In [1]:
```python
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
train_df=pd.read_csv(r'F:\Data Science Assignmrnt GI Bots\DATA  Scientist Assignment\train.csv')
train_target_df=pd.read_csv(r'F:\Data Science Assignmrnt GI Bots\DATA  Scientist Assignment\trainLabels.csv')
```

In [3]:
```python
train_df.shape
```

Out[3]:
```
(9999, 146)
```

In [4]:
```python
train_df.head(5)
```

Out[4]:

	id	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
0	1	NO	NO	dqOiM6yBYgnVSezBRiQXs9bvOFnRqrtIoXRIElxD7g8=	GNjrXXA3SxbgD0dTRbIAPO9jFJ7AIaZnu/f48g5XSUk=	0.576561	0.073139	0.481394	0.115697	0.472474	...	0.0	0.810	3306	4676	YES	NO	YES	2	0.375535	0.464610
1	2	NaN	NaN	NaN	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.0	0.510	4678	3306	YES	NO	YES	4	0.741682	0.593630
2	3	NO	NO	ib4VpsEsqJHzDiyL0dZLQ+xQzDPrkxE+9T3mx5fv2wI=	X6dDAI/DZOWvu0Dg6gCgRoNr2vTUz/mc4SdHTNUPS38=	1.341803	0.051422	0.935572	0.041440	0.501710	...	0.0	0.850	4678	3306	NO	NO	NO	1	0.776467	0.493159
3	4	YES	NO	BfrqME7vdLw3suQp6YAT16W2piNUmpKhMzuDrVrFQ4w=	YGCdISifn4fLao/ASKdZFhGIq23oqzfSbUVb6px1pig=	0.653912	0.041471	0.940787	0.090851	0.556564	...	0.0	0.945	3306	4678	NO	NO	YES	3	0.168234	0.546582
4	5	NO	NO	RTjsrrR8DTIJyaIP9Q3Z8s0zseqlVQTrISe97GCWfbk=	3yK2OPj1uYDsoMgsxsjY1FxXkOIID8Xfh20VYGqT+nU=	1.415919	0.000000	1.000000	0.000000	0.375297	...	0.0	1.000	1263	892	NO	NO	NO	1	0.246637	0.361045

5 rows × 146 columns

In [5]:
```python
train_target_df.head(5)
```

Out[5]:

	id	y1	y2	y3	y4	y5	y6	y7	y8	y9	...	y24	y25	y26	y27	y28	y29	y30	y31	y32	y33
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
1	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	0
2	3	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
4	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1

5 rows × 34 columns

Preprocessing the Data for ML

In [6]:
```python
missing_percent_training_data=train_df.isna().sum().sort_values(ascending=False)*100/len(train_df)
missing_percent_training_data
```

Out[6]:
```
x26     14.261426
x12     14.261426
x2      14.261426
x3      14.261426
x4      14.261426
          ...
x53      0.000000
x52      0.000000
x51      0.000000
x50      0.000000
x145     0.000000
Length: 146, dtype: float64
```

In [7]:
```python
missing_percent_train_target_data=train_target_df.isna().sum().sort_values(ascending=False)*100/len(train_target_df)
missing_percent_train_target_data
```

Out[7]:
```
id     0.0
y25    0.0
y19    0.0
y20    0.0
y21    0.0
y22    0.0
y23    0.0
y24    0.0
y26    0.0
y1     0.0
y27    0.0
y28    0.0
y29    0.0
y30    0.0
y31    0.0
y32    0.0
y18    0.0
y17    0.0
y16    0.0
y15    0.0
y14    0.0
y13    0.0
y12    0.0
y11    0.0
y10    0.0
y9     0.0
y8     0.0
y7     0.0
y6     0.0
y5     0.0
y4     0.0
y3     0.0
y2     0.0
y33    0.0
dtype: float64
```

In [8]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9999 entries, 0 to 9998
Columns: 146 entries, id to x145
dtypes: float64(55), int64(31), object(60)
memory usage: 11.1+ MB
```

In [9]:
```python
# Assuming train_df is your DataFrame
object_columns = train_df.select_dtypes(include=['object']).columns
train_df[object_columns] = train_df[object_columns].fillna('Not Available')
```

In [10]:
```python
train_df.isna().sum().sort_values(ascending=False)
```

Out[10]:
```
id      0
x109    0
x93     0
x94     0
x95     0
       ..
x49     0
x50     0
x51     0
x52     0
x145    0
Length: 146, dtype: int64
```

In [11]:
```
list_col = train_df.select_dtypes(include='object').columns
output_count = 0  # Counter for the number of outputs

for col in list_col:
    unique_values = train_df[col].unique()
    if len(unique_values) < 10:
        output_count += 1
        print('{}: {}'.format(col.upper(), unique_values))

