End-to-End Credit Card Fraud Detection with Machine Learning Models

In [3]:
```
# import libraries
import pandas as pd
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
# load the dataset
df = pd.read_csv(r'C:\Users\User\Downloads\creditcard.csv')
df.head()
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.0986
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.0851
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.2476
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.3774
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.2705

5 rows × 31 columns

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

This project utilizes the **Credit Card Fraud Detection dataset** from Kaggle, which contains anonymized transactions made by European cardholders in September 2013. The dataset consists of **284,807 transactions** and is characterized by an **extremely imbalanced target variable**, with fraudulent transactions representing approximately **0.17%** of the data.

Metric	Value
Number of rows	284,807
Number of columns	31
Features	28 PCA components (V1–V28), Time, Amount
Target Variable	Class (0 = Non-fraud, 1 = Fraud)
Class Distribution	~0.17% fraud cases (492 frauds)

The dataset includes:

- **Time** — Seconds elapsed between each transaction and the first transaction
- **V1–V28** — PCA-transformed features (due to confidentiality)
- **Amount** — Transaction amount
- **Class** — Binary target variable (fraud indicator)

In [9]:

```
df.Class.value_counts()
```

Out[9]:

```
Class
0    284315
1       492
Name: count, dtype: int64
```

```
Data is imbalanced, we nedd to handlethe imbalanced data
```

Problem Statement

Fraudulent credit card transactions result in significant financial losses and customer dissatisfaction for financial institutions.
The goal of this project is to build and benchmark machine learning classification models that can accurately detect fraudulent transactions within a highly imbalanced dataset, while minimizing false negatives and improving fraud detection efficiency.

🏆 Project Objective

- To address **class imbalance** using undersampling techniques.
- To train and evaluate multiple **classification models** (Logistic Regression, KNN, Decision Tree, Random Forest, AdaBoost).
- To optimize model performance through **hyperparameter tuning** and compare model results.
- To identify the most effective model(s) for detecting fraudulent credit card transactions.

Data Preprocessing

Balancing the data

Undersampling

In [425…

```
# dependent and independent data

x = df.drop('Class', axis = 1)
```

```
y = df.Class
```

In [427…

```
# train test split
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)
```

In [429…

```
x_train
```

Out[429…

	Time	V1	V2	V3	V4	V5	V6	V
228122	145367.0	2.053311	0.089735	-1.681836	0.454212	0.298310	-0.953526	0.15200
283298	171505.0	2.072657	-0.059176	-1.127889	0.382489	-0.078354	-1.131236	0.17676
49603	44132.0	0.041351	-2.448057	-0.455488	0.406956	-1.569721	-0.870497	0.72670
238026	149493.0	1.990593	-0.330605	-0.920831	0.041564	-0.286964	-0.653376	-0.24149
138828	82866.0	0.762289	-0.301791	-1.368812	1.679729	2.128077	3.782476	-0.31997
...	...	...	...	...	...	...	...	
42487	41121.0	-0.687671	0.162012	0.637712	-0.341793	1.855939	4.173013	-0.66666
161032	113807.0	-0.017840	0.755066	0.613992	-0.647947	0.044703	-0.885837	0.36294
46440	42787.0	-0.341879	0.636188	2.053224	0.600069	0.176559	0.512507	0.45655
211250	138329.0	-0.617552	0.005754	0.001910	-0.777948	0.635097	-0.466782	1.15854
145579	87062.0	-5.068390	-3.517645	-1.442207	-0.503810	7.459502	0.650672	-2.12290

199364 rows × 30 columns

In [431…

```
y_train
```

Out[431…

```
228122    0
283298    0
49603     0
238026    0
138828    0
         ..
42487     0
161032    0
46440     0
211250    0
145579    0
Name: Class, Length: 199364, dtype: int64
```

In [433…

