Import libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Import dataset

```
df = pd.read_csv('onlinefraud.csv')
df.head()
```

```
   step      type    amount     nameOrig  oldbalanceOrg
newbalanceOrig  \
0     1   PAYMENT   9839.64  C1231006815       170136.0
160296.36
1     1   PAYMENT   1864.28  C1666544295        21249.0
19384.72
2     1  TRANSFER    181.00  C1305486145          181.0
0.00
3     1  CASH_OUT    181.00   C840083671          181.0
0.00
4     1   PAYMENT  11668.14  C2048537720        41554.0
29885.86

      nameDest  oldbalanceDest  newbalanceDest  isFraud
isFlaggedFraud
0  M1979787155             0.0             0.0        0
0
1  M2044282225             0.0             0.0        0
0
2   C553264065             0.0             0.0        1
0
3    C38997010         21182.0             0.0        1
0
4  M1230701703             0.0             0.0        0
0
```

Description

About the Dataset

To identify online payment fraud with machine learning, we need to train a model capable of classifying transactions as fraudulent or non-fraudulent. This requires a dataset containing

detailed information on online payment transactions, specifically those flagged for fraud. The dataset I collected from Kaggle includes historical data on fraudulent transactions, which will be instrumental in training our fraud detection model. Below is a description of the columns included in this dataset:

1. **step**: Represents a unit of time, where 1 step equals 1 hour.
2. **type**: Type of online transaction.
3. **amount**: The amount of the transaction.
4. **nameOrig**: Customer initiating the transaction.
5. **oldbalanceOrg**: Account balance before the transaction.
6. **newbalanceOrig**: Account balance after the transaction.
7. **nameDest**: Recipient of the transaction.
8. **oldbalanceDest**: Initial balance of the recipient before the transaction.
9. **newbalanceDest**: New balance of the recipient after the transaction.
10. **isFraud**: Indicator of whether the transaction is fraudulent (1) or not (0).

This dataset forms the foundation of our machine learning model to detect online payment fraud. In the following sections, I will outline the methods and Python tools we'll use to develop and test our fraud detection model.

Explore the dataset

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype  
---  ------          -----  
 0   step            int64  
 1   type            object 
 2   amount          float64
 3   nameOrig        object 
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object 
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64  
 10  isFlaggedFraud  int64  
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

Now, we don't need nameOrig and nameDest columns for our analysis. Hence, we will drop these two columns. Additionally, we also have isFlaggedFraud column which is actually a prediction. we don't need this right now hence we will be dropping this column too.

```
cols_to_drop = ['nameOrig', 'nameDest', 'isFlaggedFraud']

df.drop(columns=cols_to_drop,inplace = True)

df.head()
```

```
   step      type    amount  oldbalanceOrg  newbalanceOrig
oldbalanceDest  \
0     1   PAYMENT   9839.64       170136.0       160296.36
0.0
1     1   PAYMENT   1864.28        21249.0        19384.72
0.0
2     1  TRANSFER    181.00          181.0            0.00
0.0
3     1  CASH_OUT    181.00          181.0            0.00
21182.0
4     1   PAYMENT  11668.14        41554.0        29885.86
0.0

   newbalanceDest  isFraud
0             0.0        0
1             0.0        0
2             0.0        1
3             0.0        1
4             0.0        0
```

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

```
step              0
type              0
amount            0
oldbalanceOrg     0
newbalanceOrig    0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
dtype: int64
```

We don't have any null values

```
df.duplicated().sum()
```

```
543
```

We will remove duplicated data.

```
df.drop_duplicates(inplace = True)
```

```
df.duplicated().sum()
```

```
0
```

```
df.describe()
```