print("Number of Column:", output_count)
```

```
X1: ['NO' 'Not Available' 'YES']
X2: ['NO' 'Not Available' 'YES']
X10: ['YES' 'Not Available' 'NO']
X11: ['NO' 'Not Available' 'YES']
X12: ['NO' 'Not Available' 'YES']
X13: ['NO' 'Not Available' 'YES']
X14: ['NO' 'Not Available' 'YES']
X24: ['YES' 'Not Available' 'NO']
X25: ['NO' 'Not Available' 'YES']
X26: ['YES' 'Not Available' 'NO']
X30: ['NO' 'YES']
X31: ['NO' 'YES']
X32: ['NO' 'YES' 'Not Available']
X33: ['NO' 'YES' 'Not Available']
X41: ['YES' 'NO' 'Not Available']
X42: ['NO' 'YES' 'Not Available']
X43: ['YES' 'NO' 'Not Available']
X44: ['NO' 'YES' 'Not Available']
X45: ['NO' 'YES' 'Not Available']
X55: ['YES' 'NO' 'Not Available']
X56: ['NO' 'YES' 'Not Available']
X57: ['YES' 'NO' 'Not Available']
X62: ['NO' 'YES' 'Not Available']
X63: ['NO' 'YES' 'Not Available']
X71: ['YES' 'NO' 'Not Available']
X72: ['NO' 'Not Available' 'YES']
X73: ['NO' 'YES' 'Not Available']
X74: ['NO' 'Not Available' 'YES']
X75: ['NO' 'YES' 'Not Available']
X85: ['YES' 'NO' 'Not Available']
X86: ['NO' 'YES' 'Not Available']
X87: ['YES' 'NO' 'Not Available']
X92: ['NO' 'YES' 'Not Available']
X93: ['NO' 'YES' 'Not Available']
X101: ['YES' 'NO' 'Not Available']
X102: ['NO' 'Not Available' 'YES']
X103: ['NO' 'YES' 'Not Available']
X104: ['NO' 'Not Available' 'YES']
X105: ['NO' 'YES' 'Not Available']
X115: ['YES' 'NO' 'Not Available']
X116: ['NO' 'Not Available' 'YES']
X117: ['YES' 'NO' 'Not Available']
X126: ['YES' 'NO']
X127: ['NO' 'YES']
X128: ['NO' 'YES']
X129: ['NO' 'YES']
X130: ['NO' 'YES']
X140: ['YES' 'NO']
X141: ['NO' 'YES']
X142: ['YES' 'NO']
Number of Column: 50
```

In [12]:
```
list_col = train_df.select_dtypes(include='object').columns
unique_values_dict = {}  # Dictionary to store unique values for each column

for col in list_col:
    unique_values = train_df[col].nunique()
    unique_values_dict[col] = unique_values

# Sort the dictionary by values in descending order
sorted_unique_values = sorted(unique_values_dict.items(), key=lambda x: x[1], reverse=True)

# Print the sorted unique values
for col, unique_count in sorted_unique_values:
    print('{}: {}'.format(col.upper(), unique_count))

total_unique_count = sum(unique_values_dict.values())
print("Total unique values across all columns:", total_unique_count)
```

```
X61: 7115
X64: 5678
X34: 5569
X3: 4752
X94: 4648
X91: 3396
X65: 1019
X35: 981
X95: 760
X4: 759
X1: 3
X2: 3
X10: 3
X11: 3
X12: 3
X13: 3
X14: 3
X24: 3
X25: 3
X26: 3
X32: 3
X33: 3
X41: 3
X42: 3
X43: 3
X44: 3
X45: 3
X55: 3
X56: 3
X57: 3
X62: 3
X63: 3
X71: 3
X72: 3
X73: 3
X74: 3
X75: 3
X85: 3
X86: 3
X87: 3
X92: 3
X93: 3
X101: 3
X102: 3
X103: 3
X104: 3
X105: 3
X115: 3
X116: 3
X117: 3
X30: 2
X31: 2
X126: 2
X127: 2
X128: 2
X129: 2
X130: 2
X140: 2
X141: 2
X142: 2
Total unique values across all columns: 34817
```

In [13]:
```
#Manual Encoding     Converting Categorical to Numerical
```

In [14]:
```
for col in train_df:
    train_df[col].replace({'YES':1, 'NO':0,'Not Available':2},inplace=True)
```

In [15]:
```
train_df.head()
```

Out[15]:

	id	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
0	1	0	0	dqOiM6yBYgnVSezBRiQXs9bvOFnRqrtIoXRIEIxD7g8=	GNjrXXA3SxbgD0dTRbIAPO9jFJ7AIaZnu/f48g5XSUk=	0.576561	0.073139	0.481394	0.115697	0.472474	...	0.0	0.810	3306	4676	1	0	1	2	0.375535	0.464610
1	2	2	2	2	2	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.0	0.510	4678	3306	1	0	1	4	0.741682	0.593630
2	3	0	0	ib4VpsEsqJHzDiyL0dZLQ+xQzDPrkxE+9T3mx5fv2wI=	X6dDAI/DZOWvu0Dg6gCgRoNr2vTUz/mc4SdHTNUPS38=	1.341803	0.051422	0.935572	0.041440	0.501710	...	0.0	0.850	4678	3306	0	0	0	1	0.776467	0.493159
3	4	1	0	BfrqME7vdLw3suQp6YAT16W2piNUmpKhMzuDrVrFQ4w=	YGCdISifn4fLao/ASKdZFhGIq23oqzfSbUVb6px1pig=	0.653912	0.041471	0.940787	0.090851	0.556564	...	0.0	0.945	3306	4678	0	0	1	3	0.168234	0.546582
4	5	0	0	RTjsrrR8DTIJyaIP9Q3Z8s0zseqIVQTrISe97GCWfbk=	3yK2OPj1uYDsoMgsxsjY1FxXkOIID8Xfh20VYGqT+nU=	1.415919	0.000000	1.000000	0.000000	0.375297	...	0.0	1.000	1263	892	0	0	0	1	0.246637	0.361045

5 rows × 146 columns

In [16]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9999 entries, 0 to 9998
Columns: 146 entries, id to x145
dtypes: float64(55), int64(81), object(10)
memory usage: 11.1+ MB
```

In [17]:
```
object_columns = train_df.select_dtypes(include='object').columns
print(object_columns)
```

```
Index(['x3', 'x4', 'x34', 'x35', 'x61', 'x64', 'x65', 'x91', 'x94', 'x95'], dtype='object')
```

In [18]:
```
#Drop Column which have High Unique Values
```

In [19]:
```
train_df=train_df.drop(['id','x3', 'x4', 'x34', 'x35', 'x61', 'x64', 'x65', 'x91', 'x94', 'x95'], axis=1)
```

In [20]:
```
train_df
```

Out[20]:

	x1	x2	x5	x6	x7	x8	x9	x10	x11	x12	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
0	0	0	0.576561	0.073139	0.481394	0.115697	0.472474	1	0	0	...	0.0	0.810	3306	4676	1	0	1	2	0.375535	0.464610
1	2	2	0.000000	0.000000	0.000000	0.000000	0.000000	2	2	2	...	0.0	0.510	4678	3306	1	0	1	4	0.741682	0.593630
2	0	0	1.341803	0.051422	0.935572	0.041440	0.501710	0	0	1	...	0.0	0.850	4678	3306	0	0	0	1	0.776467	0.493159
3	1	0	0.653912	0.041471	0.940787	0.090851	0.556564	1	0	0	...	0.0	0.945	3306	4678	0	0	1	3	0.168234	0.546582
4	0	0	1.415919	0.000000	1.000000	0.000000	0.375297	0	0	1	...	0.0	1.000	1263	892	0	0	0	1	0.246637	0.361045
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9994	0	0	1.207136	0.082855	0.918960	0.313880	0.495189	0	0	0	...	0.0	0.810	4677	3307	1	0	1	1	0.502268	0.486637
9995	0	0	1.414798	0.000000	1.000000	0.000000	0.357369	1	0	0	...	0.0	1.000	1262	892	1	0	1	15	0.890135	0.346276
9996	1	1	1.413677	0.000000	1.000000	0.000000	0.668517	1	0	0	...	0.0	1.000	1261	892	1	0	1	5	0.726457	0.659001
9997	0	0	1.294118	0.000000	1.000000	0.000000	0.570707	0	0	0	...	1.0	1.000	1188	918	0	0	0	3	0.450980	0.561448
9998	1	1	0.660897	0.042735	0.946581	0.086966	0.510278	1	0	0	...	0.0	0.880	3308	4680	1	0	1	0	0.604274	0.499395

9999 rows × 135 columns

Training the Model & Predicting the Classes

In [21]:
```
train_target_df.shape
```

Out[21]:
```
(49999, 34)
```

In [22]:
```
train_df.shape
```

Out[22]:
```
(9999, 135)
```

In [23]:
```
train_target_df=train_target_df.loc[:9998,'y1':]
```

In [24]:
```
#Train Test Split
```

In [25]:
```
from sklearn.model_selection import train_test_split
```

In [26]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(train_df, train_target_df, test_size=0.2)
```

In [27]:
```
X_train.head(5)
```

Out[27]:

	x1	x2	x5	x6	x7	x8	x9	x10	x11	x12	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
9429	0	0	1.294118	0.000000	1.000000	0.000000	0.379630	1	0	0	...	-1.0	1.00	1188	918	0	0	0	3	0.153595	0.349327
5965	0	0	1.414798	0.000000	1.000000	0.000000	0.484152	1	0	0	...	0.0	1.00	1262	892	1	0	1	9	0.572870	0.474643
2517	0	0	1.414798	0.000000	1.000000	0.000000	0.504754	0	0	0	...	0.0	1.00	1262	892	0	0	0	1	0.653587	0.495246
9699	0	0	1.204706	0.093235	0.896176	0.445294	0.503636	1	0	0	...	0.0	0.61	4400	3400	0	0	0	4	0.367941	0.482955
6301	0	0	1.141649	0.096648	0.911507	0.210812	0.313809	0	0	0	...	0.0	0.87	4678	3311	1	0	1	0	0.345515	0.304831

5 rows × 135 columns

In [28]:
```
Y_train.head(5)
```

Out[28]:

	y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	...	y24	y25	y26	y27	y28	y29	y30	y31	y32	y33
9429	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
5965	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
2517	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
9699	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
6301	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 33 columns

In [29]:
```
# Algorithm
```

NaveBayes

In [30]:
```
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.naive_bayes import GaussianNB

# initialize binary relevance multi-label classifier
# with a gaussian naive bayes base classifier
classifier1 = BinaryRelevance(classifier=GaussianNB())

# train
classifier1.fit(X_train.values, Y_train.values)

# predict
predictions1 = classifier1.predict(X_test.values)
```

In [31]:
```
#Confusion Matrix for Each Target Variable
```

In [32]:
```
from sklearn.metrics import multilabel_confusion_matrix, classification_report
import numpy as np
import matplotlib.pyplot as plt

def calculate_confusion_matrices(predictions1, true_labels, threshold=0.5):
    # Convert sparse matrix to a dense NumPy array
    binary_predictions = (predictions1.toarray() >= threshold).astype(int)
    binary_true_labels = (true_labels >= threshold).astype(int)

    # Calculate confusion matrices for each label
    confusion_matrices = multilabel_confusion_matrix(binary_true_labels, binary_predictions)

    # Print confusion matrices
    for i, confusion_matrix in enumerate(confusion_matrices):
        print(f"Confusion Matrix for Label {i + 1}:\n", confusion_matrix)

    # Get unique class labels
    unique_labels = np.unique(binary_true_labels)


    return confusion_matrices
```

In [33]:
```
confusion_matrices = calculate_confusion_matrices(predictions1, Y_test.values)
```

```
Confusion Matrix for Label 1:
 [[1792  194]
 [   2   12]]
Confusion Matrix for Label 2:
 [[1954   46]
 [   0    0]]
Confusion Matrix for Label 3:
 [[1906   45]
 [   5   44]]
Confusion Matrix for Label 4:
 [[1960    7]
 [   1   32]]
Confusion Matrix for Label 5:
 [[2000    0]
 [   0    0]]
Confusion Matrix for Label 6:
 [[1584  263]
 [   9  144]]
Confusion Matrix for Label 7:
 [[1195  729]
 [   5   71]]
Confusion Matrix for Label 8:
 [[1998    0]
 [   2    0]]
Confusion Matrix for Label 9:
 [[1554  300]
 [  28  118]]
Confusion Matrix for Label 10:
 [[1639  336]
 [   9   16]]
Confusion Matrix for Label 11:
 [[1997    2]
 [   1    0]]
Confusion Matrix for Label 12:
 [[1588  260]
 [   9  143]]
Confusion Matrix for Label 13:
 [[1732  235]
 [   8   25]]
Confusion Matrix for Label 14:
 [[2000    0]
 [   0    0]]
Confusion Matrix for Label 15:
 [[1977   19]
 [   0    4]]
Confusion Matrix for Label 16:
 [[1814  162]
 [   2   22]]
Confusion Matrix for Label 17:
 [[1999    0]
 [   1    0]]
Confusion Matrix for Label 18:
 [[1999    0]
 [   1    0]]
Confusion Matrix for Label 19:
 [[1995    4]
 [   1    0]]
Confusion Matrix for Label 20:
 [[1862  133]
 [   0    5]]
Confusion Matrix for Label 21:
 [[1817  168]
 [   1   14]]
Confusion Matrix for Label 22:
 [[1618  370]
 [   1   11]]
Confusion Matrix for Label 23:
 [[1999    0]
 [   0    1]]
Confusion Matrix for Label 24:
 [[1709  247]
 [  11   33]]
Confusion Matrix for Label 25:
 [[1753  242]
 [   0    5]]
Confusion Matrix for Label 26:
 [[1562  418]
 [   2   18]]
Confusion Matrix for Label 27:
 [[1821  160]
 [   3   16]]
Confusion Matrix for Label 28:
 [[1427  558]
 [   1   14]]
Confusion Matrix for Label 29:
 [[1515  431]
 [   8   46]]
Confusion Matrix for Label 30:
 [[1758  209]
 [   6   27]]
Confusion Matrix for Label 31:
 [[1682  269]
 [   1   48]]
Confusion Matrix for Label 32:
 [[1557  320]
 [  21  102]]
Confusion Matrix for Label 33:
 [[500 382]
 [222 896]]
```

In [34]:
```
from sklearn.metrics import multilabel_confusion_matrix, classification_report

def calculate_reports(predictions1, true_labels, threshold=0.5):
    # Convert sparse matrix to a dense NumPy array
    binary_predictions = (predictions1.toarray() >= threshold).astype(int)
    binary_true_labels = (true_labels >= threshold).astype(int)

    # Calculate and print classification reports for each label
    classification_reports = []
    for i in range(binary_true_labels.shape[1]):
        class_report = classification_report(
            binary_true_labels[:, i], binary_predictions[:, i], labels=[0, 1],
            target_names=[f'Label {i+1}_0', f'Label {i+1}_1']
        )
        classification_reports.append(class_report)
        print(f"Classification Report for Label {i + 1}:\n", class_report)

    return confusion_matrices, classification_reports
```

Classification Reports for Each Taret Variable

In [35]:
```
classification_reports = calculate_reports(predictions1, Y_test.values)
```

```
Classification Report for Label 1:
              precision    recall  f1-score   support

   Label 1_0       1.00      0.90      0.95      1986
   Label 1_1       0.06      0.86      0.11        14

    accuracy                           0.90      2000
   macro avg       0.53      0.88      0.53      2000
weighted avg       0.99      0.90      0.94      2000

Classification Report for Label 2:
              precision    recall  f1-score   support

   Label 2_0       1.00      0.98      0.99      2000
   Label 2_1       0.00      0.00      0.00         0

    accuracy                           0.98      2000
   macro avg       0.50      0.49      0.49      2000
weighted avg       1.00      0.98      0.99      2000
```

In [ ]:

Try with another Algorithm to see if we can get better Results

Decision TREE

In [36]:
```
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.tree import DecisionTreeClassifier

# initialize binary relevance multi-label classifier
# with a gaussian naive bayes base classifier
classifier2 = BinaryRelevance(classifier=DecisionTreeClassifier())

# train
classifier2.fit(X_train.values, Y_train.values)

# predict
predictions2 = classifier2.predict(X_test.values)
```

In [37]:
```
from sklearn.metrics import multilabel_confusion_matrix, classification_report

def calculate_confusion_matrices(predictions2, true_labels, threshold=0.5):
    # Convert sparse matrix to a dense NumPy array
    binary_predictions = (predictions2.toarray() >= threshold).astype(int)
    binary_true_labels = (true_labels >= threshold).astype(int)

    # Calculate confusion matrices for each label
    confusion_matrices = multilabel_confusion_matrix(binary_true_labels, binary_predictions)

    # Print confusion matrices
    for i, confusion_matrix in enumerate(confusion_matrices):
        print(f"Confusion Matrix for Label {i + 1}:\n", confusion_matrix)

    # Get unique class labels
    unique_labels = np.unique(binary_true_labels)


    return confusion_matrices
```

In [38]:
```
confusion_matrices = calculate_confusion_matrices(predictions2, Y_test.values)
```

```
Confusion Matrix for Label 1:
 [[1975   11]
 [   8    6]]
Confusion Matrix for Label 2:
 [[1999    1]
 [   0    0]]
Confusion Matrix for Label 3:
 [[1942    9]
 [  16   33]]
Confusion Matrix for Label 4:
 [[1966    1]
 [   5   28]]
Confusion Matrix for Label 5:
 [[1999    1]
 [   0    0]]
Confusion Matrix for Label 6:
 [[1783   64]
 [  47  106]]
Confusion Matrix for Label 7:
 [[1887   37]
 [  32   44]]
Confusion Matrix for Label 8:
 [[1997    1]
 [   2    0]]
Confusion Matrix for Label 9:
 [[1802   52]
 [  39  107]]
Confusion Matrix for Label 10:
 [[1955   20]
 [  11   14]]
Confusion Matrix for Label 11:
 [[1999    0]
 [   1    0]]
Confusion Matrix for Label 12:
 [[1795   53]
 [  51  101]]
Confusion Matrix for Label 13:
 [[1947   20]
 [  11   22]]
Confusion Matrix for Label 14:
 [[2000    0]
 [   0    0]]
Confusion Matrix for Label 15:
 [[1993    3]
 [   0    4]]
Confusion Matrix for Label 16:
 [[1965   11]
 [  13   11]]
Confusion Matrix for Label 17:
 [[1999    0]
 [   1    0]]
Confusion Matrix for Label 18:
 [[1999    0]
 [   1    0]]
Confusion Matrix for Label 19:
 [[1997    2]
 [   1    0]]
Confusion Matrix for Label 20:
 [[1994    1]
 [   0    5]]
Confusion Matrix for Label 21:
 [[1976    9]
 [   5   10]]
Confusion Matrix for Label 22:
 [[1977   11]
 [   6    6]]
Confusion Matrix for Label 23:
 [[1997    2]
 [   1    0]]
Confusion Matrix for Label 24:
 [[1929   27]
 [  17   27]]
Confusion Matrix for Label 25:
 [[1983   12]
 [   2    3]]
Confusion Matrix for Label 26:
 [[1965   15]
 [  11    9]]
Confusion Matrix for Label 27:
 [[1975    6]
 [   8   11]]
Confusion Matrix for Label 28:
 [[1966   19]
 [   9    6]]
Confusion Matrix for Label 29:
 [[1914   32]
 [  33   21]]
Confusion Matrix for Label 30:
 [[1938   29]
 [  15   18]]
Confusion Matrix for Label 31:
 [[1915   36]
 [  26   23]]
Confusion Matrix for Label 32:
 [[1843   34]
 [  42   81]]
Confusion Matrix for Label 33:
 [[745 137]
 [176 942]]
```

"Nave Bayes Model" have Better Results than "Decision Tree model "

In [ ]:

Test File

In [39]:
```
#Read Test file for which prediction have to be submitted
```

In [40]:
```
Live_test=pd.read_csv(r'F:\Data Science Assignmrnt GI Bots\DATA  Scientist Assignment\test.csv')
```

In [41]:
```
Live_test.head(5)
```

Out[41]:

	1698001	NO	NO.1	5KaYd5siHnBD/ljH8BF1fPz5zrCADHZia/Lrhlyxkvc=	FzMc/XY2ETaomhy8gPc9UL8LRkEnQA56+/wVF1fogk8=	1.41479820627803	0	1	0.1	0.202060221870048	...	0.30	1.8	1262.3	892.3	NO.36	NO.37	NO.38	0.31	0.08968
0	1698002	NO	NO	9ACcuXc7MMm9V7jZSr3P3VxAKyMvLAtsdwPKwgncc+k=	WV5vAHFyqkeuyFB5KVNGFOBuwjkUGKYc8wh9QfpVzAA=	0.832679	0.049834	0.945938	0.317427	0.482021	...	1.0	0.866667	4672	3311	NO	NO	NO	5	
1	1698003	NO	NO	MeBJ/ZzEIXfNKat4w1oeDxiMNKrAeY0PH41i00hpYDo=	tnLDGLnpYhzsik5+X+WPo4KQJoQA0TfWRlmEtQ3XNJQ=	1.415919	0.000000	1.000000	0.000000	0.703088	...	-1.0	1.000000	1263	892	NO	NO	NO	8	
2	1698004	NaN	NaN	NaN	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.0	0.870000	4672	3306	YES	NO	YES	0	
3	1698005	NO	NO	uduY7XWJ8eFgTltv5P0rPh5GW6KwBu+tPFH13uQRN+0=	0L7+hNDV8S57etySgdljbm2AK1zQuLP77IGk2hyEmCo=	1.129212	0.087020	0.814240	1.112804	0.874318	...	0.0	0.870000	4400	3413	YES	NO	YES	2	
4	1698006	NO	NO	kM4KU87XvnvKRvf4dN3Tu4zQYq8fpcqhDTFADWdfCg8=	4LhhvTzxwvh2SnFtcpaRasyvph66a3YDIQCshAfyS2o=	1.415919	0.000000	1.000000	0.000000	0.232779	...	0.0	1.000000	1263	892	YES	NO	YES	6	

5 rows × 146 columns

In [42]:
```
# Naming Columns
```

In [43]:
```
Live_test.columns=['id',
                   'x1','x2','x3','x4','x5','x6','x7','x8','x9','x10',
                   'x11','x12','x13','x14','x15','x16','x17','x18','x19','x20',
                   'x21','x22','x23','x24','x25','x26','x27','x28','x29','x30',
                   'x31','x32','x33','x34','x35','x36','x37','x38','x39','x40',
                   'x41','x42','x43','x44','x45','x46','x47','x48','x49','x50',
                   'x51','x52','x53','x54','x55','x56','x57','x58','x59','x60',
                   'x61','x62','x63','x64','x65','x66','x67','x68','x69','x70',
                   'x71','x72','x73','x74','x75','x76','x77','x78','x79','x80',
                   'x81','x82','x83','x84','x85','x86','x87','x88','x89','x90',
                   'x91','x92','x93','x94','x95','x96','x97','x98','x99','x100',
                   'x101','x102','x103','x104','x105','x106','x107','x108','x109','x110',
                   'x111','x112','x113','x114','x115','x116','x117','x118','x119','x120',
                   'x121','x122','x123','x124','x125','x126','x127','x128','x129','x130',
                   'x131','x132','x133','x134','x135','x136','x137','x138','x139','x140',
                   'x141','x142','x143','x144','x145']
```

In [44]:
```
Live_test.head(5)
```

Out[44]:

	id	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
0	1698002	NO	NO	9ACcuXc7MMm9V7jZSr3P3VxAKyMvLAtsdwPKwgncc+k=	WV5vAHFyqkeuyFB5KVNGFOBuwjkUGKYc8wh9QfpVzAA=	0.832679	0.049834	0.945938	0.317427	0.482021	...	1.0	0.866667	4672	3311	NO	NO	NO	5	0.945032	0.471318
1	1698003	NO	NO	MeBJ/ZzEIXfNKat4w1oeDxiMNKrAeY0PH41i00hpYDo=	tnLDGLnpYhzsik5+X+WPo4KQJoQA0TfWRImEtQ3XNJQ=	1.415919	0.000000	1.000000	0.000000	0.703088	...	-1.0	1.000000	1263	892	NO	NO	NO	8	0.557175	0.693587
2	1698004	NaN	NaN	NaN	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.0	0.870000	4672	3306	YES	NO	YES	0	0.870538	0.405822
3	1698005	NO	NO	uduY7XWJ8eFgTltv5P0rPh5GW6KwBu+tPFH13uQRN+0=	0L7+hNDV8S57etySgdljbm2AK1zQuLP77IGk2hyEmCo=	1.129212	0.087020	0.814240	1.112804	0.874318	...	0.0	0.870000	4400	3413	YES	NO	YES	2	0.224729	0.870909
4	1698006	NO	NO	kM4KU87XvnvKRvf4dN3Tu4zQYq8fpcqhDTFADWdfCg8=	4LhhvTzxwvh2SnFtcpaRasyvph66a3YDIQCshAfyS2o=	1.415919	0.000000	1.000000	0.000000	0.232779	...	0.0	1.000000	1263	892	YES	NO	YES	6	0.536996	0.223278

5 rows × 146 columns

Preprocessing the Data for ML

In [45]:
```
missing_percent_Live_test_data=Live_test.isna().sum().sort_values(ascending=False)*100/len(Live_test)
missing_percent_Live_test_data
```

Out[45]:
```
x26     14.707354
x12     14.707354
x2      14.707354
x3      14.707354
x4      14.707354
          ...
x53      0.000000
x52      0.000000
x51      0.000000
x50      0.000000
x145     0.000000
Length: 146, dtype: float64
```

In [46]:
```
# Missing Value filled with Not Available
object_columns = Live_test.select_dtypes(include=['object']).columns
Live_test[object_columns] = Live_test[object_columns].fillna('Not Available')
```

In [47]:
```
list_col = Live_test.select_dtypes(include='object').columns
output_count = 0  # Counter for the number of outputs

for col in list_col:
    unique_values = Live_test[col].unique()
    if len(unique_values) < 10:
        output_count += 1
        print('{}: {}'.format(col.upper(), unique_values))

print("Number of Column:", output_count)
```

```
X1: ['NO' 'Not Available' 'YES']
X2: ['NO' 'Not Available' 'YES']
X10: ['YES' 'NO' 'Not Available']
X11: ['NO' 'Not Available' 'YES']
X12: ['NO' 'YES' 'Not Available']
X13: ['NO' 'YES' 'Not Available']
X14: ['NO' 'YES' 'Not Available']
X24: ['YES' 'NO' 'Not Available']
X25: ['NO' 'Not Available' 'YES']
X26: ['YES' 'NO' 'Not Available']
X30: ['NO' 'YES']
X31: ['NO' 'YES']
X32: ['NO' 'Not Available' 'YES']
X33: ['NO' 'Not Available' 'YES']
X41: ['NO' 'YES' 'Not Available']
X42: ['NO' 'Not Available' 'YES']
X43: ['YES' 'NO' 'Not Available']
X44: ['NO' 'Not Available' 'YES']
X45: ['NO' 'YES' 'Not Available']
X55: ['NO' 'YES' 'Not Available']
X56: ['NO' 'Not Available' 'YES']
X57: ['NO' 'YES' 'Not Available']
X62: ['NO' 'YES' 'Not Available']
X63: ['NO' 'YES' 'Not Available']
X71: ['YES' 'NO' 'Not Available']
X72: ['NO' 'Not Available' 'YES']
X73: ['NO' 'YES' 'Not Available']
X74: ['NO' 'YES' 'Not Available']
X75: ['NO' 'YES' 'Not Available']
X85: ['YES' 'NO' 'Not Available']
X86: ['NO' 'Not Available' 'YES']
X87: ['YES' 'NO' 'Not Available']
X92: ['NO' 'Not Available' 'YES']
X93: ['NO' 'Not Available' 'YES']
X101: ['YES' 'NO' 'Not Available']
X102: ['NO' 'Not Available' 'YES']
X103: ['NO' 'YES' 'Not Available']
X104: ['NO' 'Not Available' 'YES']
X105: ['NO' 'YES' 'Not Available']
X115: ['YES' 'NO' 'Not Available']
X116: ['NO' 'Not Available' 'YES']
X117: ['YES' 'NO' 'Not Available']
X126: ['YES' 'NO']
X127: ['NO' 'YES']
X128: ['NO' 'YES']
X129: ['NO' 'YES']
X130: ['NO' 'YES']
X140: ['NO' 'YES']
X141: ['NO' 'YES']
X142: ['NO' 'YES']
Number of Column: 50
```

In [48]:
```python
list_col = Live_test.select_dtypes(include='object').columns
unique_values_dict = {}  # Dictionary to store unique values for each column

for col in list_col:
    unique_values = Live_test[col].nunique()
    unique_values_dict[col] = unique_values

# Sort the dictionary by values in descending order
sorted_unique_values = sorted(unique_values_dict.items(), key=lambda x: x[1], reverse=True)

# Print the sorted unique values
for col, unique_count in sorted_unique_values:
    print('{}: {}'.format(col.upper(), unique_count))

total_unique_count = sum(unique_values_dict.values())
print("Total unique values across all columns:", total_unique_count)
```

```
X61: 1626
X34: 1456
X64: 1455
X94: 1298
X3: 1237
X91: 921
X65: 381
X35: 358
X95: 296
X4: 281
X1: 3
X2: 3
X10: 3
X11: 3
X12: 3
X13: 3
X14: 3
X24: 3
X25: 3
X26: 3
X32: 3
X33: 3
X41: 3
X42: 3
X43: 3
X44: 3
X45: 3
X55: 3
X56: 3
X57: 3
X62: 3
X63: 3
X71: 3
X72: 3
X73: 3
X74: 3
X75: 3
X85: 3
X86: 3
X87: 3
X92: 3
X93: 3
X101: 3
X102: 3
X103: 3
X104: 3
X105: 3
X115: 3
X116: 3
X117: 3
X30: 2
X31: 2
X126: 2
X127: 2
X128: 2
X129: 2
X130: 2
X140: 2
X141: 2
X142: 2
Total unique values across all columns: 9449
```

In [49]:
```python
for col in Live_test:
    Live_test[col].replace({'YES':1, 'NO':0,'Not Available':2},inplace=True)
```

In [50]:
```python
Live_test1=Live_test
```

In [51]:
```python
Live_test=Live_test.drop(['id','x3', 'x4', 'x34', 'x35', 'x61', 'x64', 'x65', 'x91', 'x94', 'x95'], axis=1)
```

In [52]:
```python
Live_test.head(5)
```

Out[52]:

	x1	x2	x5	x6	x7	x8	x9	x10	x11	x12	...	x136	x137	x138	x139	x140	x141	x142	x143	x144	x145
0	0	0	0.832679	0.049834	0.945938	0.317427	0.482021	1	0	0	...	1.0	0.866667	4672	3311	0	0	0	5	0.945032	0.471318
1	0	0	1.415919	0.000000	1.000000	0.000000	0.703088	0	0	1	...	-1.0	1.000000	1263	892	0	0	0	8	0.557175	0.693587
2	2	2	0.000000	0.000000	0.000000	0.000000	0.000000	2	2	2	...	0.0	0.870000	4672	3306	1	0	1	0	0.870538	0.405822
3	0	0	1.129212	0.087020	0.814240	1.112804	0.874318	0	0	0	...	0.0	0.870000	4400	3413	1	0	1	2	0.224729	0.870909
4	0	0	1.415919	0.000000	1.000000	0.000000	0.232779	0	0	1	...	0.0	1.000000	1263	892	1	0	1	6	0.536996	0.223278

5 rows × 135 columns

Prediction with NaveBayes Model

In [53]:
```python
predictions_Live = classifier1.predict(Live_test.values)
```

In [54]:
```python
predictions_Live
```

Out[54]:
```
<1999x33 sparse matrix of type '<class 'numpy.int64'>'
        with 8322 stored elements in Compressed Sparse Column format>
```

In [55]:
```python
predictions_Live_arr=predictions_Live.toarray()
```

In [56]:
```python
Live_test1.id
```

Out[56]:
```
0       1698002
1       1698003
2       1698004
3       1698005
4       1698006
         ...
1994    1699996
1995    1699997
1996    1699998
1997    1699999
1998    1700000
Name: id, Length: 1999, dtype: int64
```

In [57]:
```python
target=[]
for num in Live_test1.id:
    for i in range(1,34):
        target.append(str(num)+'_y'+str(i))
```

In [58]:
```python
len(target)
```

Out[58]:
```
65967
```

In [66]:
```python
submission_df=pd.DataFrame(target,columns=['id_label'])
```

In [67]:
```
submission_df
```

Out[67]:

	id_label
0	1698002_y1
1	1698002_y2
2	1698002_y3
3	1698002_y4
4	1698002_y5
...	...
65962	1700000_y29
65963	1700000_y30
65964	1700000_y31
65965	1700000_y32
65966	1700000_y33

65967 rows × 1 columns

In [68]:
```
prediction_list=[]
for i in range(len(predictions_Live_arr)):
    prediction_list.extend(predictions_Live_arr.tolist()[i])
```

In [69]:
```
pred_df=pd.DataFrame(prediction_list,columns=['pred'])
```

In [70]:
```
test_prediction_df=pd.concat([submission_df,pred_df],axis=1)
```

In [71]:
```
test_prediction_df
```

Out[71]:

	id_label	pred
0	1698002_y1	0
1	1698002_y2	0
2	1698002_y3	0
3	1698002_y4	0
4	1698002_y5	0
...	...	...
65962	1700000_y29	0
65963	1700000_y30	0
65964	1700000_y31	0
65965	1700000_y32	0
65966	1700000_y33	0

65967 rows × 2 columns

In [72]:
```
test_prediction_df.to_csv('test_prediction.csv', index=None)
```

In [ ]: