Importing the libraries

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

```
Mounted at /content/drive
```

```
import numpy as np
import pandas as pd
```

Data Preparation

```
df = pd.read_csv("/content/drive/MyDrive/DV/transactions.csv")
```

```
df.head()
```

```
   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
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -
0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499
0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203
0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
0.592941

         V8        V9  ...       V21       V22       V23       V24
V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928
0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846
0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -
0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575
0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -
0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
```

```
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

```
df.shape
```

```
(284807, 31)
```

```
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
```

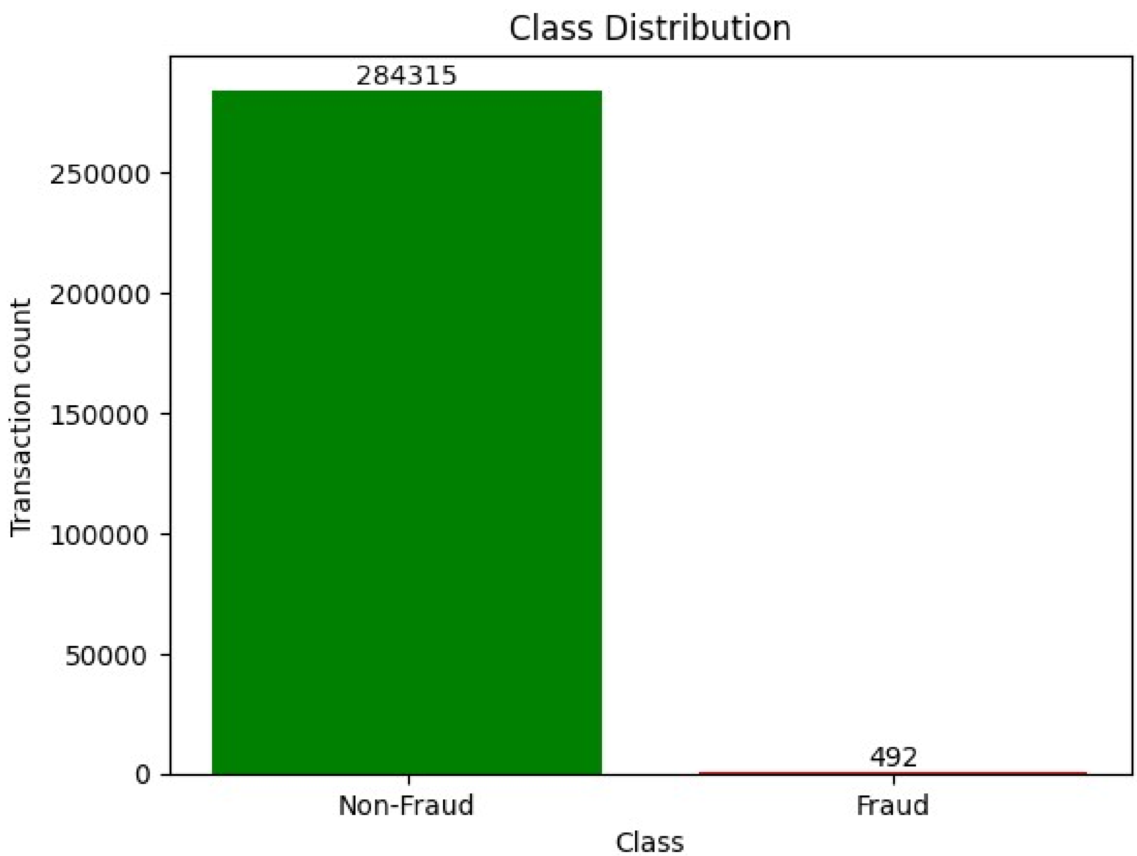
```
df.isnull().sum()
```

```
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
```

#Frequency Distribution of Class

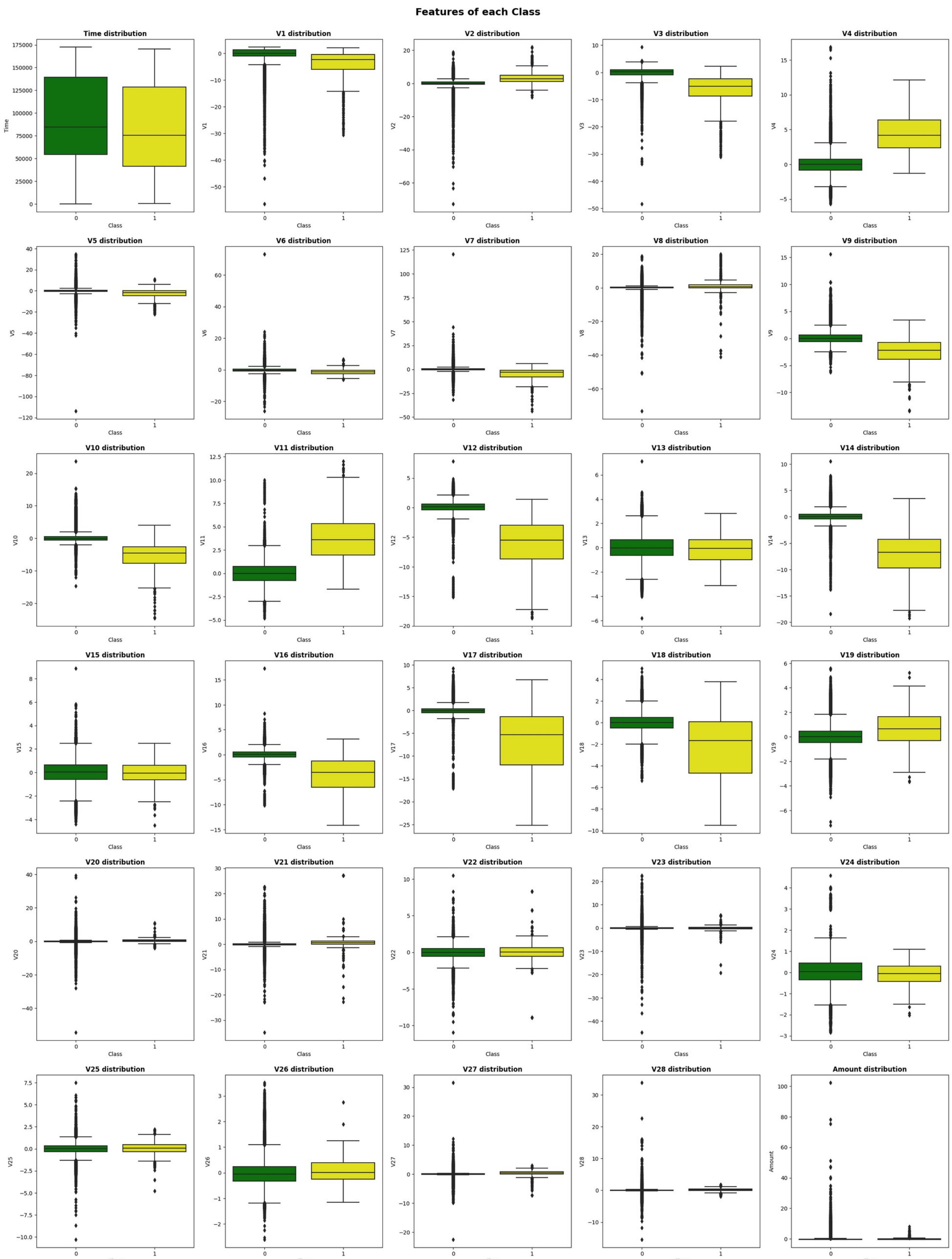
```
import matplotlib.pyplot as plt

class_counts = df['Class'].value_counts()

#Bar chart
plt.bar(class_counts.index, class_counts.values, color=['green',
'red'])
plt.xlabel('Class')
plt.ylabel('Transaction count')
plt.title('Class Distribution')
plt.xticks(class_counts.index, ['Non-Fraud', 'Fraud'])
# Adding annotations to each bar
for i, acc in enumerate(class_counts):
```