```
y_train.value_counts()
```

Out[433…

```
Class
0    199009
1       355
Name: count, dtype: int64
```

In [435…
```python
# undersampling
from imblearn.under_sampling import NearMiss
```

In [437…
```python
# initialize

nm = NearMiss()
```

In [439…
```python
x_train_nm, y_train_nm = nm.fit_resample(x_train, y_train)
```

In [441…
```python
y_train_nm.value_counts()
```

Out[441…
```
Class
0    355
1    355
Name: count, dtype: int64
```

In [443…
```python
x_test_nm, y_test_nm = nm.fit_resample(x_test, y_test)
```

In [445…
```python
x_test_nm
```

Out[445…

	Time	V1	V2	V3	V4	V5	V6	V
0	7551.0	0.861827	1.525916	-3.253113	0.707706	3.561780	2.433556	0.27902
1	7569.0	1.125274	0.715678	1.033160	2.609092	-0.134327	-0.263141	-0.02468
2	7572.0	-0.300229	1.260226	2.276756	1.366404	-0.068287	-0.582341	0.63639
3	93824.0	1.976929	-0.302019	-0.082737	0.739391	-0.767913	-0.582706	-0.69810
4	7567.0	-1.034925	0.421541	1.719689	-0.089020	2.015857	4.770585	-0.65684
...	...	...	...	...	...	...	...	...
269	65728.0	1.227614	-0.668974	-0.271785	-0.589440	-0.604795	-0.350285	-0.48636
270	14073.0	-4.153014	8.204797	-15.031714	10.330100	-3.994426	-3.250013	-10.41569
271	155965.0	-1.201398	4.864535	-8.328823	7.652399	-0.167445	-2.767695	-3.17642
272	34521.0	1.081234	0.416414	0.862919	2.520863	-0.005021	0.563341	-0.12337
273	93888.0	-10.040631	6.139183	-12.972972	7.740555	-8.684705	-3.837429	-11.90770

274 rows × 30 columns

Model Building

Trained five classifiers:

- Logistic Regression
- K-Nearest Neighbors (KNN)
- Decision Tree Classifier

- Random Forest Classifier
- AdaBoost Classifier

Logistic Regression

In [59]:
```
from sklearn.linear_model import LogisticRegression
```

In [61]:
```
LR = LogisticRegression()

LR.fit(x_train_nm, y_train_nm)
```

Out[61]:
```
▾ LogisticRegression
LogisticRegression()
```

In [63]:
```
# Predict on the balanced TEST set
y_pred_test_lr = LR.predict(x_test_nm)
```

In [65]:
```
y_pred_test_lr
```

Out[65]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
      dtype=int64)
```

In [45]:
```
# Evaluation of the logistic regression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [67]:
```
print('Accuracy score is: ', accuracy_score(y_test_nm, y_pred_test_lr))
```

```
Accuracy score is:  0.9401408450704225
```

In [69]:
```
print('Confusion Matrix:\n', confusion_matrix(y_test_nm, y_pred_test_lr))
print('Classification Report:\n', classification_report(y_test_nm, y_pred_test_lr))
```

```
Confusion Matrix:
 [[138   4]
 [ 13 129]]
Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.97      0.94       142
           1       0.97      0.91      0.94       142

    accuracy                           0.94       284
   macro avg       0.94      0.94      0.94       284
weighted avg       0.94      0.94      0.94       284
```

In [ ]:

```

```

KNN Classifier

In [74]:

```
from sklearn.neighbors import KNeighborsClassifier
```

Initialize and Train the KNN model

In [537…

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_train_nm_scaled = scaler.fit_transform(x_train_nm)
x_test_nm_scaled = scaler.fit_transform(x_test_nm)
```

In [539…

```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3, weights='distance')
knn.fit(x_train_nm_scaled, y_train_nm)
```

Out[539…

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3, weights='distance')
```

In [541…