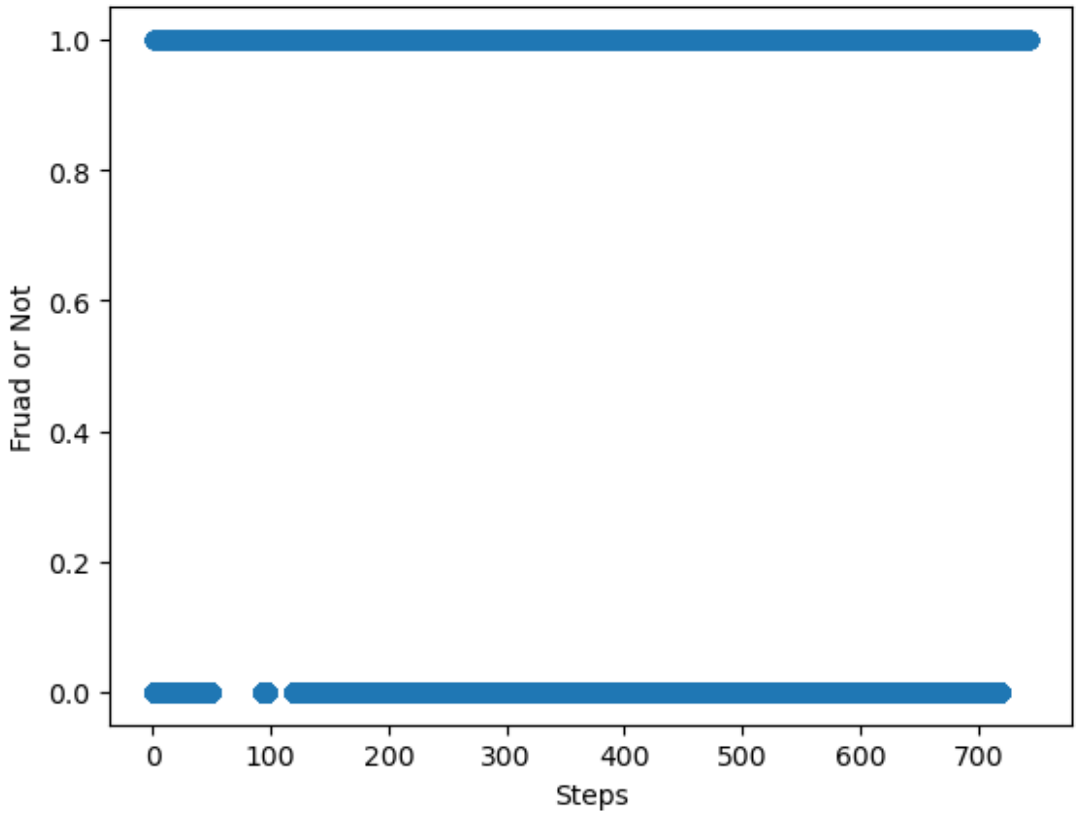
```
                step        amount  oldbalanceOrg  newbalanceOrig  \
count  6.362077e+06  6.362077e+06   6.362077e+06    6.362077e+06
mean   2.433995e+02  1.798531e+05   8.339307e+05    8.551867e+05
std    1.423323e+02  6.036937e+05   2.888322e+06    2.924163e+06
min    1.000000e+00  0.000000e+00   0.000000e+00    0.000000e+00
25%    1.560000e+02  1.339407e+04   0.000000e+00    0.000000e+00
50%    2.390000e+02  7.489334e+04   1.421800e+04    0.000000e+00
75%    3.350000e+02  2.087330e+05   1.073260e+05    1.442925e+05
max    7.430000e+02  9.244552e+07   5.958504e+07    4.958504e+07

       oldbalanceDest  newbalanceDest       isFraud
count    6.362077e+06    6.362077e+06  6.362077e+06
mean     1.100796e+06    1.225077e+06  1.288416e-03
std      3.399310e+06    3.674244e+06  3.587138e-02
min      0.000000e+00    0.000000e+00  0.000000e+00
25%      0.000000e+00    0.000000e+00  0.000000e+00
50%      1.327834e+05    2.147385e+05  0.000000e+00
75%      9.431718e+05    1.112051e+06  0.000000e+00
max      3.560159e+08    3.561793e+08  1.000000e+00
```

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

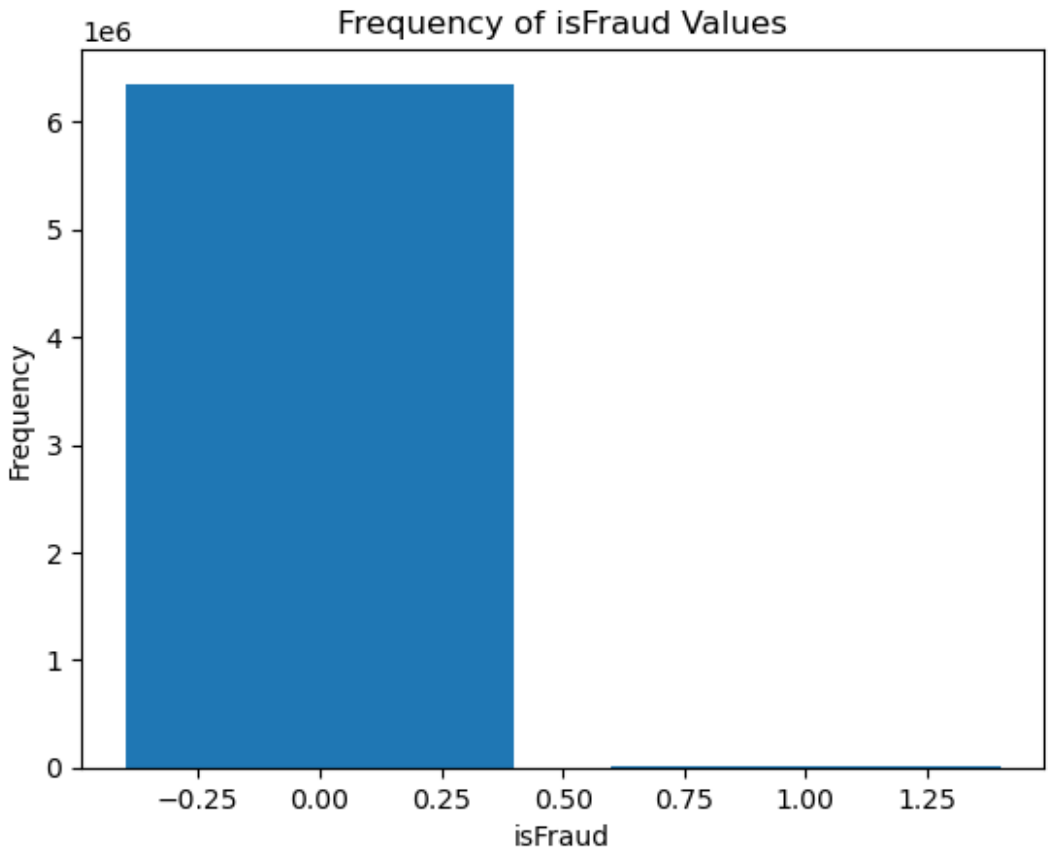
```
step
19     51340
18     49572
187    49070
235    47480
307    46965
       ...
432        4
706        4
693        4
112        2
662        2
Name: count, Length: 743, dtype: int64
```

```
plt.scatter(df['step'],df['isFraud'])
plt.xlabel('Steps')
```

```
plt.ylabel('Fruad or Not')
plt.show()
```




```
counts = df['isFraud'].value_counts()

# Plotting
plt.bar(counts.index, counts.values)
plt.xlabel('isFraud')
plt.ylabel('Frequency')
plt.title('Frequency of isFraud Values')
plt.show()
```




```
len(df[df['isFraud'] == 1])
```

```
8197
```

```
len(df[df['isFraud'] == 0])
```

```
6353880
```

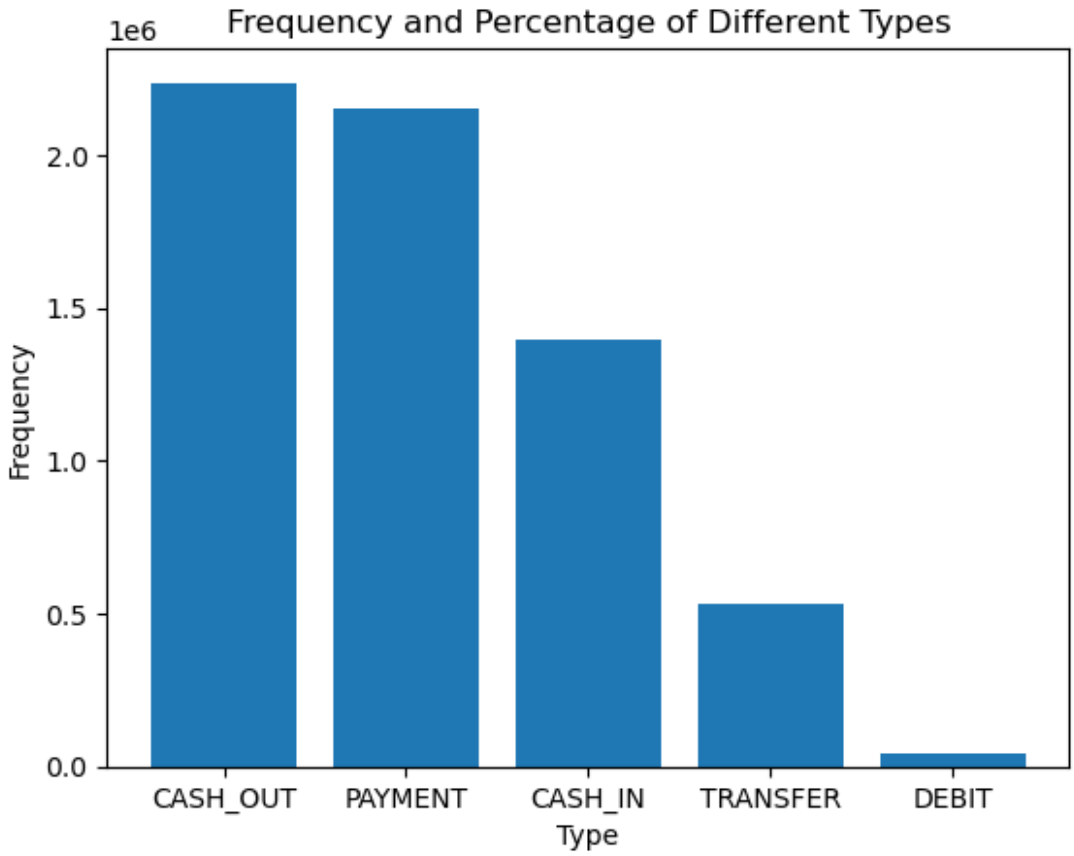
Our dataset is highly imbalanced we need to make some changes otherwise our model will be biased

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

```
type
CASH_OUT    2237484
PAYMENT     2150968
CASH_IN     1399284
TRANSFER     532909
DEBIT         41432
Name: count, dtype: int64
```

We need to change the type column into the category

```
df['type'] = df['type'].astype('category')

counts = df['type'].value_counts()

# Calculate the percentage of each category
percentages = 100 * counts / counts.sum()

# Plotting
plt.bar(counts.index, counts.values)
plt.xlabel('Type')
plt.ylabel('Frequency')
plt.title('Frequency and Percentage of Different Types')

Text(0.5, 1.0, 'Frequency and Percentage of Different Types')
```




```
df.columns

Index(['step', 'type', 'amount', 'oldbalanceOrg', 'newbalanceOrig',
       'oldbalanceDest', 'newbalanceDest', 'isFraud'],
      dtype='object')
```

We will convert these categories into numeric form

```
x= pd.get_dummies(df['type'],drop_first= True)

x
```

```
         CASH_OUT  DEBIT  PAYMENT  TRANSFER
0           False  False     True     False
1           False  False     True     False
2           False  False    False      True
3            True  False    False     False
4           False  False     True     False
...           ...    ...      ...       ...
6362615      True  False    False     False
6362616     False  False    False      True
6362617      True  False    False     False
6362618     False  False    False      True
6362619      True  False    False     False

[6362077 rows x 4 columns]
```

```
df.drop(columns = 'type',inplace = True)
df
```

```
         step      amount  oldbalanceOrg  newbalanceOrig
oldbalanceDest  \
0           1     9839.64      170136.00       160296.36
0.00
1           1     1864.28       21249.00        19384.72
0.00
2           1      181.00         181.00            0.00
0.00
3           1      181.00         181.00            0.00
21182.00
4           1    11668.14       41554.00        29885.86
0.00
...       ...         ...            ...             ...               .
..
6362615   743   339682.13      339682.13            0.00
0.00
6362616   743  6311409.28     6311409.28            0.00
0.00
6362617   743  6311409.28     6311409.28            0.00
68488.84
6362618   743   850002.52      850002.52            0.00
0.00
6362619   743   850002.52      850002.52            0.00
6510099.11

         newbalanceDest  isFraud
0                  0.00        0
```

```
1                  0.00        0
2                  0.00        1
3                  0.00        1
4                  0.00        0
...                 ...      ...
6362615       339682.13        1
6362616            0.00        1
6362617      6379898.11        1
6362618            0.00        1
6362619      7360101.63        1

[6362077 rows x 7 columns]
```

```
merged_df = pd.concat([df, x], axis = 1)
merged_df
```

```
         step      amount  oldbalanceOrg  newbalanceOrig
oldbalanceDest  \
0           1     9839.64      170136.00       160296.36
0.00
1           1     1864.28       21249.00        19384.72
0.00
2           1      181.00         181.00            0.00
0.00
3           1      181.00         181.00            0.00
21182.00
4           1    11668.14       41554.00        29885.86
0.00
...       ...         ...            ...             ...               .
..
6362615   743   339682.13      339682.13            0.00
0.00
6362616   743  6311409.28     6311409.28            0.00
0.00
6362617   743  6311409.28     6311409.28            0.00
68488.84
6362618   743   850002.52      850002.52            0.00
0.00
6362619   743   850002.52      850002.52            0.00
6510099.11

         newbalanceDest  isFraud  CASH_OUT  DEBIT  PAYMENT  TRANSFER
0                  0.00        0     False  False     True     False
1                  0.00        0     False  False     True     False
2                  0.00        1     False  False    False      True
3                  0.00        1      True  False    False     False
4                  0.00        0     False  False     True     False
...                 ...      ...       ...    ...      ...       ...
6362615       339682.13        1      True  False    False     False
6362616            0.00        1     False  False    False      True
```

```
6362617      6379898.11        1      True  False    False     False
6362618            0.00        1     False  False    False      True
6362619      7360101.63        1      True  False    False     False

[6362077 rows x 11 columns]
```

Extract the features and target

```
X = merged_df.drop(columns= 'isFraud')
y = merged_df['isFraud']

X
```

```
         step      amount  oldbalanceOrg  newbalanceOrig
oldbalanceDest  \
0           1     9839.64      170136.00       160296.36
0.00
1           1     1864.28       21249.00        19384.72
0.00
2           1      181.00         181.00            0.00
0.00
3           1      181.00         181.00            0.00
21182.00
4           1    11668.14       41554.00        29885.86
0.00
...       ...         ...            ...             ...              .
..
6362615   743   339682.13      339682.13            0.00
0.00
6362616   743  6311409.28     6311409.28            0.00
0.00
6362617   743  6311409.28     6311409.28            0.00
68488.84
6362618   743   850002.52      850002.52            0.00
0.00
6362619   743   850002.52      850002.52            0.00
6510099.11

         newbalanceDest  CASH_OUT  DEBIT  PAYMENT  TRANSFER
0                  0.00     False  False     True     False
1                  0.00     False  False     True     False
2                  0.00     False  False    False      True
3                  0.00      True  False    False     False
4                  0.00     False  False     True     False
...                 ...       ...    ...      ...       ...
6362615       339682.13      True  False    False     False
6362616            0.00     False  False    False      True
6362617      6379898.11      True  False    False     False
6362618            0.00     False  False    False      True
6362619      7360101.63      True  False    False     False
```

```
[6362077 rows x 10 columns]
```

```
y
```

```
0          0
1          0
2          1
3          1
4          0
          ..
6362615    1
6362616    1
6362617    1
6362618    1
6362619    1
Name: isFraud, Length: 6362077, dtype: int64
```

```
!pip install imblearn
```

```
Collecting imblearn
  Downloading imblearn-0.0-py2.py3-none-any.whl.metadata (355 bytes)
Requirement already satisfied: imbalanced-learn in c:\users\iamya\
anaconda3\lib\site-packages (from imblearn) (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\iamya\
anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\iamya\
anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\iamya\
anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.2.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\iamya\
anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\iamya\
anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (2.2.0)
Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
Installing collected packages: imblearn
Successfully installed imblearn-0.0
```

```
from imblearn.under_sampling import NearMiss
```

```
nm = NearMiss(version = 3)
X_res, y_res = nm.fit_resample(X, y)
```

```
C:\Users\iamya\anaconda3\Lib\site-packages\imblearn\under_sampling\
_prototype_selection\_nearmiss.py:203: UserWarning: The number of the
samples to be selected is larger than the number of samples available.
The balancing ratio cannot be ensure and all samples will be returned.
  warnings.warn(
```

```
X_res.shape
```

```
(15280, 10)
```

```
y_res.shape
```

```
(15280,)
```

Split the data into training and testing

```
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=0.2,random_state=42)
```

```
X_train
```

```
       step      amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest
\
7191      9   244068.01      244068.01            0.00            0.00
4153    187   152192.10      150604.18            0.00       285291.98
8992    169  1179716.49     1179716.49            0.00            0.00
4304    381   117345.56      110037.00            0.00        69882.55
12970   531  3547485.43     3547485.43            0.00            0.00
...     ...         ...            ...             ...             ...
5191    135   244126.73      244575.00          448.27            0.00
13418   573   457789.14      457789.14            0.00            0.00
5390    227   175005.04      175827.00          821.96            0.00
860     379   111957.76       91936.00            0.00       559448.46
7270     16  2198224.71     2198224.71            0.00            0.00


       newbalanceDest  CASH_OUT  DEBIT  PAYMENT  TRANSFER
7191         338538.16      True  False    False     False
4153         437484.08      True  False    False     False
8992        1179716.49      True  False    False     False
4304         187228.11      True  False    False     False
12970             0.00     False  False    False      True
...                ...       ...    ...      ...       ...
5191         244126.73      True  False    False     False
13418        457789.14      True  False    False     False
5390         175005.04      True  False    False     False
860          247997.65      True  False    False     False
```

```
7270              0.00     False  False    False      True

[12224 rows x 10 columns]
```

```
y_train
```

```
7191     1
4153     0
8992     1
4304     0
12970    1
        ..
5191     0
13418    1
5390     0
860      0
7270     1
Name: isFraud, Length: 12224, dtype: int64
```

Data Preprocessing

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

X_train.shape
```

```
(12224, 10)
```

```
X_test.shape
```

```
(3056, 10)
```

Let's build our ANN

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Input, Dropout

model = Sequential()
model.add(Input(shape = (X_train.shape[1],))),
model.add(Dense(8,activation='relu')),
model.add(Dense(4,activation='relu')),
model.add(Dense(2,activation='relu')),
model.add(Dropout(0.05))
#model.add(Dense(12,activation='relu')),
#model.add(Dense(10,activation='relu')),
model.add(Dense(1, activation = 'sigmoid'))
```

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

model.fit(X_train, y_train, epochs= 20, verbose = 1, batch_size=32,
validation_split=0.2)

Epoch 1/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7989 - loss:
0.4630 - val_accuracy: 0.8303 - val_loss: 0.4158
Epoch 2/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8048 - loss:
0.4459 - val_accuracy: 0.8344 - val_loss: 0.4083
Epoch 3/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8145 - loss:
0.4344 - val_accuracy: 0.8368 - val_loss: 0.4088
Epoch 4/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8167 - loss:
0.4350 - val_accuracy: 0.8401 - val_loss: 0.3979
Epoch 5/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8204 - loss:
0.4215 - val_accuracy: 0.8348 - val_loss: 0.3942
Epoch 6/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8131 - loss:
0.4284 - val_accuracy: 0.8380 - val_loss: 0.3896
Epoch 7/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8235 - loss:
0.4159 - val_accuracy: 0.8405 - val_loss: 0.3899
Epoch 8/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8168 - loss:
0.4246 - val_accuracy: 0.8434 - val_loss: 0.3822
Epoch 9/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8214 - loss:
0.4141 - val_accuracy: 0.8462 - val_loss: 0.3780
Epoch 10/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8292 - loss:
0.4053 - val_accuracy: 0.8429 - val_loss: 0.3755
Epoch 11/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8324 - loss:
0.3987 - val_accuracy: 0.8446 - val_loss: 0.3744
Epoch 12/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8292 - loss:
0.4002 - val_accuracy: 0.8495 - val_loss: 0.3701
Epoch 13/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8330 - loss:
0.3969 - val_accuracy: 0.8438 - val_loss: 0.3789
Epoch 14/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8243 - loss:
0.4070 - val_accuracy: 0.8519 - val_loss: 0.3665
Epoch 15/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8330 - loss:
```

```
0.3962 - val_accuracy: 0.8511 - val_loss: 0.3728
Epoch 16/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8382 - loss:
0.3883 - val_accuracy: 0.8515 - val_loss: 0.3693
Epoch 17/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8333 - loss:
0.4008 - val_accuracy: 0.8569 - val_loss: 0.3620
Epoch 18/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8343 - loss:
0.3922 - val_accuracy: 0.8548 - val_loss: 0.3595
Epoch 19/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8423 - loss:
0.3827 - val_accuracy: 0.8560 - val_loss: 0.3599
Epoch 20/20
306/306 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8433 - loss:
0.3851 - val_accuracy: 0.8597 - val_loss: 0.3575

<keras.src.callbacks.history.History at 0x200650e2550>

history = model.history

model.predict(X_test)

96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step

array([[0.99999493],
       [0.9999679 ],
       [0.69673455],
       ...,
       [0.74774706],
       [0.1943732 ],
       [0.21349598]], dtype=float32)

loss, accuracy = model.evaluate(X_test, y_test, verbose=1)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")

96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 965us/step - accuracy: 0.8556 - loss:
0.3602
Test Loss: 0.36462610960006714
Test Accuracy: 0.8537303805351257
```

Decision Tree

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

clf = DecisionTreeClassifier()

clf.fit(X_train, y_train)
```

```
DecisionTreeClassifier()

# Predict on test data
y_pred = clf.predict(X_test)

# Evaluate the classifier
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
print("Classification Report:\n", classification_report(y_test,
y_pred))

Accuracy: 90.97%
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.90      0.90      1420
           1       0.92      0.92      0.92      1636

    accuracy                           0.91      3056
   macro avg       0.91      0.91      0.91      3056
weighted avg       0.91      0.91      0.91      3056


from sklearn.model_selection import GridSearchCV

# Create a dictionary of all values we want to test for n_neighbors
param_grid = {
   'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': [None, 'sqrt', 'log2'],
    'criterion': ['gini', 'entropy']
}

# Use grid search to test all values for hyperparameters
dtree_gscv = GridSearchCV(clf, param_grid, cv=5)  # cv is the number
of folds; increase it for more rigorous testing

# Fit model to data
dtree_gscv.fit(X_train, y_train)

GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [10, 20, 30],
                         'max_features': [None, 'sqrt', 'log2'],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10]})

# Check top performing hyperparameters
best_parameters = dtree_gscv.best_params_
```

```
# Check mean score for the top performing value of hyperparameters
best_score = dtree_gscv.best_score_

print("Best parameters:", best_parameters)
print("Best cross-validation score:", best_score)
```

```
Best parameters: {'criterion': 'entropy', 'max_depth': 10,
'max_features': None, 'min_samples_leaf': 2, 'min_samples_split': 5}
Best cross-validation score: 0.9154942281753403
```

```
report = classification_report(y_test, y_pred)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.76      0.78      0.77      1420
           1       0.80      0.79      0.80      1636

    accuracy                           0.78      3056
   macro avg       0.78      0.78      0.78      3056
weighted avg       0.78      0.78      0.78      3056
```

Logistics Regression

```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression()

lr.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
# Predict on test data
y_pred = lr.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
print("Classification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 78.44%
Classification Report:
               precision    recall  f1-score   support

           0       0.76      0.78      0.77      1420
           1       0.80      0.79      0.80      1636
```

```
    accuracy                           0.78      3056
   macro avg       0.78      0.78      0.78      3056
weighted avg       0.78      0.78      0.78      3056
```