```
    plt.text(i, acc + 0.5, acc, ha='center', va='bottom')
plt.show()
```



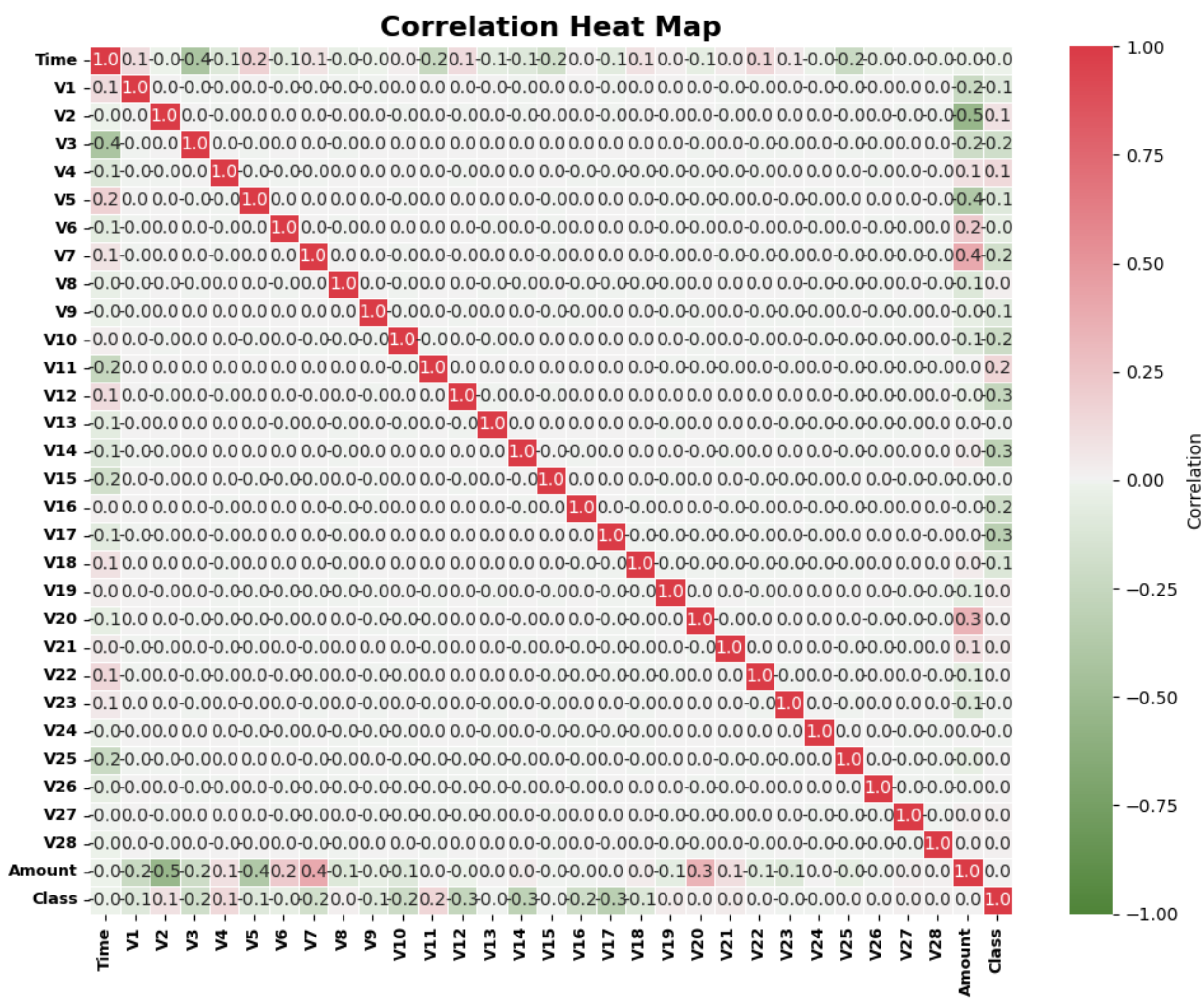
#Box Plot of Features of each Class

```
fig, axes = plt.subplots(nrows=6, ncols=5,figsize=(30,40))
fig.suptitle('Features of each Class', size = 18, y=0.9,
fontweight='bold')
fila=0
colum=0

for i in df.columns[:-1]:
  sns.boxplot(ax=axes[fila,colum], data=df, x='Class', y=i,
palette=['green','yellow'])
  axes[fila,colum].set_title(f"{i} distribution",fontweight='bold')
  colum= colum+1
  if colum == 5:
    colum=0
    fila+=1
```

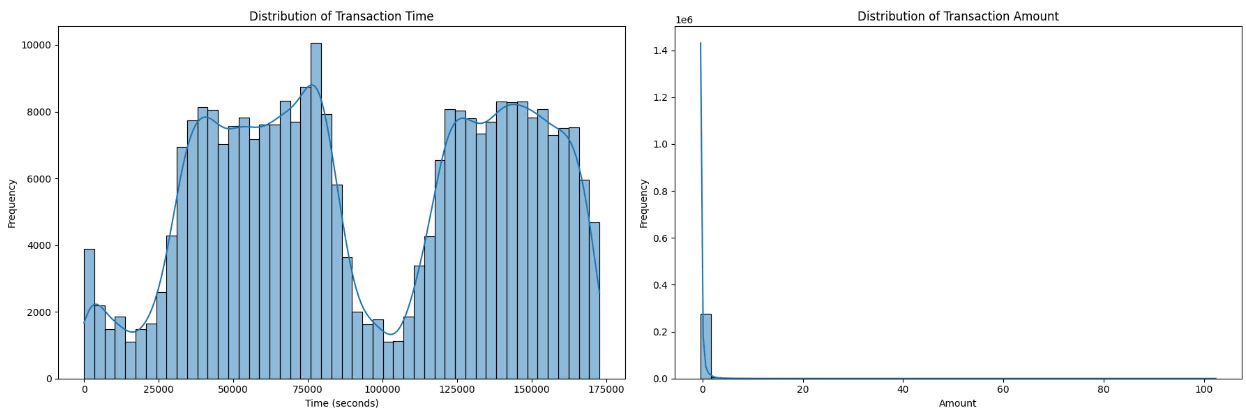


#Correlation Heat Map

```
correlation_matrix = df.corr()

plt.figure(figsize=(10, 8))
cmap_custom = sns.diverging_palette(120, 10, as_cmap=True)

sns.heatmap(correlation_matrix, annot=True, cmap=cmap_custom,
fmt='.1f', linewidths=0.5, vmin=-1, vmax=1,
            cbar_kws={'label': 'Correlation'})

plt.title('Correlation Heat Map', fontsize=16,fontweight='bold')

plt.xticks(fontsize=9,fontweight='bold')
plt.yticks(fontsize=9,fontweight='bold')

plt.tight_layout()

plt.show()
```



```python
# Creating subplots
fig, ax = plt.subplots(1, 2, figsize=(18, 6))

# Histogram for 'Time' feature
sns.histplot(df['Time'], bins=50, ax=ax[0], kde=True)
ax[0].set_title('Distribution of Transaction Time')
ax[0].set_xlabel('Time (seconds)')
ax[0].set_ylabel('Frequency')

# Histogram for 'Amount' feature
sns.histplot(df['Amount'], bins=50, ax=ax[1], kde=True)
ax[1].set_title('Distribution of Transaction Amount')
ax[1].set_xlabel('Amount')
ax[1].set_ylabel('Frequency')

# Adjust layout
plt.tight_layout()
plt.show()
```



The histograms for the 'Time' and 'Amount' features show the following:

1. Transaction Time: The distribution of transaction times shows some periodic patterns, which could be related to daily or weekly cycles in transaction frequency. This is common in financial transaction data, where activity can vary significantly depending on the time of day or week.

2. Transaction Amount: Most transactions are of lower amounts, with the frequency rapidly decreasing as the amount increases. This long-tailed distribution is typical in financial datasets, where small transactions are common and large transactions are relatively rare.

Feature Scaling

```python
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
df['Amount']= sc.fit_transform(pd.DataFrame(df['Amount']))
df.head()
```

```
   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
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -
0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499
0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203
0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
0.592941

         V8        V9  ...       V21       V22       V23       V24
V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928
0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846
0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -
0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575
0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -
0.206010

        V26       V27       V28    Amount  Class
0 -0.189115  0.133558 -0.021053  0.244964      0
1  0.125895 -0.008983  0.014724 -0.342475      0
2 -0.139097 -0.055353 -0.059752  1.160686      0
3 -0.221929  0.062723  0.061458  0.140534      0
4  0.502292  0.219422  0.215153 -0.073403      0

[5 rows x 31 columns]
```

```
df['Amount'].describe()
```

```
count    2.848070e+05
mean    -1.596686e-17
std      1.000002e+00
min     -3.532294e-01
25%     -3.308401e-01
50%     -2.652715e-01
75%     -4.471707e-02
max      1.023622e+02
Name: Amount, dtype: float64
```

```
df = df.drop(['Time'],axis=1)

df.head()

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

         V8        V9       V10  ...       V21       V22       V23
V24  \
0  0.098698  0.363787  0.090794  ... -0.018307  0.277838 -0.110474
0.066928
1  0.085102 -0.255425 -0.166974  ... -0.225775 -0.638672  0.101288 -
0.339846
2  0.247676 -1.514654  0.207643  ...  0.247998  0.771679  0.909412 -
0.689281
3  0.377436 -1.387024 -0.054952  ... -0.108300  0.005274 -0.190321 -
1.175575
4 -0.270533  0.817739  0.753074  ... -0.009431  0.798278 -0.137458
0.141267