```
y_pred_knn = knn.predict(x_test_nm_scaled)
```

In [543…

```
print("KNN Accuracy:", accuracy_score(y_test_nm, y_pred_knn))
```

```
KNN Accuracy: 0.9343065693430657
```

Decision Tree Classifier

In [106…

```
from sklearn.tree import DecisionTreeClassifier
```

In [110…
```
dt = DecisionTreeClassifier(random_state=42)
```

In [112…
```
dt.fit(x_train_nm, y_train_nm)
```

Out[112…
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

In [114…
```
y_pred_test_dt = dt.predict(x_test_nm)
```

In [116…
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

print('Accuracy Score:', accuracy_score(y_test_nm, y_pred_test_dt))
print('Confusion Matrix:\n', confusion_matrix(y_test_nm, y_pred_test_dt))
print('Classification Report:\n', classification_report(y_test_nm, y_pred_test_dt))
```

```
Accuracy Score: 0.6197183098591549
Confusion Matrix:
 [[ 45  97]
 [ 11 131]]
Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.32      0.45       142
           1       0.57      0.92      0.71       142

    accuracy                           0.62       284
   macro avg       0.69      0.62      0.58       284
weighted avg       0.69      0.62      0.58       284
```

Hyperparameter tunning

In [119…
```
# Hyperparameter tuning

parameters = {
    'criterion' : ['gini', 'entropy', 'log_loss'],
    'splitter' : ['best', 'random'],
    'max_depth' : [1,2,3,4,5,6,7],
    'max_features' : ["auto", "sqrt", "log2"]
}
```

In [121…
```
# GridSearchCV  (CV= Cross Validation)

from sklearn.model_selection import GridSearchCV

treemodel = DecisionTreeClassifier()

gscv = GridSearchCV(treemodel, param_grid=parameters, cv=5, scoring='accuracy')

gscv.fit(x_train, y_train)
```

Out[121…

GridSearchCV

best_estimator_: DecisionTreeClassifier

DecisionTreeClassifier

In [123…

```
gscv.best_params_
```

Out[123…

```
{'criterion': 'log_loss',
 'max_depth': 7,
 'max_features': 'sqrt',
 'splitter': 'best'}
```

In [125…

```
dt_model = DecisionTreeClassifier(criterion='log_loss', max_depth = 7, max_features
```

In [127…

```
dt_model.fit(x_train_nm, y_train_nm)
```

Out[127…

DecisionTreeClassifier

```
DecisionTreeClassifier(criterion='log_loss', max_depth=7, max_features='sq
rt')
```

In [129…

```
# Prediction

y_pred_train_DT = dt_model.predict(x_train_nm)

y_pred_test_DT = dt_model.predict(x_test_nm)
```

In [131…

```
print(f'Training Accuracy {accuracy_score(y_pred_train, y_train_nm)}')
print(f'Testing Accuracy {accuracy_score(y_pred_test, y_test_nm)}')
```

```
Training Accuracy 0.96
Testing Accuracy 0.9119718309859155
```

Random Forest Classifier

In [485…

```
from sklearn.ensemble import RandomForestClassifier
```

In [487…

```
rf = RandomForestClassifier(random_state=42)
```

In [489…

```
rf.fit(x_train_nm, y_train_nm)
```

Out[489…

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

In [491…

```
y_pred_test_rf = rf.predict(x_test_nm)
```

In [493…

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

print('Accuracy Score:', accuracy_score(y_test_nm, y_pred_test_rf))
```

```
Accuracy Score: 0.9306569343065694
```

Hyperparameter tunning

In [392…

```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [508…

```
params = { 'n_estimators' : [100,200,300],
          'criterion' : ['gini','entropy'],
          'max_depth' : [5,10,15,None],
          'min_samples_split':np.arange(2,10),
          'min_samples_leaf' : np.arange(1,10)
}
```

Grid Search CV

In [510…

```
rf_gscv = GridSearchCV(rf, param_grid= params)
```

In [515…

```
rf_gscv.fit(x_train, y_train)
```

Randomized Search CV

In [400…

```
rfrs = RandomizedSearchCV(rf, param_distributions = params, cv=10, n_iter=15)
```

In [404…

```
rfrs.fit(x_train_nm, y_train_nm)
```

Out[404…

```
RandomizedSearchCV
best_estimator_:
RandomForestClassifier
RandomForestClassifier
```

In [496…

```
rfrs.best_params_
```

Out[496… {'n_estimators': 100,
 'min_samples_split': 8,
 'min_samples_leaf': 2,
 'max_depth': 15,
 'criterion': 'gini'}

In [498…
```
rf_model = RandomForestClassifier(n_estimators = 100, criterion='gini', max_depth =
```

In [500…
```
rf_model.fit(x_train_nm, y_train_nm)
```

Out[500…

RandomForestClassifier

RandomForestClassifier(max_depth=15, min_samples_leaf=2, min_samples_split
=8)

In [502…
```
# Prediction

y_pred_train_RF = rf_model.predict(x_train_nm)

y_pred_test_RF = rf_model.predict(x_test_nm)
```

In [504…
```
print('Accuracy Score (final)):', accuracy_score(y_test_nm, y_pred_test_RF))
print('Confusion Matrix:\n', confusion_matrix(y_test_nm, y_pred_test_rf))
print('Classification Report:\n', classification_report(y_test_nm, y_pred_test_rf))
```

```
Accuracy Score (final)): 0.927007299270073
Confusion Matrix:
 [[128   9]
 [ 10 127]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.93      0.93       137
           1       0.93      0.93      0.93       137

    accuracy                           0.93       274
   macro avg       0.93      0.93      0.93       274
weighted avg       0.93      0.93      0.93       274
```

AdaBoost Classifier

In [461…
```
from sklearn.ensemble import AdaBoostClassifier
```

In [463…
```
base_est = DecisionTreeClassifier(random_state=42)
```

In [465…
```
# Define base estimator (Decision stump)
adaboost = AdaBoostClassifier(estimator=base_est, random_state=42)
```

```
# Initialize AdaBoost with estimator (new versions only)
adaboost.fit(x_train_nm, y_train_nm)
```

Out[465…

```
AdaBoostClassifier
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [467…

```
y_pred_test_ada = adaboost.predict(x_test_nm)
```

In [469…

```
## Evaluation parameters
print('Accuracy Score:', accuracy_score(y_test_nm, y_pred_test_ada))
```

```
Accuracy Score: 0.6496350364963503
```

Hyperparameter tunning

In [219…

```
# Define parameter grid
params = {
    'n_estimators': [50, 100, 150],
    'learning_rate': [0.01, 0.1, 1],
    'estimator__max_depth': [1, 2, 3]
}
```

In [223…

```
treemodel = AdaBoostClassifier()

# GridSearchCV
gscv = GridSearchCV(estimator=adaboost, param_grid=params, cv=5, scoring='accuracy'
```

In [225…

```
gscv.fit(x_train_nm, y_train_nm)
```

Out[225…

```
GridSearchCV
best_estimator_: AdaBoostClassifier
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [471…

```
gscv.best_params_
```

Out[471…

```
{'estimator__max_depth': 3, 'learning_rate': 1, 'n_estimators': 100}
```

In [473…

```
# Retrain final model
ADAB = AdaBoostClassifier(learning_rate= 1, n_estimators= 100, random_state=42)

ADAB.fit(x_train_nm, y_train_nm)
```

Out[473…

```
AdaBoostClassifier

AdaBoostClassifier(learning_rate=1, n_estimators=100, random_state=42)
```

In [523…

```
# Predict on test data
y_pred_test_ADAB = ADAB.predict(x_test_nm)
```

In [525…

```
# Evaluate

print('Test Accuracy:', accuracy_score(y_test_nm, y_pred_test_ADAB))
print('Confusion Matrix:\n', confusion_matrix(y_test_nm, y_pred_test_ADAB))
print('Classification Report:\n', classification_report(y_test_nm, y_pred_test_ADAB
```

```
Test Accuracy: 0.8321167883211679
Confusion Matrix:
 [[ 98  39]
 [  7 130]]
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.72      0.81       137
           1       0.77      0.95      0.85       137

    accuracy                           0.83       274
   macro avg       0.85      0.83      0.83       274
weighted avg       0.85      0.83      0.83       274
```

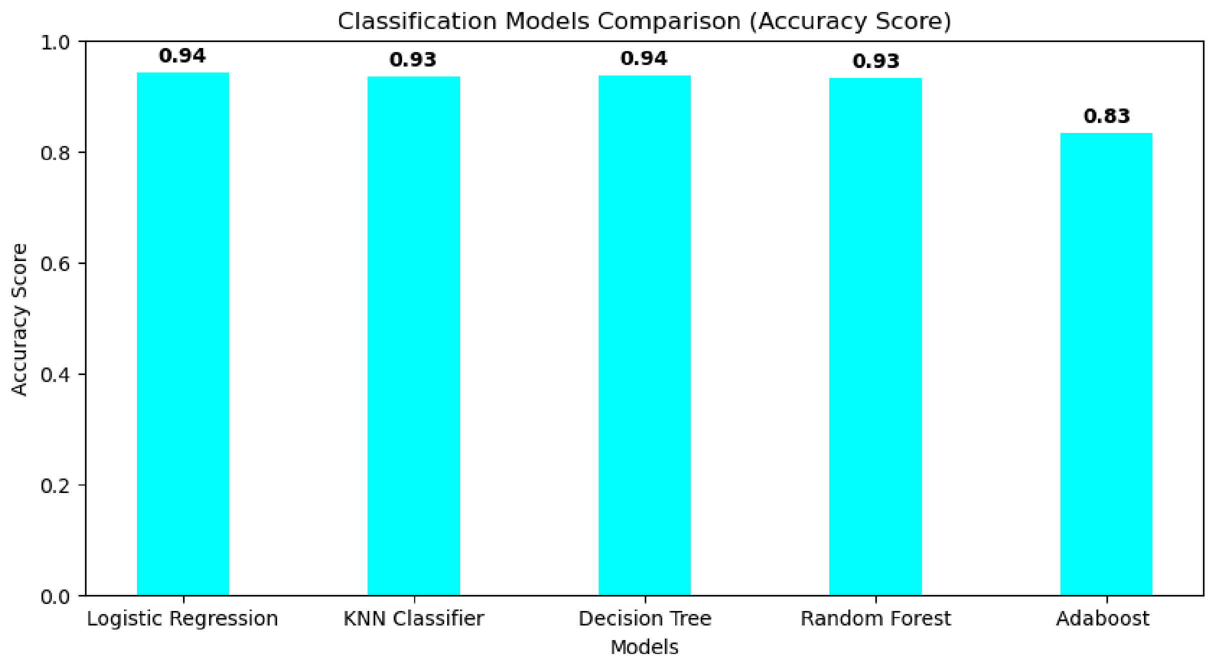
In [ ]:

Model Comparison and Interpretation

In [545…

```
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

# Model names
models = ['Logistic Regression', 'KNN Classifier', 'Decision Tree', 'Random Forest'

# Predicted values from each model
y_pred_test_lr = LR.predict(x_test_nm)
y_pred_knn = knn.predict(x_test_nm_scaled)
y_pred_test_DT = dt_model.predict(x_test_nm)
y_pred_test_rf = rf.predict(x_test_nm)
y_pred_test_ADAB = ADAB.predict(x_test_nm)

# Calculate R2 scores
```

```python
accuracy_scores = [
    accuracy_score(y_test_nm, y_pred_test_lr),
    accuracy_score(y_test_nm, y_pred_knn),
    accuracy_score(y_test_nm, y_pred_test_DT),
    accuracy_score(y_test_nm, y_pred_test_rf),
    accuracy_score(y_test_nm, y_pred_test_ADAB)
]

# Plot
plt.figure(figsize=(10,5))
plt.bar(models, accuracy_scores, color='cyan', width=0.4)
# Annotate accuracy score values on bars
for i, v in enumerate(accuracy_scores):
    plt.text(i, v + 0.02, f"{v:.2f}", ha='center', fontweight='bold')

plt.xlabel('Models')
plt.ylabel('Accuracy Score')
plt.title('Classification Models Comparison (Accuracy Score)')
plt.ylim(0, 1)  # Optional: to make chart scale uniform
plt.show()
```



Logistic Regression and Decision Tree Classifier model gives highest acuracy for this dataset.

Thank you!

In [ ]: