Importing the Dependencies

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy score

loading the dataset to a Pandas DataFrame
credit_card_data = pd.read_csv('creditcard.csv')

first 5 rows of the dataset
credit_card_data.head()

→		Time	V1	V2	V3	V4	V 5	V6	V7	V8
	0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
	1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
	2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
	3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
	4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

credit_card_data.tail()

→		Time	V1	V2	V3	V4	V5	V6	V7
	284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
	284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
	284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
	284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
	284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

dataset informations
credit_card_data.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
d+vn	oc. floa	+64/30)	in+61(1)	

dtypes: float64(30), int64(1)

memory usage: 67.4 MB

checking the number of missing values in each column
credit_card_data.isnull().sum()

$\overline{\Rightarrow}$	Time	0
	V1	0
	V2	0
	V3	0
	V4	0
	V5	0
	V6	0
	V7	0
	V8	0
	V9	0
	V10	0
	V11	0
	V12	0
	V13	0
	V14	0
	V15	0
	V16	0

```
V17
           0
V18
           0
V19
           0
V20
           0
V21
           0
V22
           0
V23
           0
V24
           0
V25
           0
V26
           0
V27
           0
V28
           0
Amount
           0
Class
           0
dtype: int64
```

distribution of legit transactions & fraudulent transactions
credit_card_data['Class'].value_counts()

This Dataset is highly unblanced

0 --> Normal Transaction

std

min

25%

50%

75%

1 --> fraudulent transaction

250.105092

0.000000

5.650000

22.000000

77.050000

max 25691.160000

Name: Amount, dtype: float64

fraud.Amount.describe()

$\overline{\longrightarrow}$	count	492.000000
	mean	122.211321
	std	256.683288
	min	0.000000
	25%	1.000000
	50%	9.250000
	75%	105.890000
	max	2125.870000

Name: Amount, dtype: float64

compare the values for both transactions
credit_card_data.groupby('Class').mean()

→		Time	V1	V2	V3	V4	V5	V6	
	Class								
	0	94838.202258	0.008258	-0.006271	0.012171	-0.007860	0.005453	0.002419	0.0096
	1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.5687

Under-Sampling

Build a sample dataset containing similar distribution of normal transactions and Fraudulent Transactions

Number of Fraudulent Transactions --> 492

legit_sample = legit.sample(n=492)

Concatenating two DataFrames

```
new_dataset = pd.concat([legit_sample, fraud], axis=0)
```

new_dataset.head()



	Time	V1	V2	V3	V4	V5	V6	V7
203131	134666.0	-1.220220	-1.729458	-1.118957	-0.266099	0.823338	-0.098556	-0.407751
95383	65279.0	-1.295124	0.157326	1.544771	-2.468209	-1.683113	-0.623764	-0.371798
99706	67246.0	-1.481168	1.226490	1.857550	2.980777	-0.672645	0.581449	-0.143172
153895	100541.0	-0.181013	1.395877	1.204669	4.349279	1.330126	1.277520	1.568221
249976	154664.0	0.475977	-0.573662	0.480520	-2.524647	-0.616284	-0.361317	-0.347861

new_dataset.tail()



	Time	V1	V2	V3	V4	V5	V6	V7	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-

new_dataset['Class'].value_counts()

 $\overline{\mathbf{T}}$

1 492

0 492

Name: Class, dtype: int64

new_dataset.groupby('Class').mean()

	~

	Time	V1	V2	V3	V4	V5	V6	ν
Class								
0	96783.638211	-0.053037	0.055150	-0.036786	-0.046439	0.077614	-0.023218	-0.00070
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.56873

Splitting the data into Features & Targets

```
X = new_dataset.drop(columns='Class', axis=1)
```

Y = new_dataset['Class']

print(X)

```
\rightarrow
                 Time
                              ٧1
                                        V2
                                                       V27
                                                                 V28
                                                                       Amount
             134666.0 -1.220220 -1.729458
    203131
                                                  0.173995 -0.023852
                                                                       155.00
                                             . . .
    95383
              65279.0 -1.295124
                                 0.157326
                                                                        70.00
                                                  0.317321
                                                            0.105345
    99706
                                  1.226490
                                                                        40.14
              67246.0 -1.481168
                                                -0.546577
                                                            0.076538
    153895
             100541.0 -0.181013
                                  1.395877
                                                 -0.229857 -0.329608
                                                                       137.04
    249976
             154664.0 0.475977 -0.573662
                                                  0.058961
                                                            0.012816
                                                                        19.60
    279863
             169142.0 -1.927883
                                  1.125653
                                                  0.292680
                                                            0.147968
                                                                       390.00
                                             . . .
    280143
             169347.0 1.378559
                                  1.289381
                                                  0.389152
                                                            0.186637
                                                                         0.76
                                                                        77.89
    280149
             169351.0 -0.676143
                                  1.126366
                                                  0.385107
                                                            0.194361
    281144
             169966.0 -3.113832
                                 0.585864
                                                  0.884876 -0.253700
                                                                       245.00
    281674
             170348.0 1.991976
                                 0.158476
                                                  0.002988 -0.015309
                                                                        42.53
```

print(Y)

```
203131
           0
95383
           0
99706
           0
153895
           0
249976
           0
279863
           1
280143
           1
280149
           1
           1
281144
281674
           1
Name: Class, Length: 984, dtype: int64
```

[984 rows x 30 columns]

Split the data into Training data & Testing Data

Model Training

Logistic Regression

```
model = LogisticRegression()
```

training the Logistic Regression Model with Training Data
model.fit(X_train, Y_train)

LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None, max_iter=100, multi_class='auto', n_jobs=None, penalty='l2', random_state=None, solver='lbfgs', tol=0.0001, verbose=0, warm start=False)

Model Evaluation

Accuracy Score

```
# accuracy on training data

X_train_prediction = model.predict(X_train)

training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

print('Accuracy on Training data : ', training_data_accuracy)

Accuracy on Training data : 0.9415501905972046

print('Accuracy score on Test Data : ', test_data_accuracy)

Accuracy score on Test Data : 0.9390862944162437
```

```
# Convert continuous target variable into binary classification labels
# Assuming 1 represents fraud and 0 represents non-fraud
y_train_binary = (y_train > 0).astype(int)
# Resampling to balance the classes
oversampler = RandomOverSampler(random_state=42)
X_resampled, y_resampled = oversampler.fit_resample(X_train, y_train_binary)
# Model training and evaluation
models = {
    'Random Forest': RandomForestClassifier(),
    'Decision Tree': DecisionTreeClassifier(),
    'KNN': KNeighborsClassifier(),
    'Logistic Regression': LogisticRegression(),
    'SVM': SVC()
}
# Train and evaluate models on resampled data
for name, model in models.items():
    model.fit(X resampled, y resampled)
   y pred = model.predict(X test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred)
    print(f'{name} Metrics:')
    print(f'Accuracy: {accuracy:.4f}')
    print(f'Precision: {precision:.4f}')
    print(f'Recall: {recall:.4f}')
    print(f'F1 Score: {f1:.4f}')
    print(f'ROC AUC: {roc_auc:.4f}')
    print()
→ /usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Undefir
       _warn_prf(average, modifier, msg_start, len(result))
     /usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Undefir
       _warn_prf(average, modifier, msg_start, len(result))
     Random Forest Metrics:
     Accuracy: 0.9992
     Precision: 0.0000
     Recall: 0.0000
     F1 Score: 0.0000
     ROC AUC: 0.5000
     Decision Tree Metrics:
     Accuracy: 0.9975
     Precision: 0.0000
     Recall: 0.0000
     F1 Score: 0.0000
```

ROC AUC: 0.4992

KNN Metrics:
Accuracy: 0.9992
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
ROC AUC: 0.5000

Logistic Regression Metrics:

Accuracy: 0.9900 Precision: 0.0769 Recall: 1.0000 F1 Score: 0.1429 ROC AUC: 0.9950

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: Converger

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:

https://scikit-learn.org/stable/modules/preprocessing.html

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear model.html#logistic-regression

n_iter_i = _check_optimize_result(

SVM Metrics:
Accuracy: 0.8234
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
ROC AUC: 0.4121

```
# Importing necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc
from sklearn.impute import SimpleImputer
from imblearn.over sampling import RandomOverSampler
# Load your dataset
# Assuming 'data' is your DataFrame with features and labels, and 'target' is your label col
# Replace 'data.csv' with your actual dataset file
data = pd.read csv('creditcard.csv')
# Handling missing values
imputer = SimpleImputer(strategy='mean')
data = pd.DataFrame(imputer.fit transform(data), columns=data.columns)
# Splitting the data into features and labels
X = data.drop('Class', axis=1) # Assuming 'Class' is the label column
y = data['Class']
# Splitting the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Convert continuous target variable into binary classification labels
# Assuming 1 represents fraud and 0 represents non-fraud
y_train_binary = (y_train > 0).astype(int)
y_test_binary = (y_test > 0).astype(int)
# Resampling to balance the classes for training data only
oversampler = RandomOverSampler(random state=42)
X_resampled, y_resampled = oversampler.fit_resample(X_train, y_train_binary)
# Model training and evaluation
models = {
    'Random Forest': RandomForestClassifier(),
    'Decision Tree': DecisionTreeClassifier(),
    'KNN': KNeighborsClassifier(),
    'Logistic Regression': LogisticRegression(),
    'SVM': SVC()
}
# Train and evaluate models on training data
print("Training Data Metrics:")
for name, model in models.items():
   model.fit(X resampled, y resampled)
```

```
y_train_pred = model.predict(X_resampled)
    accuracy_train = accuracy_score(y_resampled, y_train_pred)
    precision_train = precision_score(y_resampled, y_train_pred)
    recall_train = recall_score(y_resampled, y_train_pred)
    f1_train = f1_score(y_resampled, y_train_pred)
    roc auc train = roc auc score(y resampled, y train pred)
    print(f'{name} Metrics:')
    print(f'Accuracy: {accuracy train:.4f}')
    print(f'Precision: {precision_train:.4f}')
    print(f'Recall: {recall train:.4f}')
    print(f'F1 Score: {f1_train:.4f}')
    print(f'ROC AUC: {roc_auc_train:.4f}')
    print()
# Evaluate models on testing data
print("Testing Data Metrics:")
for name, model in models.items():
   y_test_pred = model.predict(X_test)
    accuracy_test = accuracy_score(y_test_binary, y_test_pred)
    precision_test = precision_score(y_test_binary, y_test_pred)
    recall_test = recall_score(y_test_binary, y_test_pred)
    f1_test = f1_score(y_test_binary, y_test_pred)
    roc_auc_test = roc_auc_score(y_test_binary, y_test_pred)
    print(f'{name} Metrics:')
    print(f'Accuracy: {accuracy_test:.4f}')
    print(f'Precision: {precision_test:.4f}')
    print(f'Recall: {recall_test:.4f}')
    print(f'F1 Score: {f1_test:.4f}')
    print(f'ROC AUC: {roc_auc_test:.4f}')
    print()
→ Training Data Metrics:
     Random Forest Metrics:
     Accuracy: 1.0000
     Precision: 1.0000
     Recall: 1.0000
     F1 Score: 1.0000
     ROC AUC: 1.0000
     Decision Tree Metrics:
     Accuracy: 1.0000
     Precision: 1.0000
     Recall: 1.0000
     F1 Score: 1.0000
     ROC AUC: 1.0000
     KNN Metrics:
```

```
Accuracy: 0.9996
     Precision: 0.9992
     Recall: 1.0000
     F1 Score: 0.9996
     ROC AUC: 0.9996
     /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: Conver
     STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
     Increase the number of iterations (max iter) or scale the data as shown in:
         https://scikit-learn.org/stable/modules/preprocessing.html
     Please also refer to the documentation for alternative solver options:
         https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
       n iter i = check optimize result(
     Logistic Regression Metrics:
     Accuracy: 0.9961
     Precision: 0.9923
     Recall: 1.0000
     F1 Score: 0.9961
from sklearn.ensemble import RandomForestClassifier
# Instantiate the Random Forest classifier
rf classifier = RandomForestClassifier()
# Train the Random Forest classifier on the resampled training data
rf_classifier.fit(X_resampled, y_resampled)
# Predictions on training data
y_train_pred_rf = rf_classifier.predict(X_resampled)
# Predictions on testing data
y test pred rf = rf classifier.predict(X test)
# Calculate accuracy on training data
accuracy train rf = accuracy score(y resampled, y train pred rf)
# Calculate accuracy on testing data
accuracy test rf = accuracy score(y test binary, y test pred rf)
```