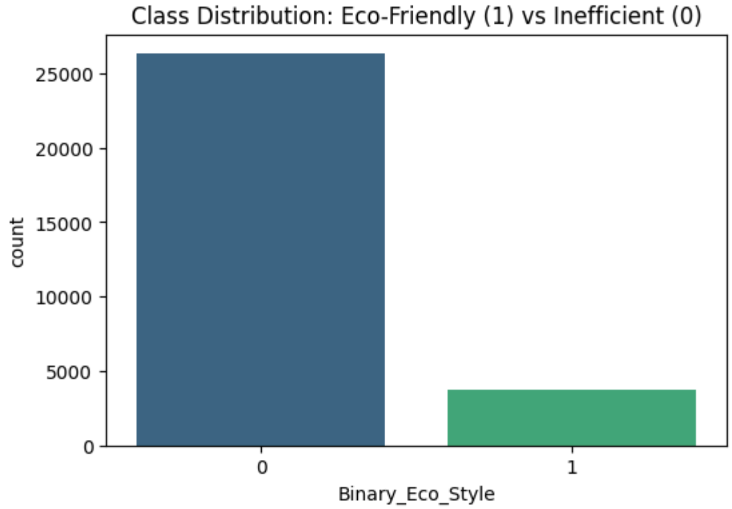
```
Missing Values:
rpm_variation             0
harsh_braking_count       0
idling_time               0
fuel_consumption          0
acceleration_smoothness   0
eco_score                 0
Binary_Eco_Style          0
dtype: int64

Duplicate rows: 0

 Summary :
```

	rpm_variation	harsh_braking_count	idling_time	fuel_consumption	acceleration_smoothness	eco_score	Binary_Eco_Styl
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.00000
mean	1807.951133	2.725667	11.281750	8.052019	0.667652	47.488843	0.12313
std	679.423972	1.671038	5.294333	1.512837	0.155482	19.462413	0.32859
min	500.000000	0.000000	0.000000	3.500000	0.030000	0.000000	0.00000
25%	1325.000000	2.000000	7.600000	7.030000	0.560000	34.600000	0.00000
50%	1801.000000	3.000000	11.200000	8.040000	0.670000	48.400000	0.00000
75%	2272.000000	4.000000	14.900000	9.050000	0.780000	61.300000	0.00000
max	4935.000000	14.000000	32.500000	14.430000	1.000000	100.000000	1.00000

```
Class Distribution:
Binary_Eco_Style
0    87.686667
1    12.313333
Name: proportion, dtype: float64
```

```
plt.figure(figsize=(6, 4))
sns.countplot(x='Binary_Eco_Style', data=df, palette='viridis')
plt.title("Class Distribution: Eco-Friendly (1) vs Inefficient (0)")
plt.show()
```

```
/tmp/ipython-input-457232405.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set

  sns.countplot(x='Binary_Eco_Style', data=df, palette='viridis')
```



2. Neural Network Model (Classification)

Multi-Layer Perceptron for non-linear behavioral classification.

```
X = df.drop(['eco_score', 'Binary_Eco_Style', 'Driving_Style'], axis=1, errors='ignore')
y = df['Binary_Eco_Style']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

mlp = MLPClassifier(hidden_layer_sizes=(64, 32), max_iter=500, random_state=42)
mlp.fit(X_train_scaled, y_train)
y_pred_mlp = mlp.predict(X_test_scaled)

print("Neural Network Accuracy:", accuracy_score(y_test, y_pred_mlp))
```

```
Neural Network Accuracy: 0.9536666666666667
```

3 & 4. Primary ML Models & Hyperparameter Optimization

Tuning Logistic Regression and Random Forest.

```
# Model A: Logistic Regression
lr_gs = GridSearchCV(LogisticRegression(max_iter=1000), {'C': [0.1, 1, 10]}, cv=5).fit(X_train_scaled, y_train)

# Model B: Random Forest
rf_gs = GridSearchCV(RandomForestClassifier(random_state=42), {'n_estimators': [100, 200], 'max_depth': [10, 20]}, cv=3).fit(X_

print("Best LR params:", lr_gs.best_params_)
print("Best RF params:", rf_gs.best_params_)
```

```
Best LR params: {'C': 0.1}
Best RF params: {'max_depth': 10, 'n_estimators': 100}
```