        V25       V26       V27       V28    Amount  Class
0  0.128539 -0.189115  0.133558 -0.021053  0.244964      0
1  0.167170  0.125895 -0.008983  0.014724 -0.342475      0
2 -0.327642 -0.139097 -0.055353 -0.059752  1.160686      0
3  0.647376 -0.221929  0.062723  0.061458  0.140534      0
4 -0.206010  0.502292  0.219422  0.215153 -0.073403      0

[5 rows x 30 columns]

df.shape

(284807, 30)

df.duplicated().any()

True
```

REMOVE DUPLICATED VALUES

```
df = df.drop_duplicates()
df.shape
```

```
(275663, 30)
```

```
284807 - 275663
```

```
9144
```

NOT HANDLING IMBALANCED

```
df['Class'].value_counts()
```

```
0    275190
1       473
Name: Class, dtype: int64
```

STORE FEATURE MATRIX IN x AND RESPONSE IN VECTOR y

```
X = df.drop('Class',axis=1)
y = df['Class']
```

SPLITTING THE DATASET INTO THE TRAINING SET AND TEST SET

```
from sklearn.model_selection import train_test_split
X_train,X_test , y_train, y_test  =
train_test_split(X,y,test_size=0.20,random_state=42)
```

Handling Imbalanced Dataset

Undersampling

```
normal = df[df['Class']==0]
fraud = df[df['Class']==1]
```

```
normal.shape
```

```
(275190, 30)
```

```
fraud.shape
```

```
(473, 30)
```

```
normal_sample=normal.sample(n=473)
```

```
normal_sample.shape
```

```
(473, 30)
```

```python
new_data = pd.concat([normal_sample,fraud],ignore_index=True)
```

```python
new_data.head()
```

```
         V1        V2        V3        V4        V5        V6
V7  \
0 -1.478278  1.872233 -1.248675 -1.602380  1.549607 -1.184753
2.337972
1  2.092500 -1.006312 -1.835767 -0.672136 -0.568465 -1.470872 -
0.028210
2  0.311762 -2.602832 -2.942923  1.880832 -0.090804 -0.480139
1.865720
3 -0.625405  0.069174 -1.475244 -2.459043  2.304930  3.373235
0.033103
4  2.095020  0.040510 -1.847722  0.338714  0.574470 -0.840730
0.485067

         V8        V9       V10  ...       V21       V22       V23
V24  \
0 -1.049094  1.282513  2.288424  ... -0.168881  0.852646 -0.298441
0.657866
1 -0.383493 -0.243969  0.836672  ...  0.240261  0.550606 -0.039937 -
0.011346
2 -0.549267 -0.303862  0.069705  ...  0.718151  0.220383 -0.913711 -
0.332605
3  1.197842 -1.841251 -0.157792  ... -0.348845 -0.877869  0.167975
0.682458
4 -0.340795  0.577797 -0.077917  ... -0.013551  0.188564  0.062087
0.630235

        V25       V26       V27       V28    Amount  Class
0  0.029204  0.011506  0.624286  0.194931 -0.199223      0
1  0.243252  0.006025 -0.083359 -0.069236 -0.013952      0
2  0.278026 -0.474820 -0.200782  0.073386  3.233054      0
3 -0.342840  0.450133 -0.034917  0.067017 -0.085478      0
4  0.386115 -0.243627 -0.036975 -0.061877 -0.349231      0

[5 rows x 30 columns]
```

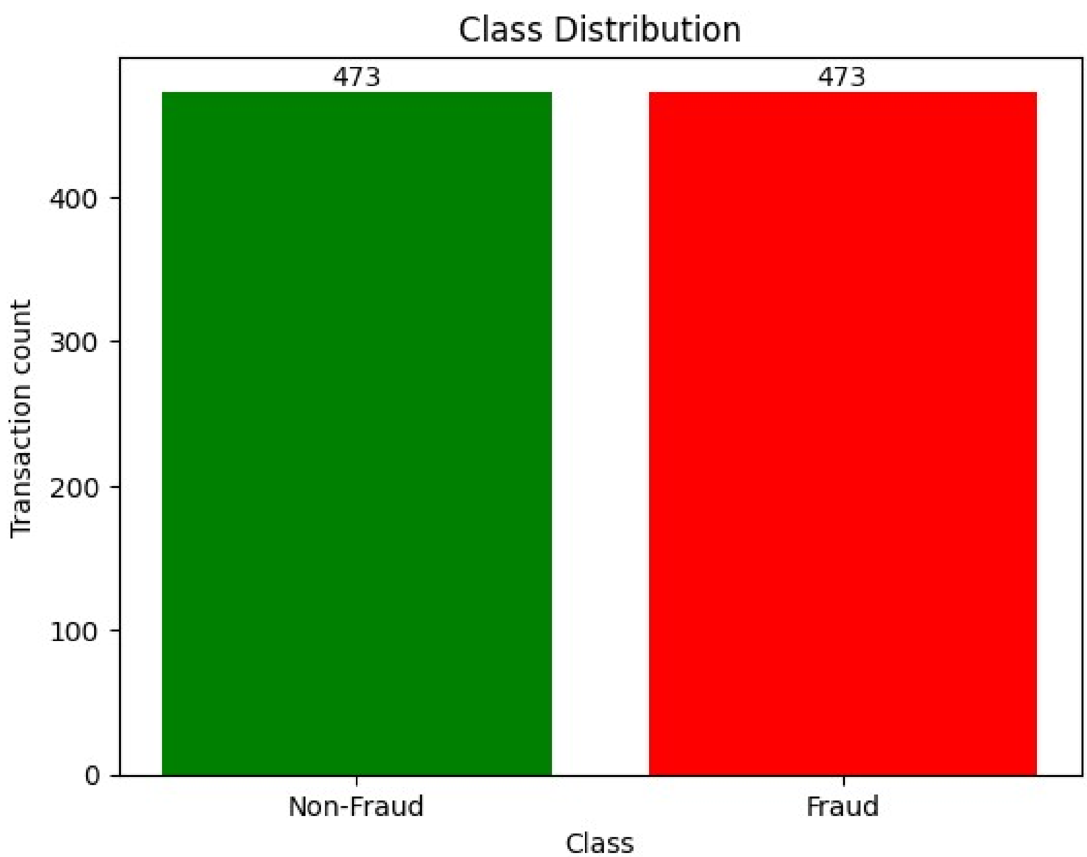
```python
new_data.shape
```

```
(946, 30)
```

```python
new_data['Class'].value_counts()
```

```
0    473
1    473
Name: Class, dtype: int64
```

```
import matplotlib.pyplot as plt

class_counts = new_data['Class'].value_counts()

#Bar chart
plt.bar(class_counts.index, class_counts.values, color=['green',
'red'])
plt.xlabel('Class')
plt.ylabel('Transaction count')
plt.title('Class Distribution')
plt.xticks(class_counts.index, ['Non-Fraud', 'Fraud'])
# Adding annotations to each bar
for i, acc in enumerate(class_counts):
    plt.text(i, acc + 0.5, acc, ha='center', va='bottom')
plt.show()
```




```
new_data.head()

         V1        V2        V3        V4        V5        V6
V7  \
0  1.900368 -0.754937 -0.029267  0.455184 -0.966945  0.332113 -
1.208030
1  1.342034 -0.601087 -0.397937 -0.770990 -0.475795 -0.685272 -
```

```
0.072419
2  1.956950 -0.001275 -1.813899  0.603469  0.028823 -1.554520
0.277435
3  1.337227  0.290879 -0.387485  0.166632  0.567025  0.250590 -
0.025959
4  1.507577 -1.024466  0.559104 -1.413875 -1.543809 -0.704107 -
1.066982

         V8        V9       V10  ...       V21       V22       V23
V24  \
0  0.462351  1.537534  0.225682  ...  0.034383  0.074968  0.371245
0.640507
1 -0.243450 -0.945197  0.663080  ... -0.837065 -2.191765  0.112161 -
0.662780
2 -0.351745  0.737834 -0.507092  ...  0.209335  0.615825 -0.053269 -
0.052135
3  0.030460 -0.171999 -0.123140  ... -0.345309 -1.001003 -0.100966 -
1.427895
4 -0.159086 -1.726180  1.407877  ... -0.385481 -0.777162  0.125373 -
0.018079

        V25       V26       V27       V28    Amount  Class
0 -0.647078  0.133690 -0.012905 -0.042023 -0.293258      0
1  0.072125  0.680915 -0.095004  0.009330 -0.033502      0
2  0.198322 -0.105898 -0.017494 -0.022135 -0.136293      0
3  0.431179  0.182841 -0.026243  0.003852 -0.349831      0
4  0.177906 -0.389423  0.041005  0.028210 -0.258875      0

[5 rows x 30 columns]
```

```
X = new_data.drop('Class',axis=1)
y = new_data['Class']
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.20,random_state=42)
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression()
log.fit(X_train,y_train)
```

```
LogisticRegression()
```

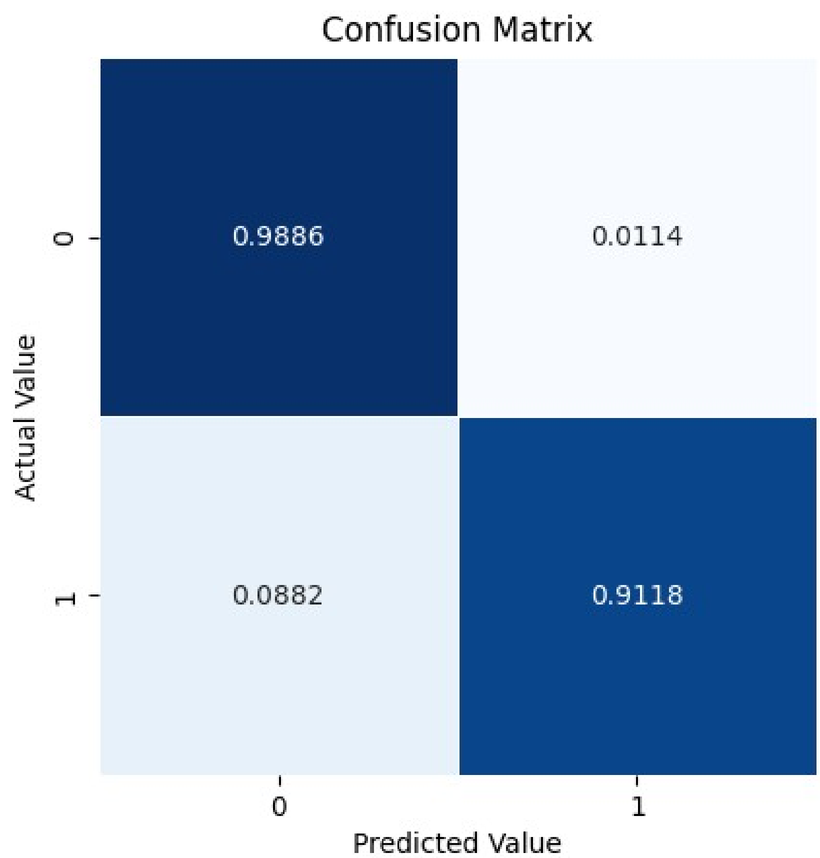
```
y_pred1 = log.predict(X_test)
```

```
# Calculate evaluation metrics
from sklearn.metrics import accuracy_score, precision_score,
```

```
recall_score, f1_score
accuracy1 = accuracy_score(y_test, y_pred1)
precision = precision_score(y_test, y_pred1)
recall = recall_score(y_test, y_pred1)
f1 = f1_score(y_test, y_pred1)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy1, precision, recall, f1]
})
metrics_df
```

	Metric	Score
0	Accuracy	0.947368
1	Precision	0.989362
2	Recall	0.911765
3	F1 Score	0.948980

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred1)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



		Predicted	
		Negative **(N)** **-**	Positive **(P)** **+**
Actual	Negative **-**	True Negative **(TN)**	**False Positive (FP)** **Type I Error**
	Positive **+**	**False Negative (FN)** **Type II Error**	True Positive **(TP)**

Decision Tree Classifier

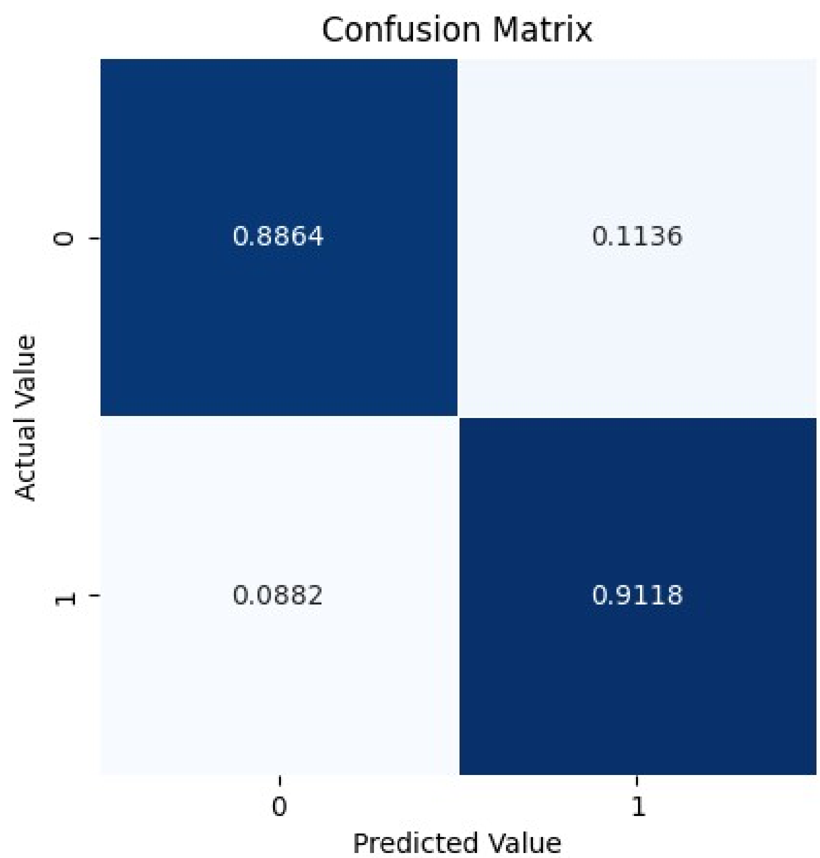
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
```

```
DecisionTreeClassifier()
```

```
y_pred2 = dt.predict(X_test)

# Calculate evaluation metrics
accuracy2 = accuracy_score(y_test, y_pred2)
precision = precision_score(y_test, y_pred2)
recall = recall_score(y_test, y_pred2)
f1 = f1_score(y_test, y_pred2)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy2, precision, recall, f1]
})

print(metrics_df)
```

```
      Metric     Score
0   Accuracy  0.900000
1  Precision  0.902913
2     Recall  0.911765
3   F1 Score  0.907317
```

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred2)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



Random Forest Classifier

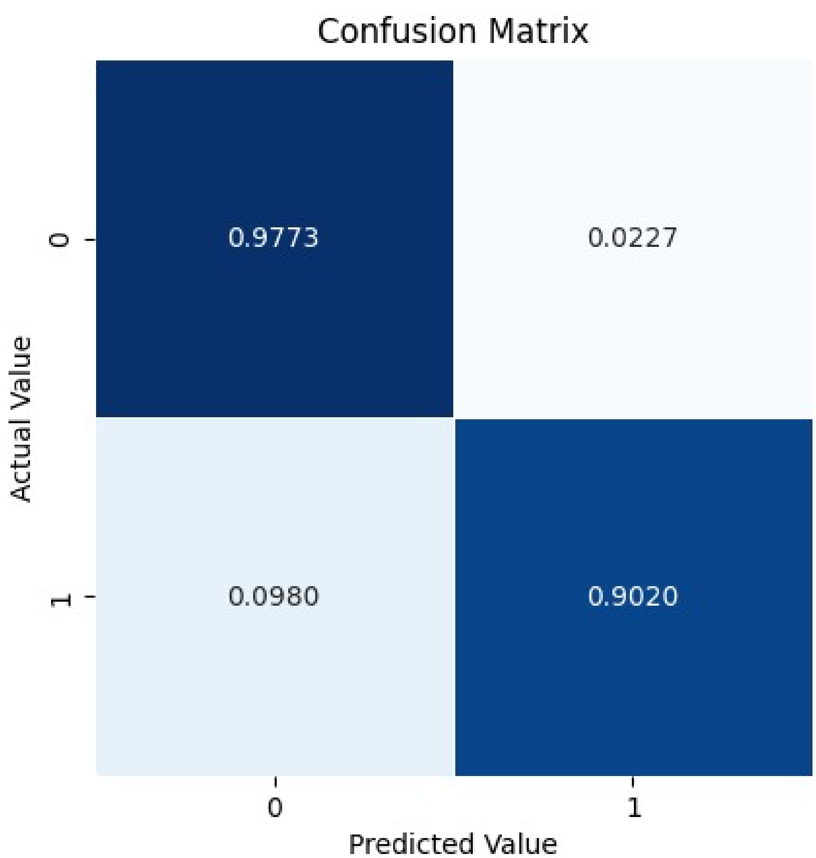
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,y_train)
```

```
RandomForestClassifier()
```

```
y_pred3 = rf.predict(X_test)
```

```
# Calculate evaluation metrics
accuracy3 = accuracy_score(y_test, y_pred3)
precision = precision_score(y_test, y_pred3)
recall = recall_score(y_test, y_pred3)
f1 = f1_score(y_test, y_pred3)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy3, precision, recall, f1]
})

print(metrics_df)
```

```
      Metric     Score
0   Accuracy  0.936842
1  Precision  0.978723
2     Recall  0.901961
3   F1 Score  0.938776

from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred3)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



Artificial Neural Network

```
import tensorflow as tf
from tensorflow import keras

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

# Build the ANN model
model = keras.Sequential([
    keras.layers.Dense(units=128, activation='relu',
input_dim=X_train.shape[1]),
    keras.layers.Dense(units=64, activation='relu'),
    keras.layers.Dense(units=1, activation='sigmoid')  # Binary
classification, so using sigmoid activation
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

# Train the model
model.fit(X_train_scaled, y_train, epochs=10, batch_size=32,
validation_split=0.2)

Epoch 1/10
19/19 [==============================] - 2s 16ms/step - loss: 0.4642 -
accuracy: 0.8477 - val_loss: 0.3449 - val_accuracy: 0.8882
Epoch 2/10
19/19 [==============================] - 0s 6ms/step - loss: 0.2727 -
accuracy: 0.9089 - val_loss: 0.2432 - val_accuracy: 0.9079
Epoch 3/10
19/19 [==============================] - 0s 7ms/step - loss: 0.2114 -
accuracy: 0.9305 - val_loss: 0.1891 - val_accuracy: 0.9145
Epoch 4/10
19/19 [==============================] - 0s 8ms/step - loss: 0.1851 -
accuracy: 0.9371 - val_loss: 0.1682 - val_accuracy: 0.9211
Epoch 5/10
19/19 [==============================] - 0s 10ms/step - loss: 0.1699 -
accuracy: 0.9437 - val_loss: 0.1462 - val_accuracy: 0.9539
Epoch 6/10
19/19 [==============================] - 0s 7ms/step - loss: 0.1563 -
accuracy: 0.9470 - val_loss: 0.1360 - val_accuracy: 0.9474
Epoch 7/10
19/19 [==============================] - 0s 5ms/step - loss: 0.1446 -
accuracy: 0.9487 - val_loss: 0.1294 - val_accuracy: 0.9539
Epoch 8/10
19/19 [==============================] - 0s 7ms/step - loss: 0.1347 -
```

```
accuracy: 0.9503 - val_loss: 0.1212 - val_accuracy: 0.9671
Epoch 9/10
19/19 [==============================] - 0s 6ms/step - loss: 0.1270 -
accuracy: 0.9503 - val_loss: 0.1200 - val_accuracy: 0.9539
Epoch 10/10
19/19 [==============================] - 0s 6ms/step - loss: 0.1217 -
accuracy: 0.9570 - val_loss: 0.1185 - val_accuracy: 0.9605

<keras.src.callbacks.History at 0x7bb58c16bf40>
```

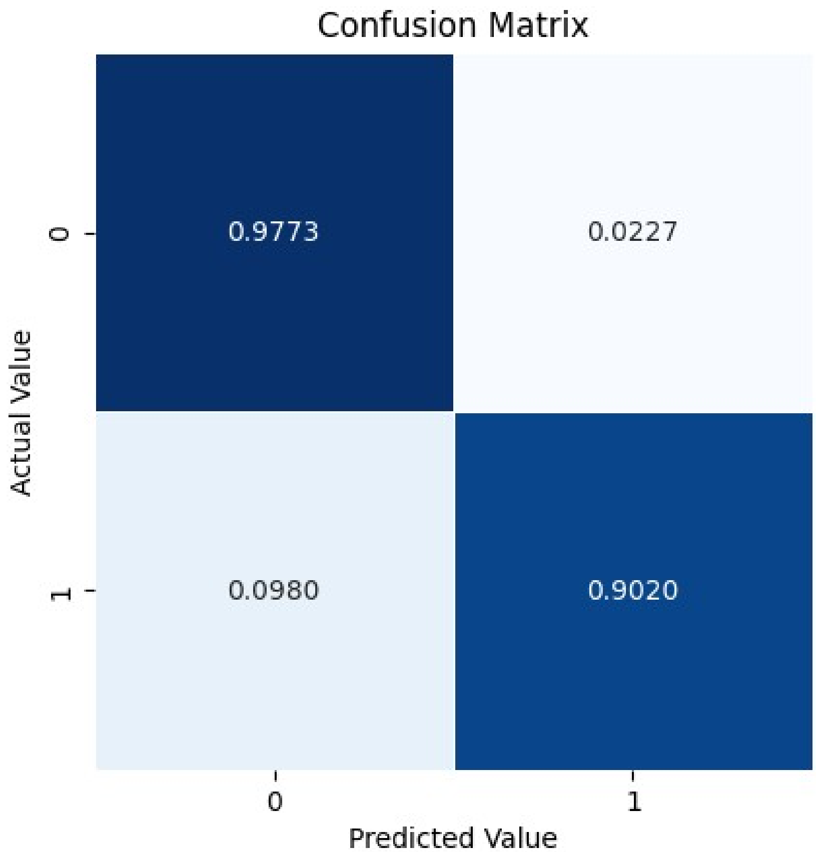
```
# Make predictions on the test set
y_pred_proba = model.predict(X_test_scaled)
y_pred4 = (y_pred_proba > 0.5).astype(int)
```

```
6/6 [==============================] - 0s 2ms/step
```

```
# Evaluate the model
accuracy4 = accuracy_score(y_test, y_pred4)
accuracy4
```

```
0.9368421052631579
```

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred4)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



#Gradient Boosting

```
from sklearn.ensemble import GradientBoostingClassifier

# Train the Gradient Boosting classifier
gb_classifier = GradientBoostingClassifier()
gb_classifier.fit(X_train, y_train)
```

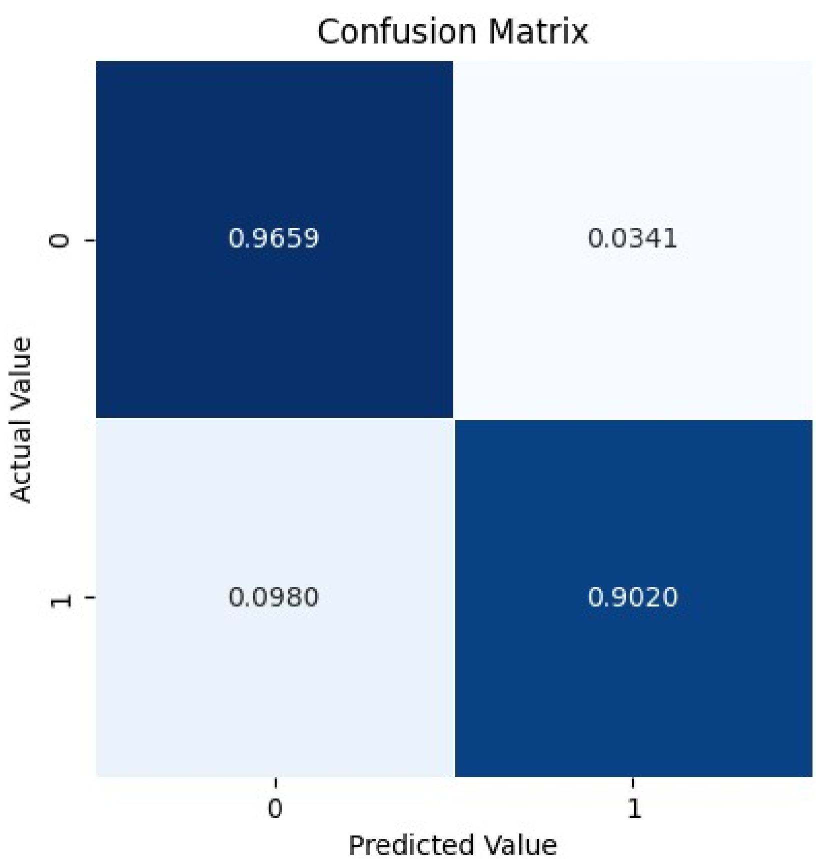
```
GradientBoostingClassifier()
```

```
# Make predictions on the test data
y_pred5 = gb_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy5 = accuracy_score(y_test, y_pred5)
precision_gb = precision_score(y_test, y_pred5)
recall_gb = recall_score(y_test, y_pred5)
f1_gb = f1_score(y_test, y_pred5)

# Display the metrics
metrics_gb_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy5, precision_gb, recall_gb, f1_gb]
})
```

```python
print(metrics_gb_df)
```

```
      Metric     Score
0   Accuracy  0.931579
1  Precision  0.968421
2     Recall  0.901961
3   F1 Score  0.934010
```

```python
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred5)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```

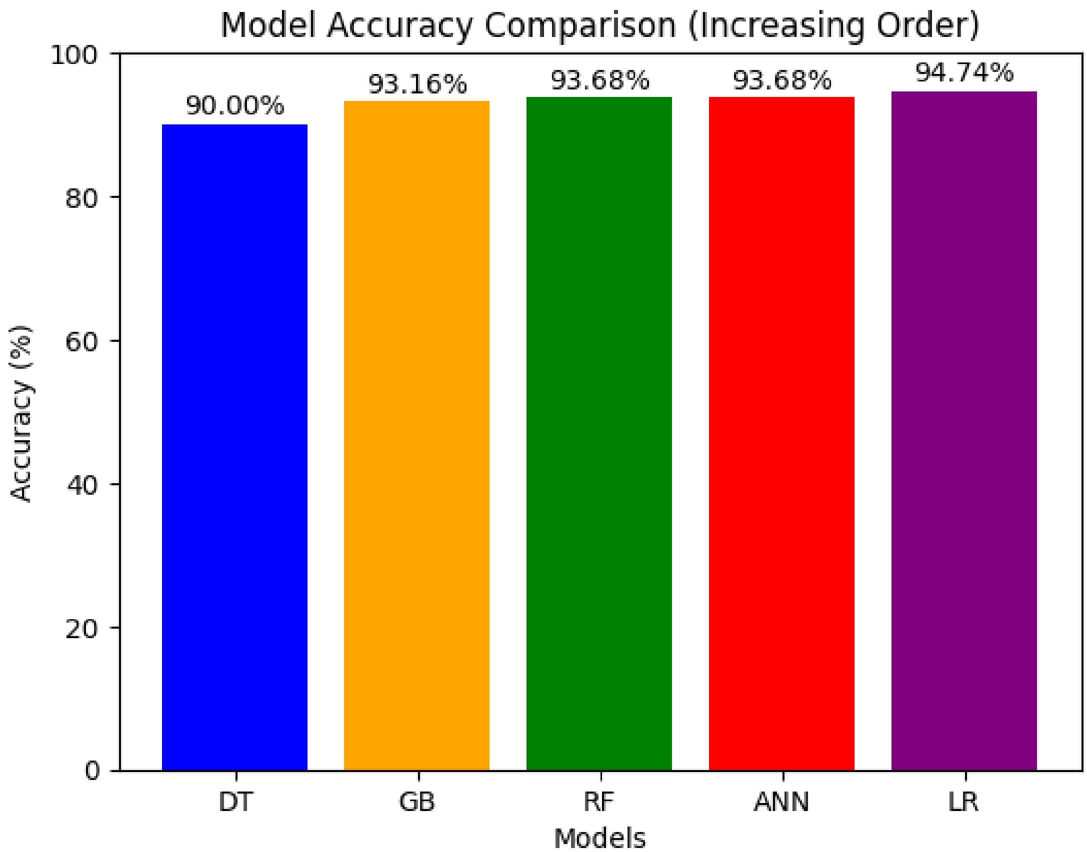


Results

```
final_data = pd.DataFrame({'Models':['LR','DT','RF','ANN','GB'],
              "ACC":[accuracy1*100,
                     accuracy2*100,
                     accuracy3*100,
                     accuracy4*100,
                     accuracy5*100,
                    ]})

final_data
```

```
  Models        ACC
0     LR  94.736842
1     DT  90.000000
2     RF  93.684211
3    ANN  93.684211
4     GB  93.157895
```

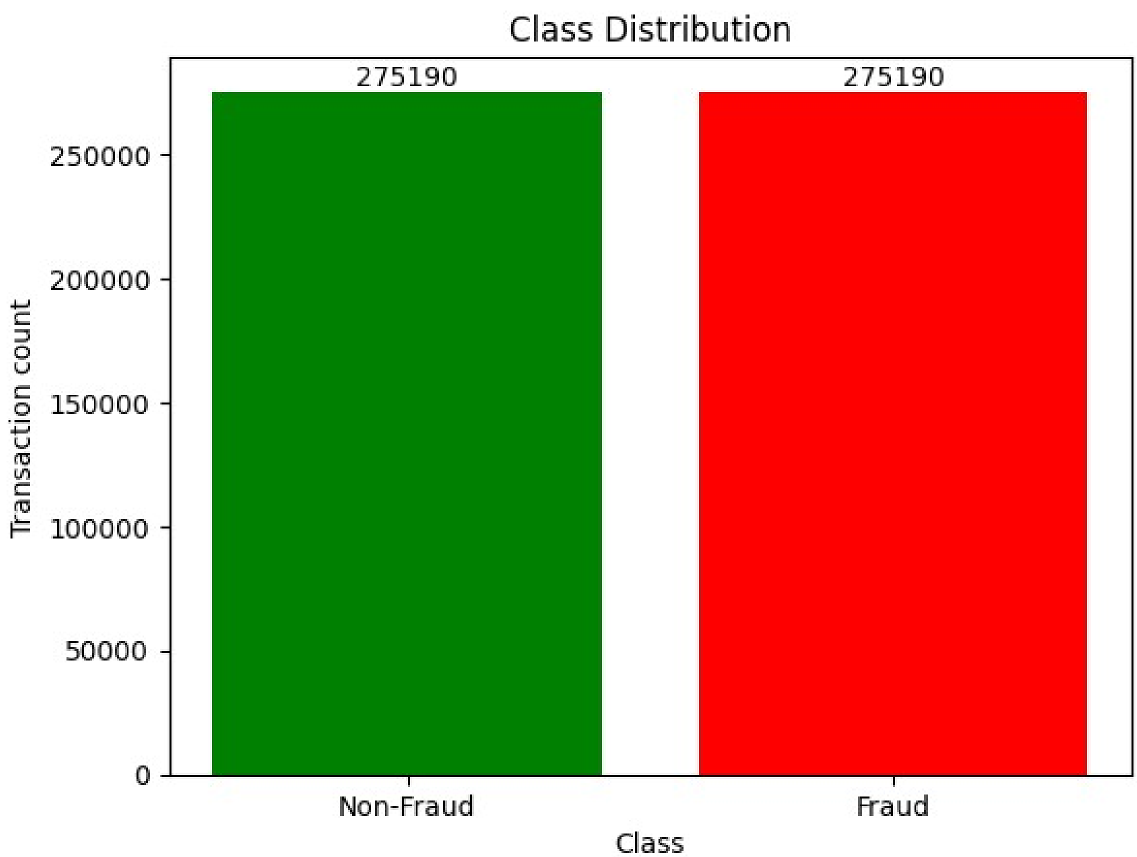
```
import matplotlib.pyplot as plt

# Sort the DataFrame by the 'ACC' column in ascending order
final_data_sorted = final_data.sort_values(by='ACC')

# Plotting the bar chart
plt.bar(final_data_sorted['Models'], final_data_sorted['ACC'],
color=['blue', 'orange', 'green', 'red', 'purple'])
plt.xlabel('Models')
plt.ylabel('Accuracy (%)')
plt.title('Model Accuracy Comparison (Increasing Order)')
plt.ylim(0, 100)  # Set the y-axis limits to ensure proper
visualization of percentages

# Adding annotations to each bar
for i, acc in enumerate(final_data_sorted['ACC']):
    plt.text(i, acc + 0.5, f'{acc:.2f}%', ha='center', va='bottom')

plt.show()
```



Oversampling

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

y=df['Class']

X.shape

(275663, 29)

y.shape

(275663,)

from imblearn.over_sampling import SMOTE

X_res,y_res = SMOTE().fit_resample(X,y)

y_res.value_counts()

0    275190
1    275190
Name: Class, dtype: int64
```

```python
import matplotlib.pyplot as plt

class_counts = y_res.value_counts()

#Bar chart
plt.bar(class_counts.index, class_counts.values, color=['green',
'red'])
plt.xlabel('Class')
plt.ylabel('Transaction count')
plt.title('Class Distribution')
plt.xticks(class_counts.index, ['Non-Fraud', 'Fraud'])
# Adding annotations to each bar
for i, acc in enumerate(class_counts):
    plt.text(i, acc + 0.5, acc, ha='center', va='bottom')
plt.show()
```




```python
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test =
train_test_split(X_res,y_res,test_size=0.20,random_state=42)
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression()
log.fit(X_train,y_train)
```

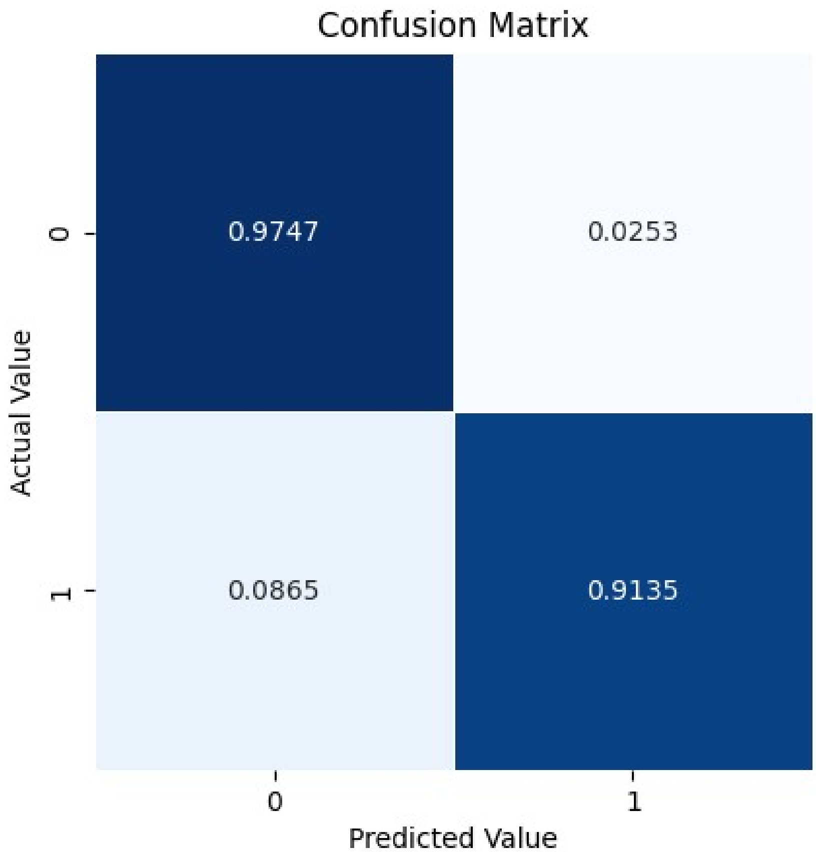
```
LogisticRegression()
```

```
y_pred1 = log.predict(X_test)
```

```
# Calculate evaluation metrics
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
accuracy1 = accuracy_score(y_test, y_pred1)
precision = precision_score(y_test, y_pred1)
recall = recall_score(y_test, y_pred1)
f1 = f1_score(y_test, y_pred1)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy1, precision, recall, f1]
})
metrics_df
```

	Metric	Score
0	Accuracy	0.944148
1	Precision	0.973062
2	Recall	0.913514
3	F1 Score	0.942348

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred1)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```

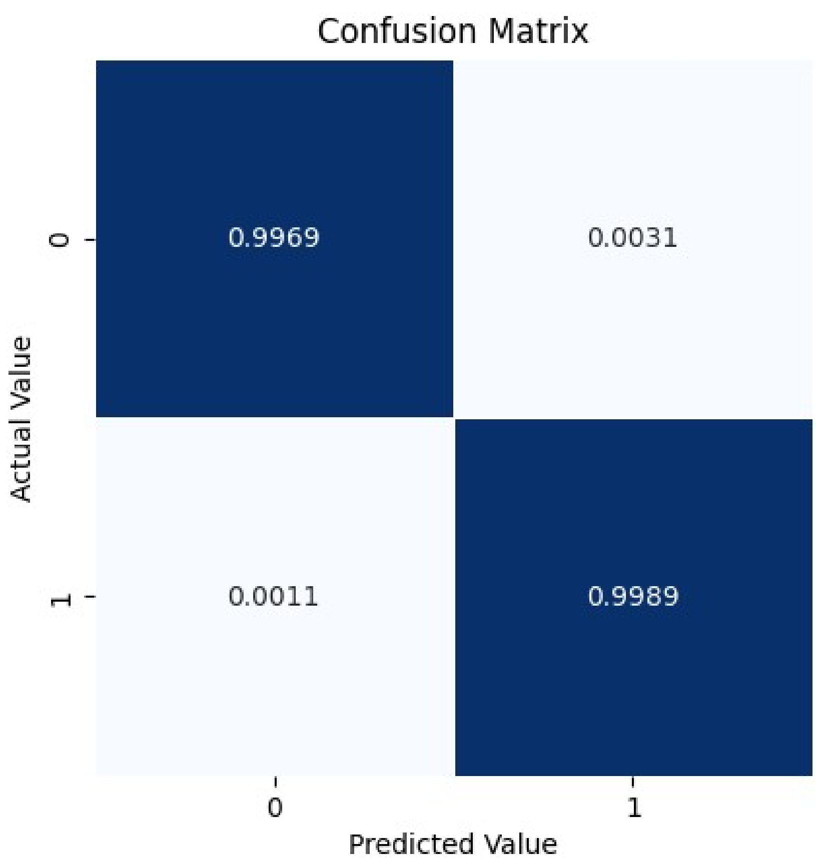


Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier()
dt.fit(X_train,y_train)

DecisionTreeClassifier()

y_pred2 = dt.predict(X_test)

# Calculate evaluation metrics
accuracy2 = accuracy_score(y_test, y_pred2)
precision = precision_score(y_test, y_pred2)
recall = recall_score(y_test, y_pred2)
f1 = f1_score(y_test, y_pred2)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy2, precision, recall, f1]
})

print(metrics_df)
```

```
      Metric     Score
0   Accuracy  0.997892
1  Precision  0.996915
2     Recall  0.998873
3   F1 Score  0.997893
```

```python
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred2)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



Random Forest Classifier

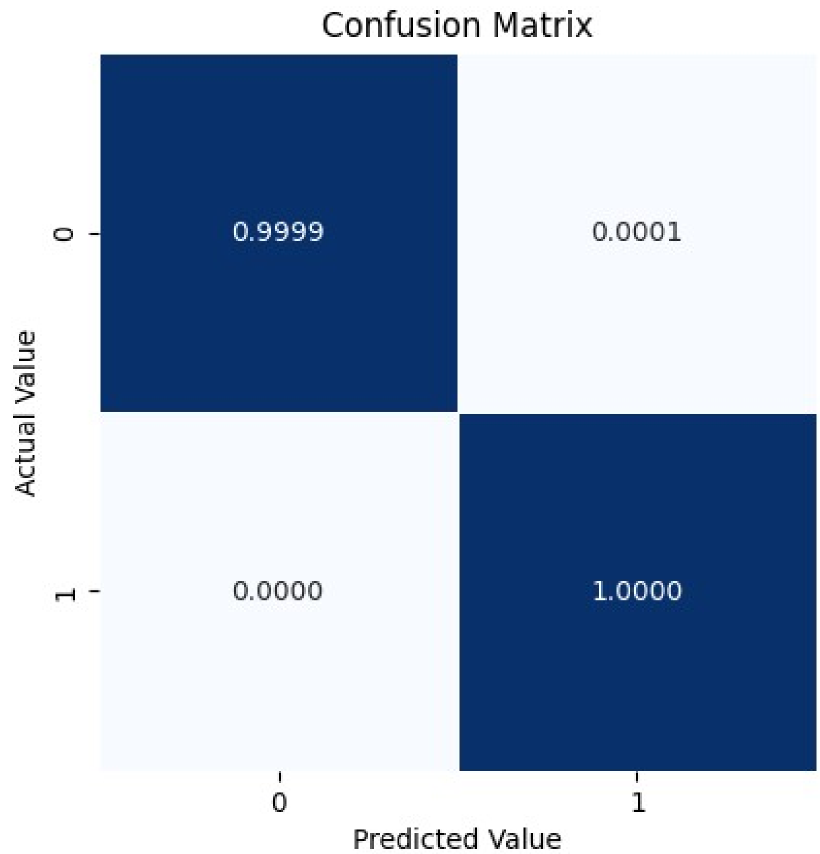
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,y_train)
```

```
RandomForestClassifier()
```

```
y_pred3 = rf.predict(X_test)

# Calculate evaluation metrics
accuracy3 = accuracy_score(y_test, y_pred3)
precision = precision_score(y_test, y_pred3)
recall = recall_score(y_test, y_pred3)
f1 = f1_score(y_test, y_pred3)

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy3, precision, recall, f1]
})

print(metrics_df)
```

```
      Metric     Score
0   Accuracy  0.999927
1  Precision  0.999855
2     Recall  1.000000
3   F1 Score  0.999927
```

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred3)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



Artificial Neural Network

```
import tensorflow as tf
from tensorflow import keras

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

# Build the ANN model
model = keras.Sequential([
    keras.layers.Dense(units=128, activation='relu',
input_dim=X_train.shape[1]),
    keras.layers.Dense(units=64, activation='relu'),
    keras.layers.Dense(units=1, activation='sigmoid')  # Binary
classification, so using sigmoid activation
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
```

```
# Train the model
model.fit(X_train_scaled, y_train, epochs=10, batch_size=32,
validation_split=0.2)
```

```
Epoch 1/10
11008/11008 [==============================] - 31s 3ms/step - loss:
0.0285 - accuracy: 0.9906 - val_loss: 0.0077 - val_accuracy: 0.9981
Epoch 2/10
11008/11008 [==============================] - 30s 3ms/step - loss:
0.0078 - accuracy: 0.9979 - val_loss: 0.0052 - val_accuracy: 0.9986
Epoch 3/10
11008/11008 [==============================] - 29s 3ms/step - loss:
0.0055 - accuracy: 0.9985 - val_loss: 0.0077 - val_accuracy: 0.9976
Epoch 4/10
11008/11008 [==============================] - 31s 3ms/step - loss:
0.0042 - accuracy: 0.9988 - val_loss: 0.0037 - val_accuracy: 0.9991
Epoch 5/10
11008/11008 [==============================] - 31s 3ms/step - loss:
0.0034 - accuracy: 0.9991 - val_loss: 0.0053 - val_accuracy: 0.9988
Epoch 6/10
11008/11008 [==============================] - 31s 3ms/step - loss:
0.0033 - accuracy: 0.9991 - val_loss: 0.0026 - val_accuracy: 0.9993
Epoch 7/10
11008/11008 [==============================] - 48s 4ms/step - loss:
0.0027 - accuracy: 0.9992 - val_loss: 0.0038 - val_accuracy: 0.9994
Epoch 8/10
11008/11008 [==============================] - 28s 3ms/step - loss:
0.0026 - accuracy: 0.9994 - val_loss: 0.0032 - val_accuracy: 0.9992
Epoch 9/10
11008/11008 [==============================] - 30s 3ms/step - loss:
0.0024 - accuracy: 0.9994 - val_loss: 0.0029 - val_accuracy: 0.9993
Epoch 10/10
11008/11008 [==============================] - 30s 3ms/step - loss:
0.0021 - accuracy: 0.9995 - val_loss: 0.0020 - val_accuracy: 0.9995
```

```
<keras.src.callbacks.History at 0x7bb539fd4f70>
```

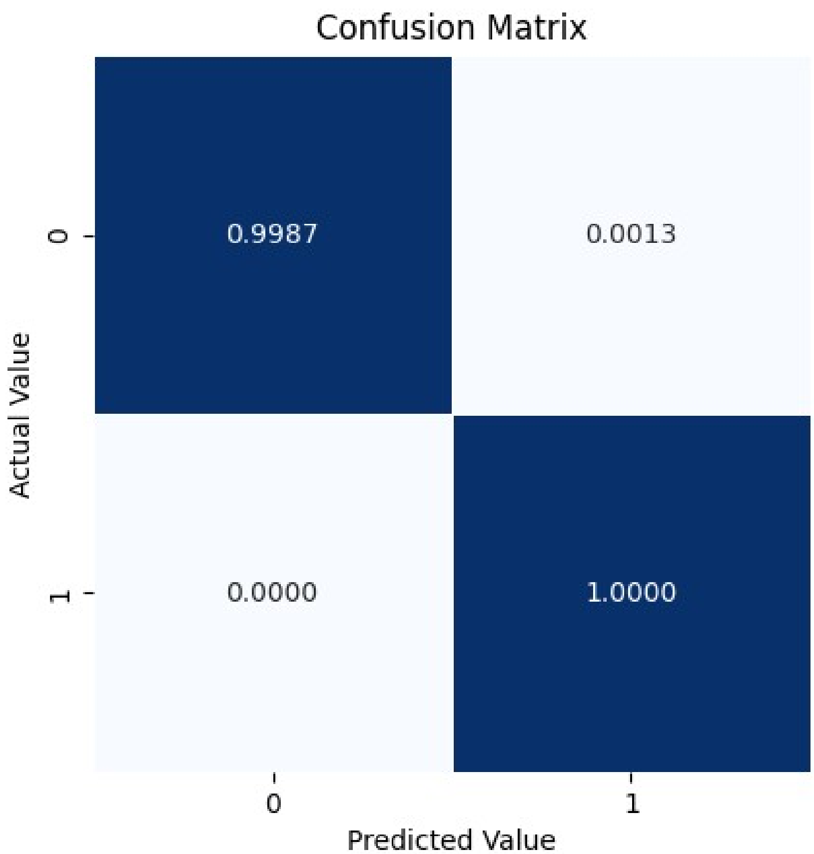
```
# Make predictions on the test set
y_pred_proba = model.predict(X_test_scaled)
y_pred4 = (y_pred_proba > 0.5).astype(int)
```

```
3440/3440 [==============================] - 5s 1ms/step
```

```
# Evaluate the model
accuracy4 = accuracy_score(y_test, y_pred4)
accuracy4
```

```
0.9993731603619318
```

```
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred4)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



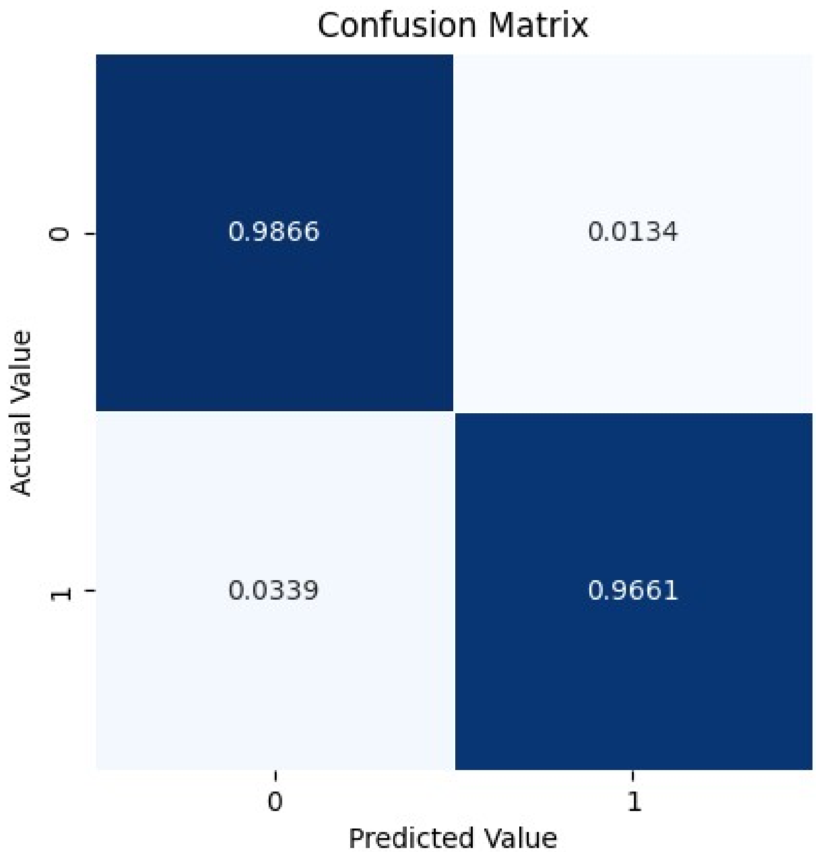
#Gradient Boosting

```
from sklearn.ensemble import GradientBoostingClassifier

# Train the Gradient Boosting classifier
gb_classifier = GradientBoostingClassifier()
gb_classifier.fit(X_train, y_train)

GradientBoostingClassifier()
```

```python
# Make predictions on the test data
y_pred5 = gb_classifier.predict(X_test)

# Calculate evaluation metrics
accuracy5 = accuracy_score(y_test, y_pred5)
precision_gb = precision_score(y_test, y_pred5)
recall_gb = recall_score(y_test, y_pred5)
f1_gb = f1_score(y_test, y_pred5)

# Display the metrics
metrics_gb_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Score': [accuracy5, precision_gb, recall_gb, f1_gb]
})

print(metrics_gb_df)
```

```
      Metric     Score
0   Accuracy  0.976353
1  Precision  0.986266
2     Recall  0.966129
3   F1 Score  0.976094
```

```python
from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(y_test, y_pred5)
conf_matrix_norm = conf_matrix.astype('float') /
conf_matrix.sum(axis=1)[:, np.newaxis]


sns.heatmap(conf_matrix_norm, annot=True, fmt='.4f', cmap='Blues',
cbar=False, linewidths=.5, square=True)

plt.xlabel('Predicted Value')
plt.ylabel('Actual Value')
plt.title('Confusion Matrix')
plt.show()
```



#Results

```
final_data = pd.DataFrame({'Models':['LR','DT','RF','ANN','GB'],
              "ACC":[accuracy1*100,
                     accuracy2*100,
                     accuracy3*100,
                     accuracy4*100,
                     accuracy5*100,
                    ]})

final_data

  Models        ACC
0     LR  94.414768
1     DT  99.789237
2     RF  99.992732
3    ANN  99.937316
4     GB  97.635270

import matplotlib.pyplot as plt

# Sort the DataFrame by the 'ACC' column in ascending order
final_data_sorted = final_data.sort_values(by='ACC')
```

```python
# Plotting the bar chart
plt.bar(final_data_sorted['Models'], final_data_sorted['ACC'],
color=['blue', 'orange', 'green', 'red', 'purple'])
plt.xlabel('Models')
plt.ylabel('Accuracy (%)')
plt.title('Model Accuracy Comparison (Increasing Order)')
plt.ylim(0, 110)  # Set the y-axis limits to ensure proper
visualization of percentages

# Adding annotations to each bar
for i, acc in enumerate(final_data_sorted['ACC']):
    plt.text(i, acc + 0.5, f'{acc:.2f}%', ha='center', va='bottom')

plt.show()
```