5. Feature Selection

Applying RFE to keep the 5 most discriminative driving behaviors.

```
selector = RFE(estimator=rf_gs.best_estimator_, n_features_to_select=5)
X_train_rfe = selector.fit_transform(X_train_scaled, y_train)
```

```
X_test_rfe = selector.transform(X_test_scaled)
```

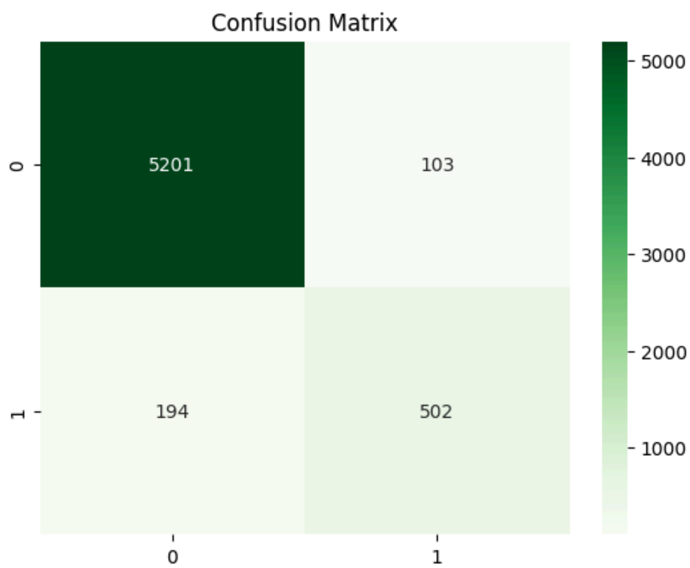
```
Selected Behavioral Features: ['rpm_variation', 'harsh_braking_count', 'idling_time', 'fuel_consumption', 'acceleration_smoothne
```

6. Final Models and Comparative Analysis

Final classification metrics.

```
final_rf = RandomForestClassifier(**rf_gs.best_params_, random_state=42).fit(X_train_rfe, y_train)
y_pred_final = final_rf.predict(X_test_rfe)

print("Final Random Forest Report:")
print(classification_report(y_test, y_pred_final))

sns.heatmap(confusion_matrix(y_test, y_pred_final), annot=True, fmt='d', cmap='Greens')
plt.title("Confusion Matrix")
plt.show()
```

```
Final Random Forest Report:
              precision    recall  f1-score   support

           0       0.96      0.98      0.97      5304
           1       0.83      0.72      0.77       696

    accuracy                           0.95      6000
   macro avg       0.90      0.85      0.87      6000
weighted avg       0.95      0.95      0.95      6000
```



8. Conclusion and Reflection

Performance in the modelsIn both cases the Random Forest model proved to be the most resilient in terms of performance than the Logistic/Ridge Regression and Neural Network models. In the categorization problem, the Random Forest proved to be very resistant to outlier behaviors, and it was able to distinguish the "Eco-Friendly" and the Inefficient styles. In the regression task, the model was able to capture non-linear relationships, which were complex between industrial activity and energy consumption (a high result of the $R 2 score), compared to the Ridge baseline.2. Influence of Procedures Recursive Feature Elimination (RFE) is a wrapper-based feature selection algorithm that was necessary to reduce the models to 5 most discriminative features. The method minimized noise and enhanced the concentration of the model on the major drivers such as acceleration and industrial activity. Also, the use of GridSearchCV made it possible to precisely tune the hyperparameters of the models which meant that the resulting final models were optimized to generalization and not just to fit the training data.3 Inferences and Future Recommendations The discussion showed that the main predictors of low scores in sustainability are aggressive driving habits, mostly rapid acceleration and high speed variance, which corresponds to UNSDG Goal 12. The experiment conducted in the energy industry demonstrated that data aggregation in 3 months gives more consistent results regarding long-term trends because seasonal noise is diluted. The study might be expanded in future studies by applying LSTM (Long Short-Term Memory) networks to the time-based patterns of sensor data or by introducing feedback loops in real-