In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings, re, joblib
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split, RandomizedSearchCV, 
from sklearn.linear_model import LogisticRegression, PassiveAggressiveClas
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier,
from xgboost import XGBClassifier, XGBRFClassifier
from catboost import CatBoostClassifier
from lightgbm import LGBMClassifier
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import GaussianNB, BernoulliNB
from sklearn.neural_network import MLPClassifier
from scipy.stats import probplot
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, SimpleImputer
from sklearn.feature_selection import SelectKBest, SelectPercentile, Selec
from sklearn.preprocessing import StandardScaler, OrdinalEncoder, PowerTra
from sklearn.metrics import ConfusionMatrixDisplay, classification_report,
from imblearn.over_sampling import SMOTE
```

Can we predict whether a customer will have a "Good" or "Bad" credit score next month based on their financial and credit-related attributes?

In [2]:
```
train = pd.read_csv('train.csv')
```

In [3]:
```
train.head()
```

Out[3]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Month
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	

5 rows × 28 columns

In [4]:
```
train.shape
```

Out[4]: (100000, 28)

In [5]:
```
train.duplicated().sum()
```

Out[5]: 0

In [6]:
```
train.isnull().sum()
```

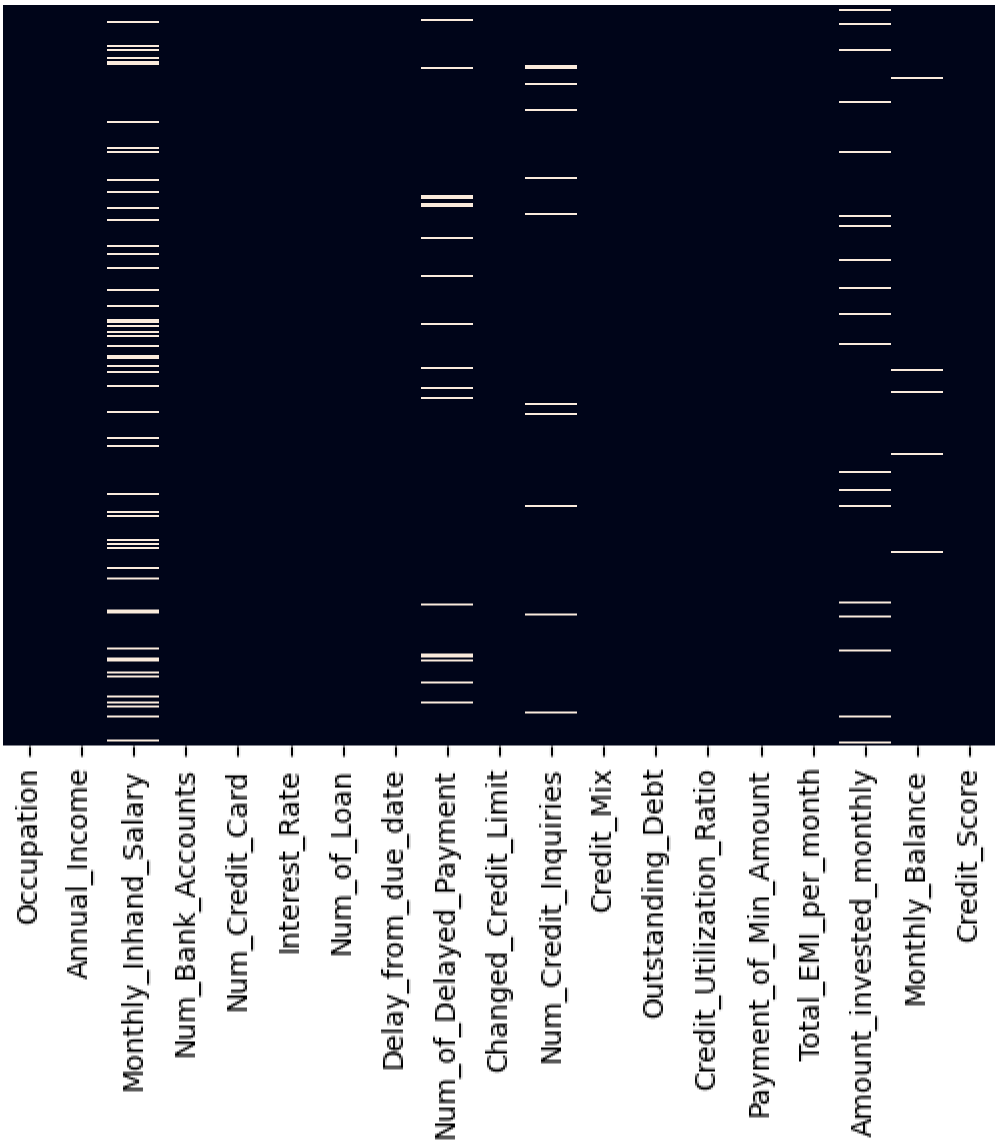
Out[6]:
```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
SSN                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                11408
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1200
Credit_Score                    0
dtype: int64
```

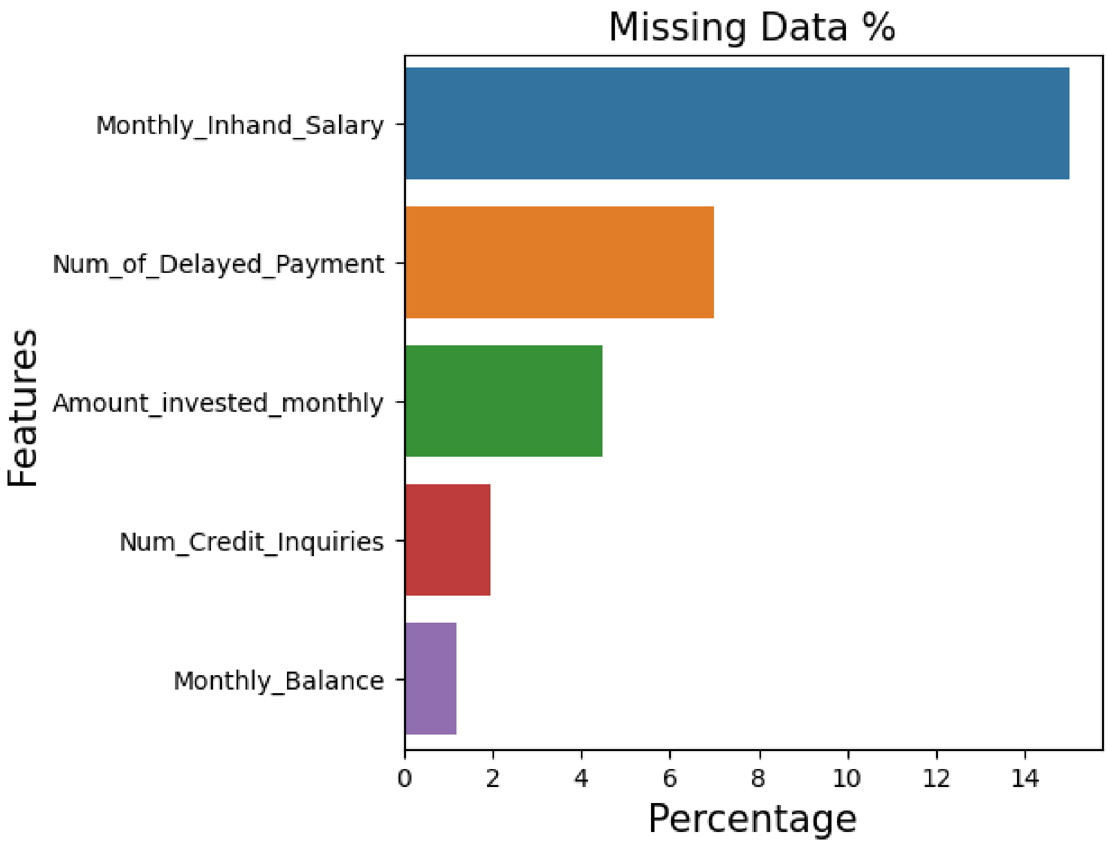
In [7]:
```
train.drop(['Month','ID',"Customer_ID","Name","SSN","Credit_History_Age",'I
```

In [8]:
```
train.shape
```

Out[8]:
```
(100000, 19)
```

In [9]:
```
def get_missing_data_details(hrdata):
    sns.heatmap(train.isnull(), yticklabels=False, cbar=False)
    total = train.isnull().sum().sort_values(ascending=False)
    percent = ((train.isnull().sum() / train.isnull().count()) * 100).sort_
    missing = pd.concat([total, percent], axis=1, keys=['Total', 'Percent']
    missing = missing[missing["Percent"] > 0]

    plt.figure(figsize=(5, 5))
    sns.barplot(x=missing["Percent"], y=missing.index)
    plt.xlabel('Percentage', fontsize=15)
    plt.ylabel('Features', fontsize=15)
    plt.title('Missing Data %', fontsize=15)

    plt.show()

# Call the function with your hrdata
get_missing_data_details(train)
```





In [10]:
```
train.isnull().sum()
```

Out[10]:
```
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Monthly_Balance              1200
Credit_Score                    0
dtype: int64
```

In [11]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 19 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   Occupation                100000 non-null  object 
 1   Annual_Income             100000 non-null  object 
 2   Monthly_Inhand_Salary     84998 non-null   float64
 3   Num_Bank_Accounts         100000 non-null  int64  
 4   Num_Credit_Card           100000 non-null  int64  
 5   Interest_Rate             100000 non-null  int64  
 6   Num_of_Loan               100000 non-null  object 
 7   Delay_from_due_date       100000 non-null  int64  
 8   Num_of_Delayed_Payment    92998 non-null   object 
 9   Changed_Credit_Limit      100000 non-null  object 
 10  Num_Credit_Inquiries      98035 non-null   float64
 11  Credit_Mix                100000 non-null  object 
 12  Outstanding_Debt          100000 non-null  object 
 13  Credit_Utilization_Ratio  100000 non-null  float64
 14  Payment_of_Min_Amount     100000 non-null  object 
 15  Total_EMI_per_month       100000 non-null  float64
 16  Amount_invested_monthly   95521 non-null   object 
 17  Monthly_Balance           98800 non-null   object 
 18  Credit_Score              100000 non-null  object 
dtypes: float64(4), int64(4), object(11)
memory usage: 14.5+ MB
```

In [12]:
```
train.head()
```

Out[12]:

	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Ca
0	Scientist	19114.12	1824.843333	3	
1	Scientist	19114.12	NaN	3	
2	Scientist	19114.12	NaN	3	
3	Scientist	19114.12	NaN	3	
4	Scientist	19114.12	1824.843333	3	

Treating anamoly and Feature engineering

changing data type for some variable as they are consider as object but they should be float

In [13]:
```
train['Annual_Income'].unique()
```

Out[13]:
```
array(['19114.12', '34847.84', '34847.84_', ..., '20002.88', '39628.99',
       '39628.99_'], dtype=object)
```

In [14]:
```
train['Annual_Income'] =train['Annual_Income'].apply(lambda x:x.replace("_'
```

In [15]:
```
train['Annual_Income'] =train['Annual_Income'].astype(float)
```

In [16]:
```
train['Num_of_Loan'] =train['Num_of_Loan'].apply(lambda x:x.replace('_',''
```

In [17]:
```
train['Num_of_Loan'] =train['Num_of_Loan'].astype(float)
```

In [18]:
```
import pandas as pd

# Assuming test is your DataFrame
train["Num_of_Delayed_Payment"] = train["Num_of_Delayed_Payment"].apply(lar
```

In [19]:
```
train['Num_of_Delayed_Payment'] =train['Num_of_Delayed_Payment'].astype(flo
```

In [20]:
```
train['Changed_Credit_Limit'] =train['Changed_Credit_Limit'].apply(lambda x
```

In [21]:
```
train['Changed_Credit_Limit'] = train['Changed_Credit_Limit'].replace('', 
```

In [22]:
```
train['Changed_Credit_Limit'] =train['Changed_Credit_Limit'].astype(float)
```

In [23]:
```
train['Outstanding_Debt'] =train['Outstanding_Debt'].apply(lambda x:x.repla
```

In [24]:
```
train['Outstanding_Debt'] =train['Outstanding_Debt'].astype(float)
```

In [25]:
```

# Assuming test is your DataFrame
train["Amount_invested_monthly"] = train["Amount_invested_monthly"].apply(l
```

In [26]:
```
train['Amount_invested_monthly'] =train['Amount_invested_monthly'].astype(
```

In [27]:

```
# Assuming test is your DataFrame
train["Monthly_Balance"] = train["Monthly_Balance"].apply(lambda x: x.repl
```

In [28]:

```
train['Monthly_Balance'] =train['Monthly_Balance'].astype(float)
```

In [29]:

```
train.info()
```

```
 1   Annual_Income             100000 non-null  float64
 2   Monthly_Inhand_Salary     84998 non-null   float64
 3   Num_Bank_Accounts         100000 non-null  int64
 4   Num_Credit_Card           100000 non-null  int64
 5   Interest_Rate             100000 non-null  int64
 6   Num_of_Loan               100000 non-null  float64
 7   Delay_from_due_date       100000 non-null  int64
 8   Num_of_Delayed_Payment    92998 non-null   float64
 9   Changed_Credit_Limit      100000 non-null  float64
 10  Num_Credit_Inquiries      98035 non-null   float64
 11  Credit_Mix                100000 non-null  object
 12  Outstanding_Debt          100000 non-null  float64
 13  Credit_Utilization_Ratio  100000 non-null  float64
 14  Payment_of_Min_Amount     100000 non-null  object
 15  Total_EMI_per_month       100000 non-null  float64
 16  Amount_invested_monthly   95521 non-null   float64
 17  Monthly_Balance           98800 non-null   float64
 18  Credit_Score              100000 non-null  object
dtypes: float64(11), int64(4), object(4)
memory usage: 14.5+ MB
```

In [30]:

```
train.isnull().sum()
```

Out[30]:

```
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Monthly_Balance              1200
Credit_Score                    0
dtype: int64
```

In [31]:
```
train2 = train.dropna()
```

In [32]:
```
train2.isnull().sum()
```

Out[32]:
```
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Monthly_Balance             0
Credit_Score                0
dtype: int64
```

In [33]:
```
train2.head()
```

Out[33]:

	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Ca
0	Scientist	19114.12	1824.843333	3	
6	Scientist	19114.12	1824.843333	3	
7	Scientist	19114.12	1824.843333	3	
8	_______	34847.84	3037.986667	2	
9	Teacher	34847.84	3037.986667	2	

In [34]:
```
train2 = train2[train2['Occupation'] != '_______']
```

In [35]:
```
train2['Occupation'].value_counts()
```

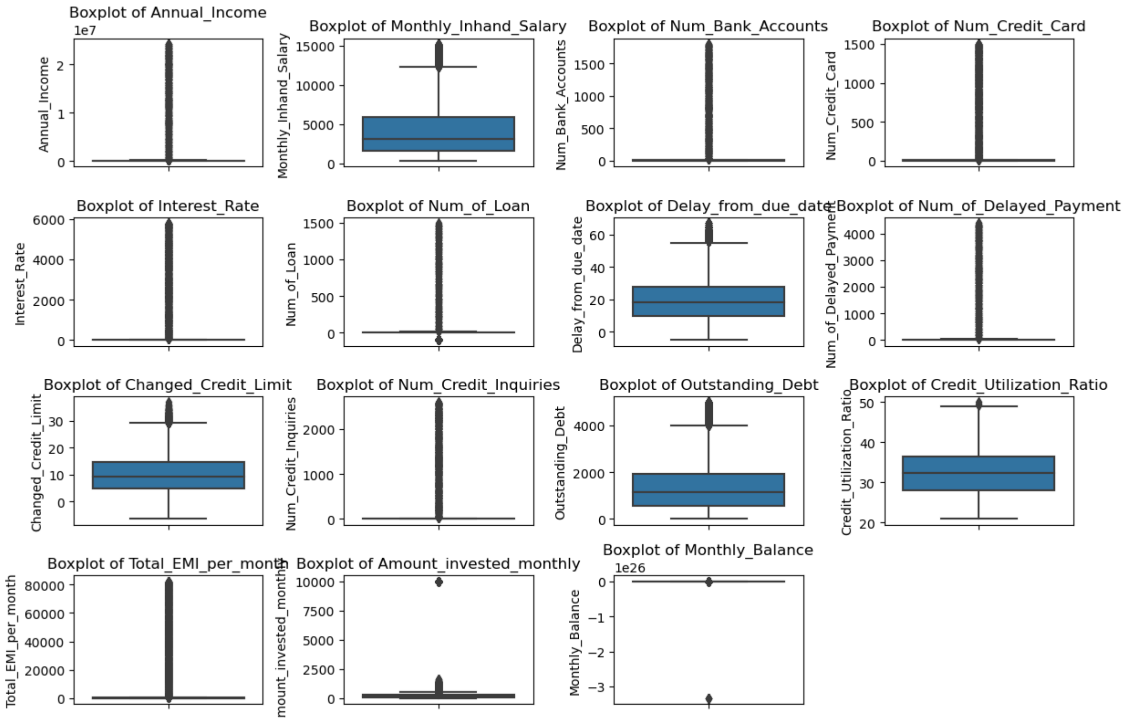
Out[35]:
```
Occupation
Lawyer           4867
Engineer         4650
Mechanic         4627
Architect        4605
Accountant       4571
Developer        4563
Media_Manager    4553
Teacher          4545
Scientist        4524
Doctor           4523
Entrepreneur     4494
Journalist       4442
Musician         4373
Manager          4350
Writer           4311
Name: count, dtype: int64
```

In [36]:
```
train2.shape
```

Out[36]:
```
(67998, 19)
```

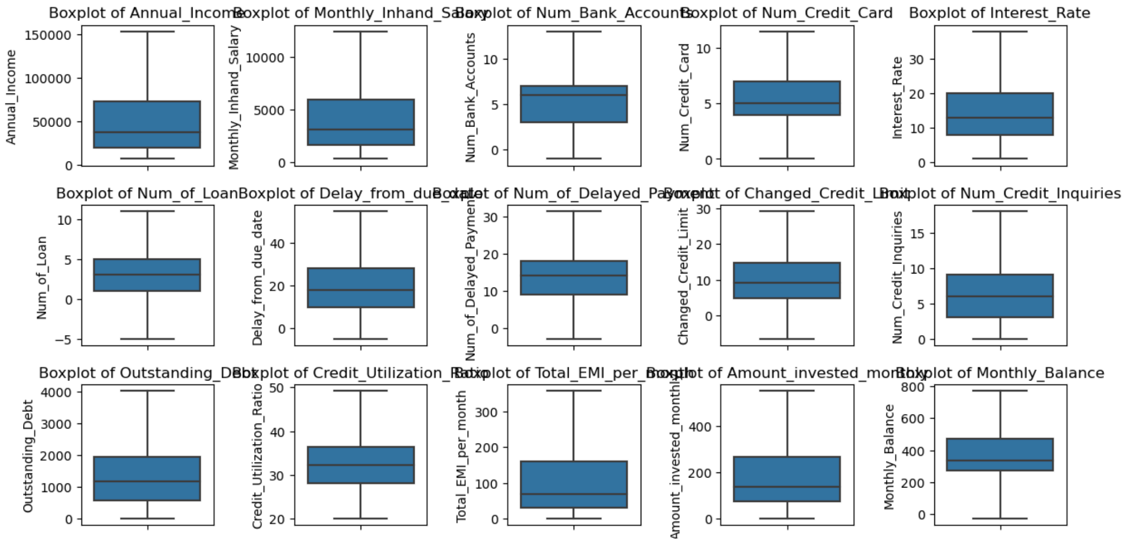
Treating and checking outliers`

In [37]:
```
# Select only the numeric columns
numeric_columns = train2.select_dtypes(include=['int', 'float'])

# Plot boxplots for each numeric feature
plt.figure(figsize=(12, 8))
for i, feature in enumerate(numeric_columns.columns):
    plt.subplot(4, 4, i + 1)
    sns.boxplot(y=numeric_columns[feature], data=train2)
    plt.title('Boxplot of {}'.format(feature))
    plt.tight_layout()

plt.show()
```



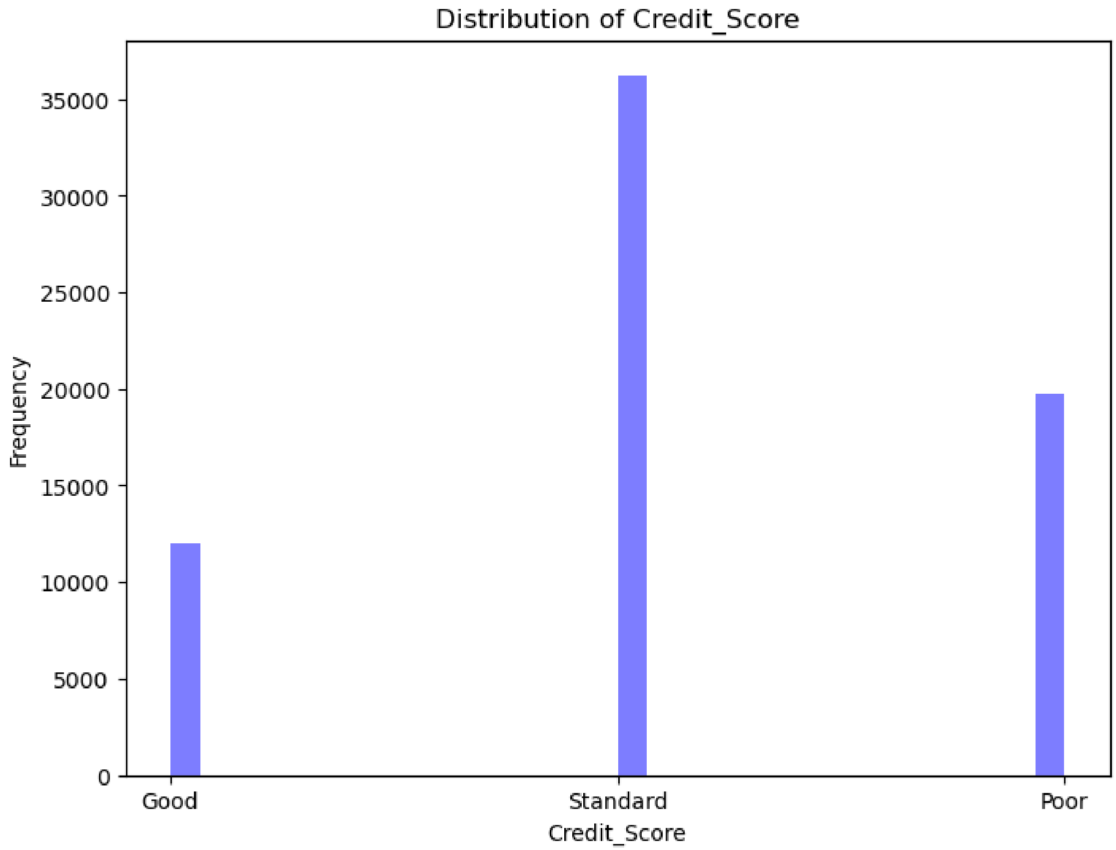
In [38]:
```
def remove_outlier(col):
    col = pd.to_numeric(col, errors='coerce')
    Q1, Q3 = col.quantile([0.25, 0.75])
    IQR = Q3 - Q1
    lower_range = Q1 - (1.5 * IQR)
    upper_range = Q3 + (1.5 * IQR)
    return lower_range, upper_range

feature_list = train.columns

for feature in feature_list:
    LL, UL = remove_outlier(train[feature])
    train[feature] = np.where(train[feature] > UL, UL, train[feature])
    train[feature] = np.where(train[feature] < LL, LL, train[feature])
```

In [39]:
```
plt.figure(figsize=(12, 8))
numeric_features = train.select_dtypes(include=[np.number]).columns

for i, feature in enumerate(numeric_features):
    plt.subplot(4, 5, i + 1)
    sns.boxplot(y=train[feature], data=train)
    plt.title('Boxplot of {}'.format(feature))
    plt.tight_layout()
```



Cheking Biasness in the data

In [40]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
plt.hist(train2['Credit_Score'], bins=30, color='blue', alpha=0.5)
plt.xlabel('Credit_Score')
plt.ylabel('Frequency')
plt.title('Distribution of Credit_Score')
plt.show()
```



In [41]:
```
train2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 67998 entries, 0 to 99999
Data columns (total 19 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Occupation                67998 non-null  object 
 1   Annual_Income             67998 non-null  float64
 2   Monthly_Inhand_Salary     67998 non-null  float64
 3   Num_Bank_Accounts         67998 non-null  int64  
 4   Num_Credit_Card           67998 non-null  int64  
 5   Interest_Rate             67998 non-null  int64  
 6   Num_of_Loan               67998 non-null  float64
 7   Delay_from_due_date       67998 non-null  int64  
 8   Num_of_Delayed_Payment    67998 non-null  float64
 9   Changed_Credit_Limit      67998 non-null  float64
 10  Num_Credit_Inquiries      67998 non-null  float64
 11  Credit_Mix                67998 non-null  object 
 12  Outstanding_Debt          67998 non-null  float64
 13  Credit_Utilization_Ratio  67998 non-null  float64
 14  Payment_of_Min_Amount     67998 non-null  object 
 15  Total_EMI_per_month       67998 non-null  float64
 16  Amount_invested_monthly   67998 non-null  float64
 17  Monthly_Balance           67998 non-null  float64
 18  Credit_Score              67998 non-null  object 
dtypes: float64(11), int64(4), object(4)
memory usage: 10.4+ MB
```

Convert Object Feature types for Linear Discriminant Analysis

Doing label and hot encdoing

In [73]:
```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
```

In [74]:
```
categorical_cols = ['Credit_Score', 'Payment_of_Min_Amount', 'Credit_Mix',

label_encoder = LabelEncoder()
for col in categorical_cols:
    if col in train2.columns:

        train2[col] = label_encoder.fit_transform(train2[col].astype(str))
```

In [75]:
```
        # Display the mapping of original labels to encoded values
        print(f"Mapping for {col}:")
        for original_label, encoded_value in zip(label_encoder.classes_, la
            print(f"  {original_label} is encoded as {encoded_value}")

# Display the updated DataFrame
print("\nUpdated DataFrame:")
print(train2)
```

```
Mapping for Occupation:
  0 is encoded as 0
  1 is encoded as 1
  10 is encoded as 2
  11 is encoded as 3
  12 is encoded as 4
  13 is encoded as 5
  14 is encoded as 6
  2 is encoded as 7
  3 is encoded as 8
  4 is encoded as 9
  5 is encoded as 10
  6 is encoded as 11
  7 is encoded as 12
  8 is encoded as 13
  9 is encoded as 14

Updated DataFrame:
       Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Account
s  \
0               4       19114.12            1824.843333
3
6               4       19114.12            1824.843333
3
7               4       19114.12            1824.843333
3
9               5       34847.84            3037.986667
2
10              5       34847.84            3037.986667
2
...           ...            ...                    ...
...
99994          14       39628.99            3359.415833
4
99995          14       39628.99            3359.415833
4
99996          14       39628.99            3359.415833
4
99997          14       39628.99            3359.415833
4
99999          14       39628.99            3359.415833
4

       Num_Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date
\
0                    4              3          4.0                    3
6                    4              3          4.0                    3
7                    4              3          4.0                    3
9                    4              6          1.0                    7
10                1385              6          1.0                    3
...                ...            ...          ...                  ...
99994                6              7          2.0                   20
99995                6              7          2.0                   23
99996                6              7          2.0                   18
99997                6           5729          2.0                   27
99999                6              7          2.0                   18

       Num_of_Delayed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries
\
0                         7.0                 11.27                   4.0
6                         8.0                 11.27                   4.0
```

```
7                       6.0                 11.27                  4.0
9                       1.0                  7.42                  2.0
10                     -1.0                  5.42                  2.0
...                     ...                   ...                  ...
99994                   6.0                  9.50                  3.0
99995                   7.0                 11.50                  3.0
99996                   7.0                 11.50                  3.0
99997                   6.0                 11.50                  3.0
99999                   6.0                 11.50                  3.0

       Credit_Mix  Outstanding_Debt  Credit_Utilization_Ratio  \
0               3            809.98                 26.822620
6               1            809.98                 22.537593
7               1            809.98                 23.933795
9               1            605.03                 38.550848
10              3            605.03                 33.224951
...           ...               ...                       ...
99994           3            502.38                 39.323569
99995           3            502.38                 34.663572
99996           3            502.38                 40.565631
99997           1            502.38                 41.255522
99999           1            502.38                 34.192463

       Payment_of_Min_Amount  Total_EMI_per_month  Amount_invested_monthl
y  \
0                          1            49.574949                80.41529
5
6                          1            49.574949               178.34406
7
7                          1            49.574949                24.78521
7
9                          1            18.816215                40.39123
8
10                         1            18.816215                58.51597
6
...                      ...                  ...
...
99994                      1            35.104023               140.58140
3
99995                      1            35.104023                60.97133
3
99996                      1            35.104023                54.18595
0
99997                      1            35.104023                24.02847
7
99999                      1            35.104023               167.16386
5

       Monthly_Balance  Credit_Score
0           312.494089             2
6           244.565317             2
7           358.124168             1
9           484.591214             2
10          466.466476             1
...                ...           ...
99994       410.256158             0
99995       479.866228             0
99996       496.651610             0
99997       516.809083             0
99999       393.673696             0
```

```
[67998 rows x 19 columns]
```

ordinal encoding

In [76]:
```
#train2['Credit_Score']=np.where(train2['Credit_Score'] =='Poor', '0', trai
#train2['Credit_Score']=np.where(train2['Credit_Score'] =='Standard', '1',
#train2['Credit_Score']=np.where(train2['Credit_Score'] =='Good', '2', trai
```

In [ ]:

In [77]:
```
train2.head()
```

Out[77]:

	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	4	19114.12	1824.843333	3	
6	4	19114.12	1824.843333	3	
7	4	19114.12	1824.843333	3	
9	5	34847.84	3037.986667	2	
10	5	34847.84	3037.986667	2	1

In [78]:
```
train3 =train2
```

spliting the data in train test split

In [79]:
```
X= train3.drop("Credit_Score",axis=1)
y=train3["Credit_Score"]
```

In [80]:
```
X.value_counts()
```

Out[80]:
```
Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  Num_
Credit_Card  Interest_Rate  Num_of_Loan  Delay_from_due_date  Num_of_Dela
yed_Payment  Changed_Credit_Limit  Num_Credit_Inquiries  Credit_Mix  Outs
tanding_Debt  Credit_Utilization_Ratio  Payment_of_Min_Amount  Total_EMI_
per_month  Amount_invested_monthly  Monthly_Balance
0           7.021910e+03   507.159167             3                  9
20            7.0           27                   18.0
12.75                13.0                  3            1919.27
36.665508                2                   27.590627             29.
830585               273.294705         1
10          8.637875e+03   614.822917             9                  10
20            5.0           25                   22.0
12.63                8.0                   0            1549.11
22.891886                0                   19.940708             31.
104887               300.436696         1
            8.294385e+03   946.198750             7                  7
26            7.0           6                    11.0
7.59                 4.0                   2            1756.74
25.216641                0                   48.032063             72.
876540               263.711272         1

12.0                   7.59                  4.0                  2
1756.74          35.554515                 2                     48.032
063           112.355868               224.231944          1
            8.308130e+03   916.344167             10                 9
20            7.0           27                   10.0
15.96                11.0                  2            2683.29
33.593707                0                   27.600324             51.
617315               292.416777         1


..
5           7.708690e+03   379.390833             8                  6
25            5.0           57                   13.0
28.96                11.0                  0            4147.58
35.687940                2                   26.588314             0.0
00000                251.768000         1

15.0                   28.96                 11.0                 3
4147.58          26.663496                 2                     26.588
314           21.471077                269.879692          1

16.0                   28.96                 11.0                 0
4147.58          35.136649                 2                     26.588
314           15.370843                245.979926          1

17.0                   28.96                 11.0                 0
4147.58          38.792202                 2                     26.588
314           18.161497                273.189272          1
14          2.417715e+07   2373.828333            4                  3
6             0.0           6                    4.0
2.56                 3.0                   1            1443.42
39.408584                1                   0.000000              13
6.175542               381.207291         1
Name: count, Length: 67998, dtype: int64
```

In [81]:
```
y.value_counts()
```

Out[81]:
```
Credit_Score
1    36239
0    19737
2    12022
Name: count, dtype: int64
```

In [82]:
```
smote = SMOTE() # Synthetic Minority Oversampling TEchnique
X, y = smote.fit_resample(X,y)
```

In [83]:
```
y.value_counts()
```

Out[83]:
```
Credit_Score
2    36239
1    36239
0    36239
Name: count, dtype: int64
```

In [84]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,shuf
```

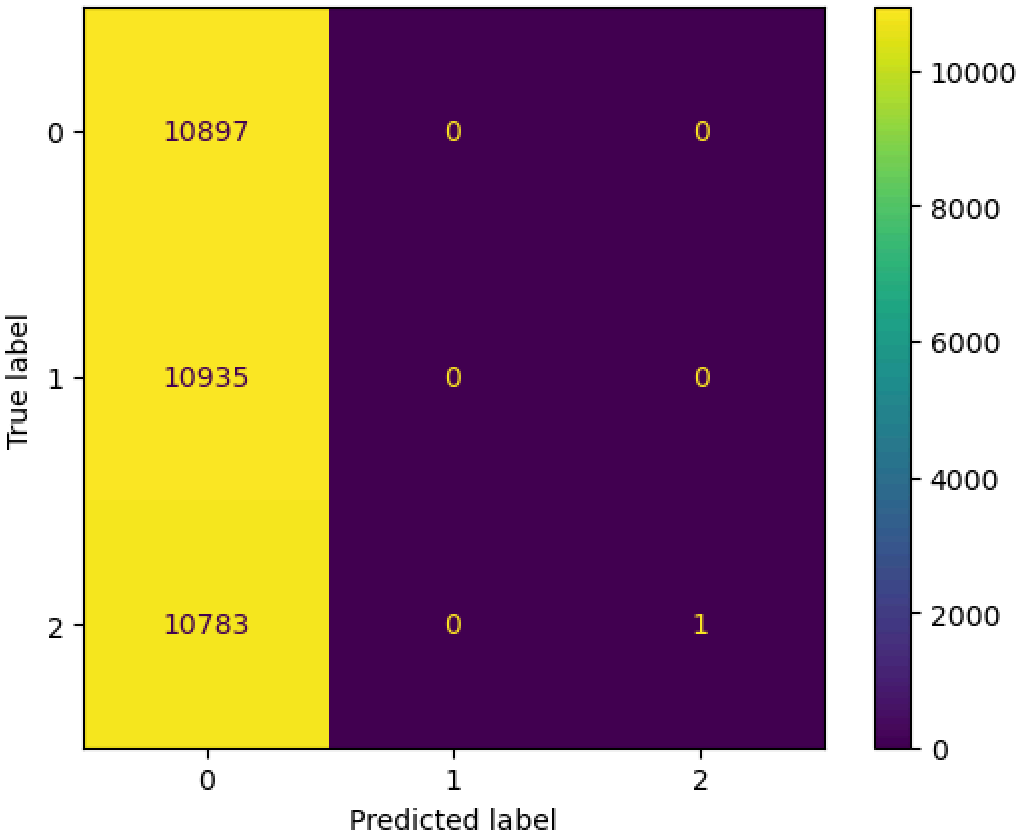
Model Training & Evaluation

In [85]:
```
model_names = []
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []
```

In [86]:
```
def train_and_evaluate_model(model):
    model.fit(X_train,y_train)
    y_pred = model.predict(X_test)
    print(classification_report(y_test,y_pred))
    acc = accuracy_score(y_test,y_pred)
    precision = precision_score(y_test,y_pred,average='micro')
    recall = recall_score(y_test,y_pred,average='micro')
    f1 = f1_score(y_test,y_pred,average='micro')
    ConfusionMatrixDisplay.from_predictions(y_test,y_pred)
    plt.show();
    model_names.append(model)
    accuracy_scores.append(acc)
    precision_scores.append(precision)
    recall_scores.append(recall)
    f1_scores.append(f1)
```

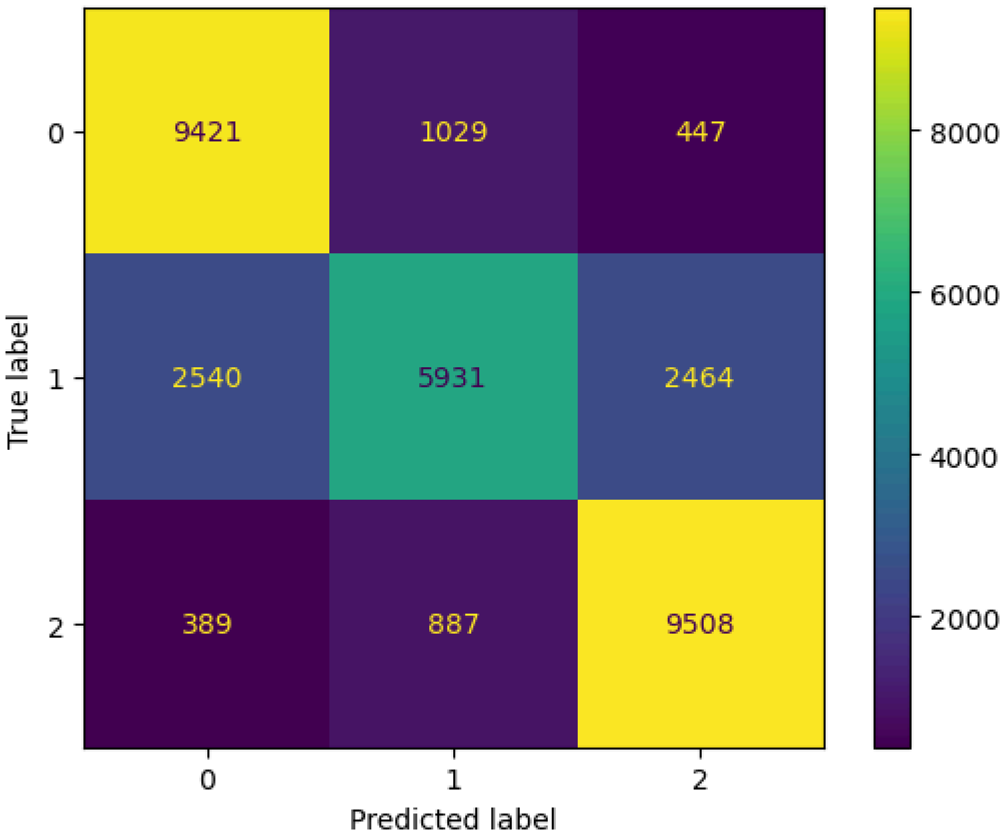
In [87]:
```
train_and_evaluate_model(LogisticRegression())
```

```
              precision    recall  f1-score   support

           0       0.33      1.00      0.50     10897
           1       0.00      0.00      0.00     10935
           2       1.00      0.00      0.00     10784

    accuracy                           0.33     32616
   macro avg       0.44      0.33      0.17     32616
weighted avg       0.44      0.33      0.17     32616
```



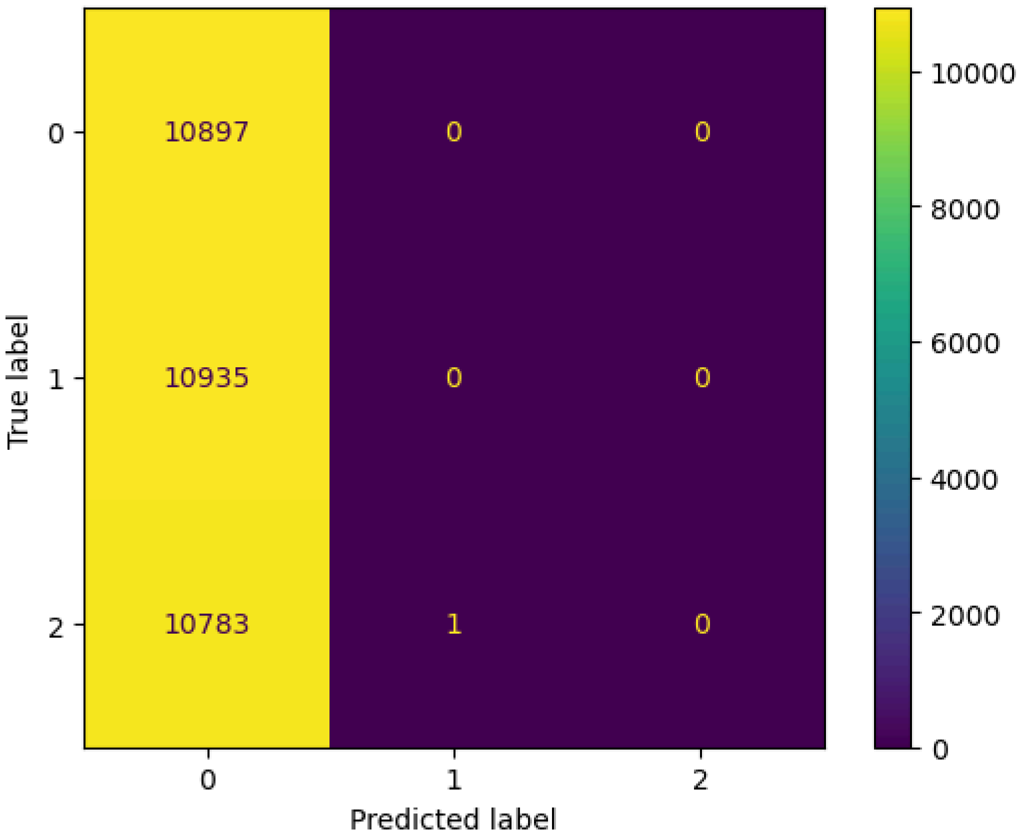
In [88]:
```
train_and_evaluate_model(KNeighborsClassifier())
```

```
              precision    recall  f1-score   support

           0       0.76      0.86      0.81     10897
           1       0.76      0.54      0.63     10935
           2       0.77      0.88      0.82     10784

    accuracy                           0.76     32616
   macro avg       0.76      0.76      0.75     32616
weighted avg       0.76      0.76      0.75     32616
```



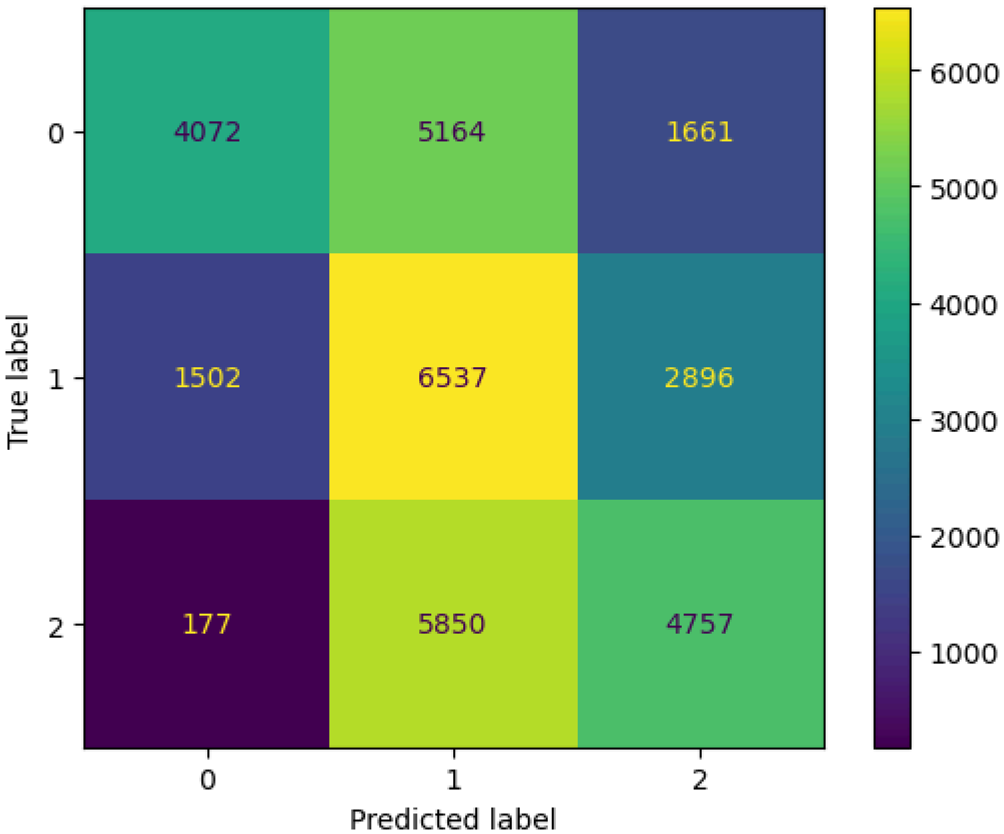
In [89]:
```
train_and_evaluate_model(GaussianNB())
```

```
              precision    recall  f1-score   support

           0       0.33      1.00      0.50     10897
           1       0.00      0.00      0.00     10935
           2       0.00      0.00      0.00     10784

    accuracy                           0.33     32616
   macro avg       0.11      0.33      0.17     32616
weighted avg       0.11      0.33      0.17     32616
```



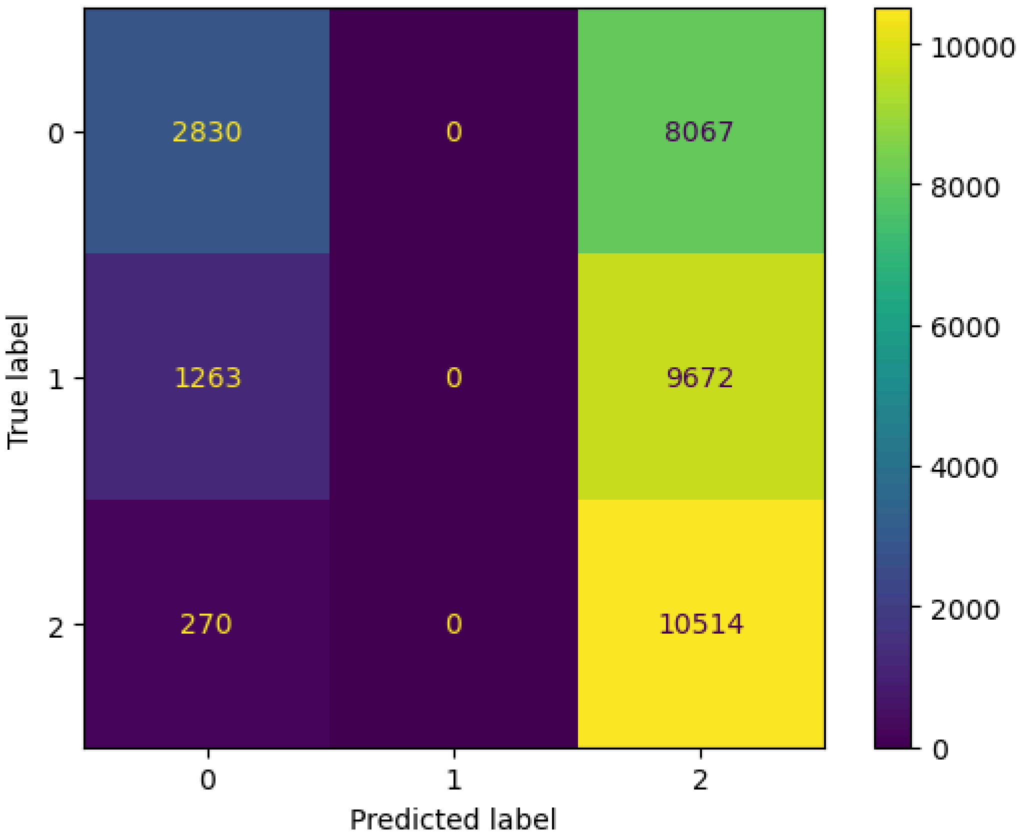
In [90]:
```
train_and_evaluate_model(BernoulliNB())
```

```
              precision    recall  f1-score   support

           0       0.71      0.37      0.49     10897
           1       0.37      0.60      0.46     10935
           2       0.51      0.44      0.47     10784

    accuracy                           0.47     32616
   macro avg       0.53      0.47      0.47     32616
weighted avg       0.53      0.47      0.47     32616
```



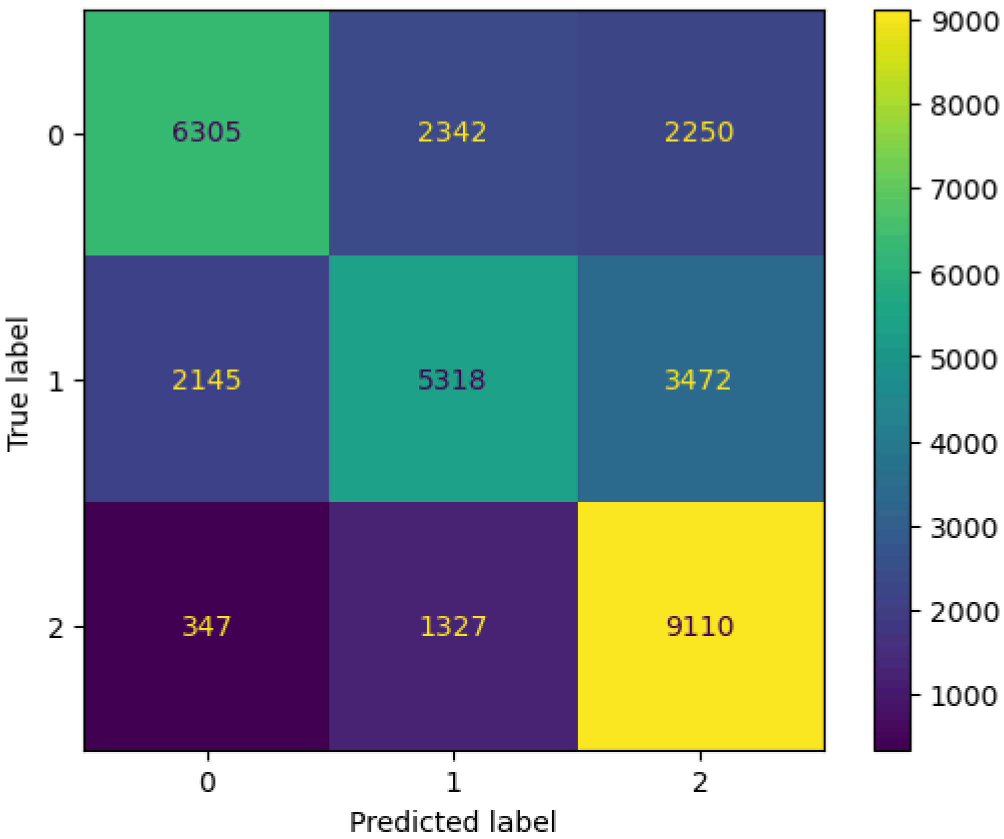
In [91]:
```
train_and_evaluate_model(PassiveAggressiveClassifier())
```

```
              precision    recall  f1-score   support

           0       0.65      0.26      0.37     10897
           1       0.00      0.00      0.00     10935
           2       0.37      0.97      0.54     10784

    accuracy                           0.41     32616
   macro avg       0.34      0.41      0.30     32616
weighted avg       0.34      0.41      0.30     32616
```



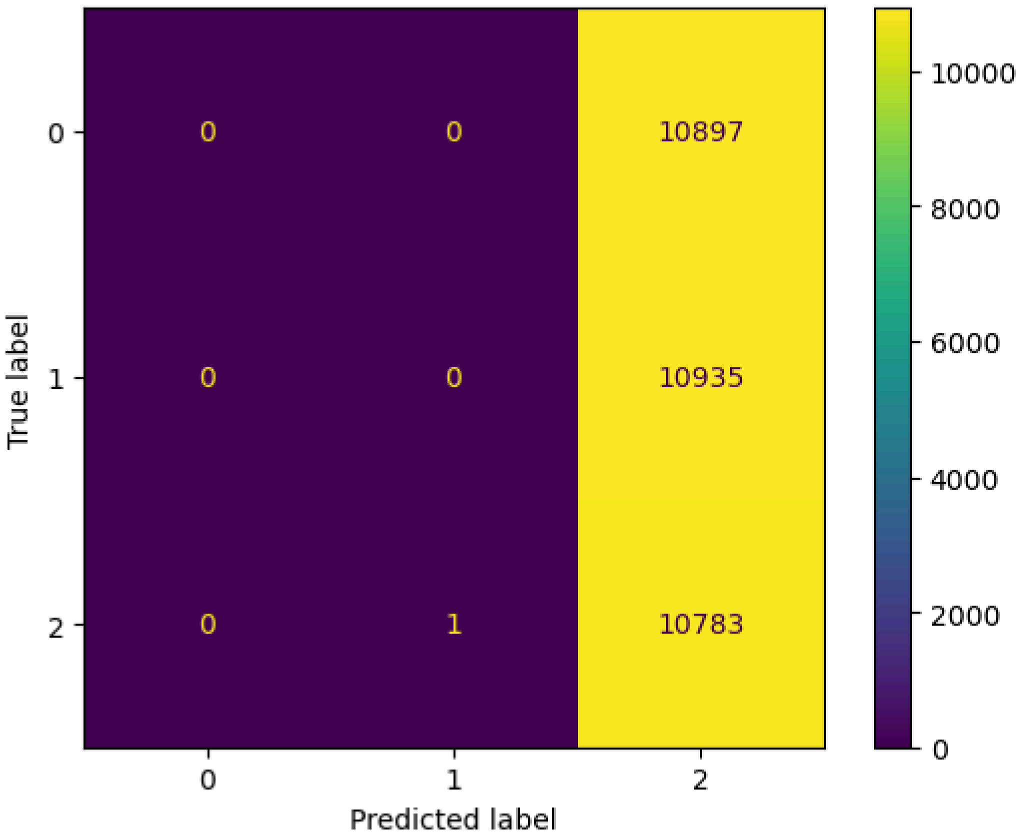
In [92]:
```
train_and_evaluate_model(RidgeClassifier())
```

```
              precision    recall  f1-score   support

           0       0.72      0.58      0.64     10897
           1       0.59      0.49      0.53     10935
           2       0.61      0.84      0.71     10784

    accuracy                           0.64     32616
   macro avg       0.64      0.64      0.63     32616
weighted avg       0.64      0.64      0.63     32616
```



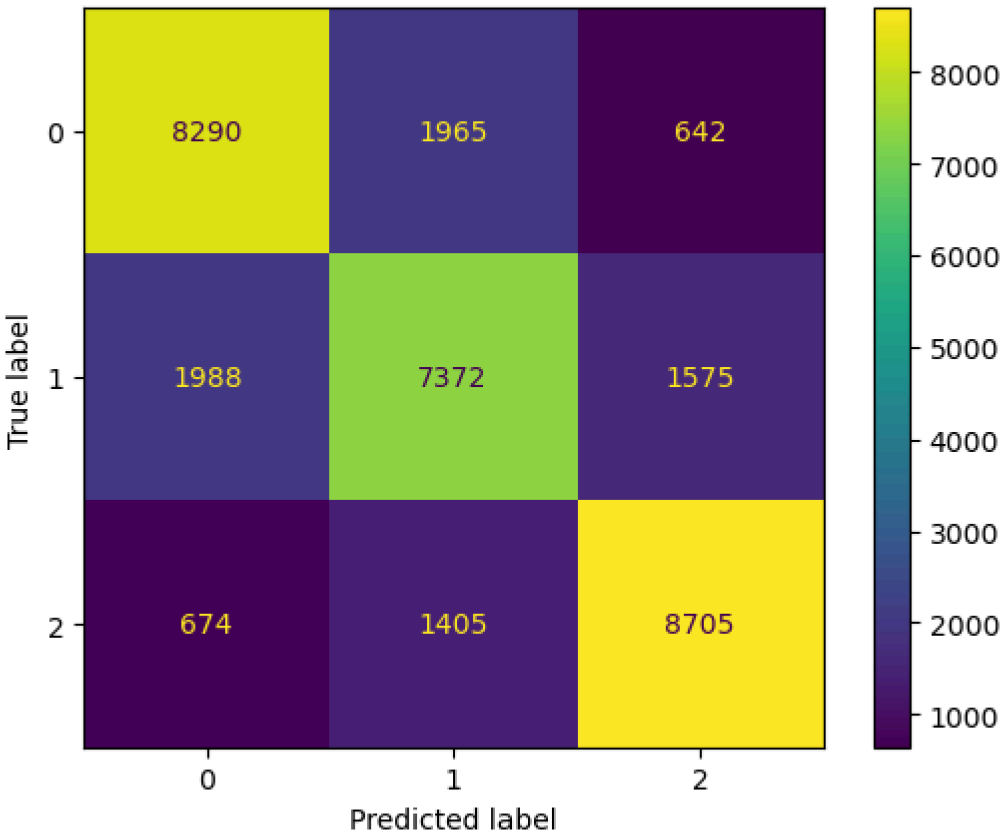
In [93]:
```
train_and_evaluate_model(SGDClassifier())
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00     10897
           1       0.00      0.00      0.00     10935
           2       0.33      1.00      0.50     10784

    accuracy                           0.33     32616
   macro avg       0.11      0.33      0.17     32616
weighted avg       0.11      0.33      0.16     32616
```



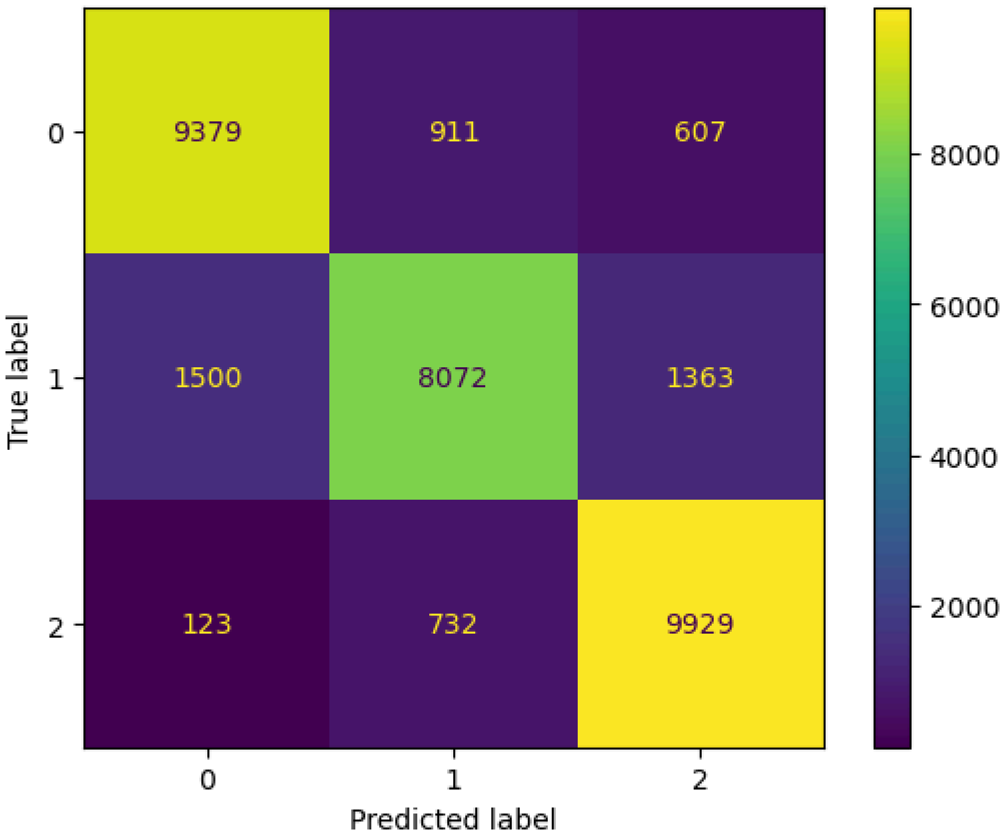
In [94]:
```
train_and_evaluate_model(DecisionTreeClassifier())
```

```
              precision    recall  f1-score   support

           0       0.76      0.76      0.76     10897
           1       0.69      0.67      0.68     10935
           2       0.80      0.81      0.80     10784

    accuracy                           0.75     32616
   macro avg       0.75      0.75      0.75     32616
weighted avg       0.75      0.75      0.75     32616
```



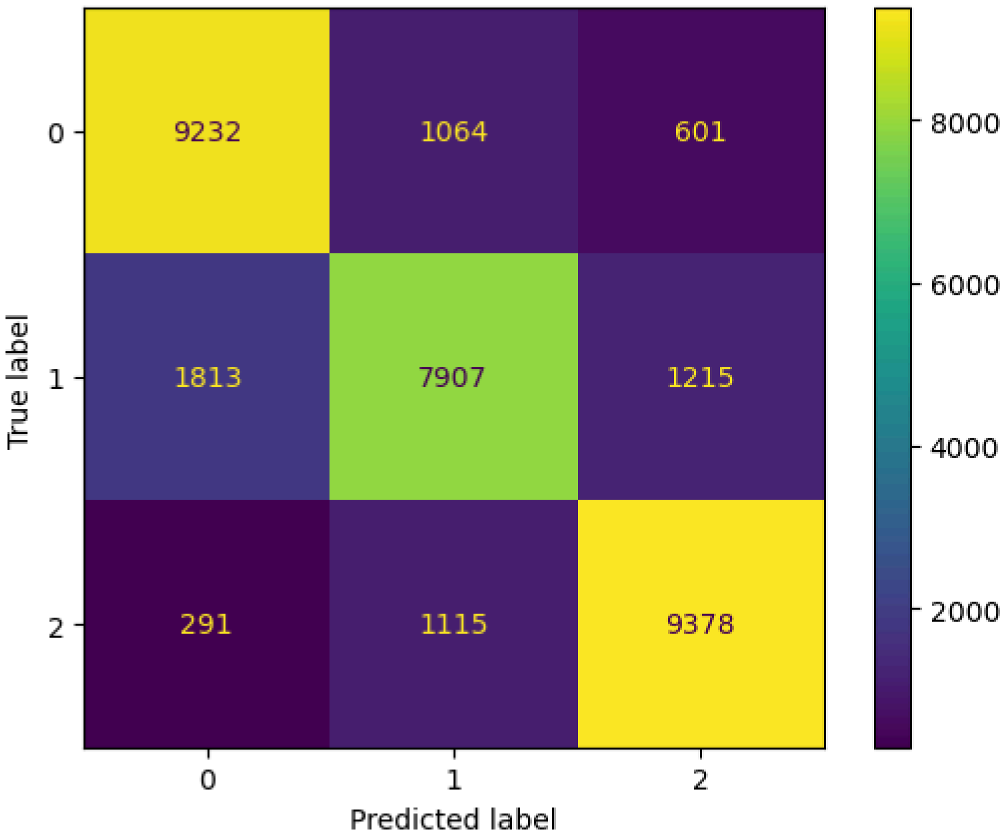
In [95]:
```
train_and_evaluate_model(RandomForestClassifier())
```

```
              precision    recall  f1-score   support

           0       0.85      0.86      0.86     10897
           1       0.83      0.74      0.78     10935
           2       0.83      0.92      0.88     10784

    accuracy                           0.84     32616
   macro avg       0.84      0.84      0.84     32616
weighted avg       0.84      0.84      0.84     32616
```



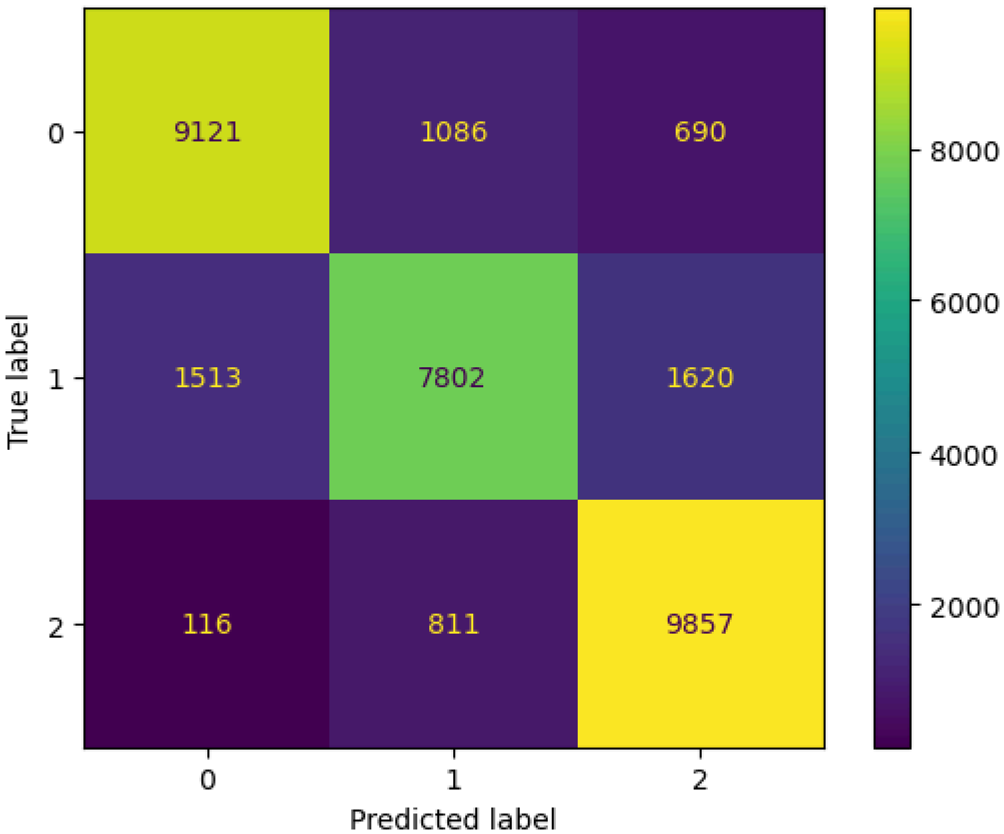
In [96]:
```
train_and_evaluate_model(BaggingClassifier())
```

```
              precision    recall  f1-score   support

           0       0.81      0.85      0.83     10897
           1       0.78      0.72      0.75     10935
           2       0.84      0.87      0.85     10784

    accuracy                           0.81     32616
   macro avg       0.81      0.81      0.81     32616
weighted avg       0.81      0.81      0.81     32616
```



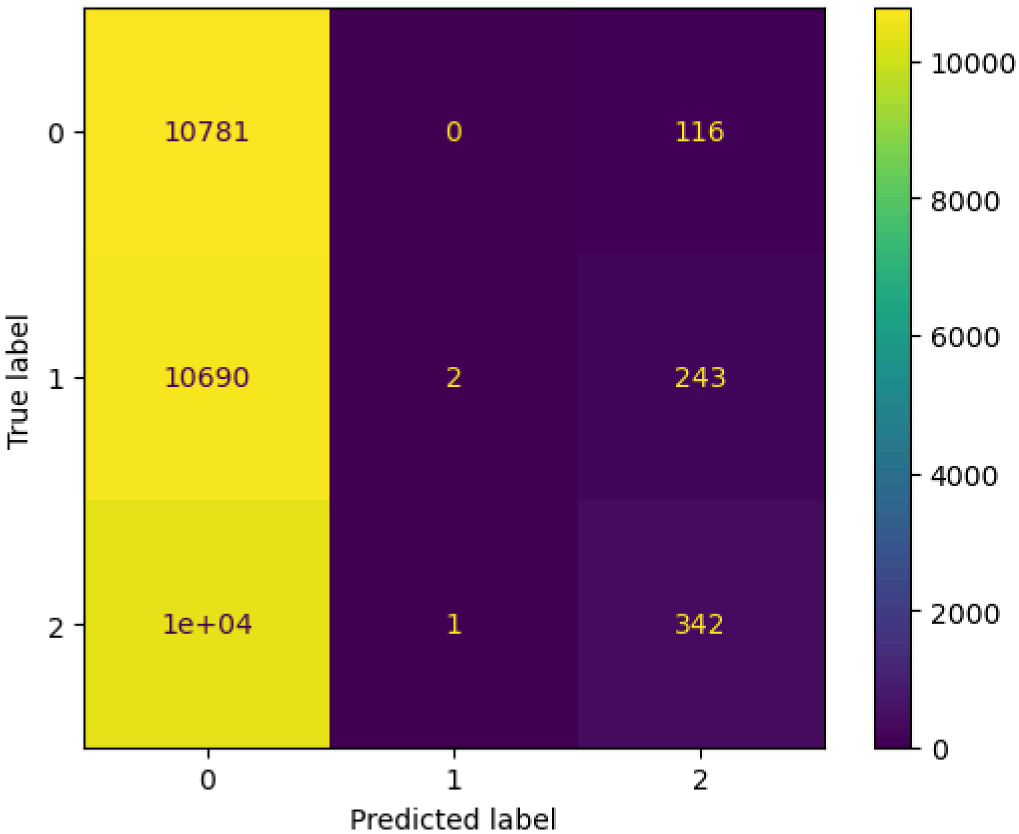
In [97]:
```
train_and_evaluate_model(ExtraTreesClassifier())
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.84     10897
           1       0.80      0.71      0.76     10935
           2       0.81      0.91      0.86     10784

    accuracy                           0.82     32616
   macro avg       0.82      0.82      0.82     32616
weighted avg       0.82      0.82      0.82     32616
```



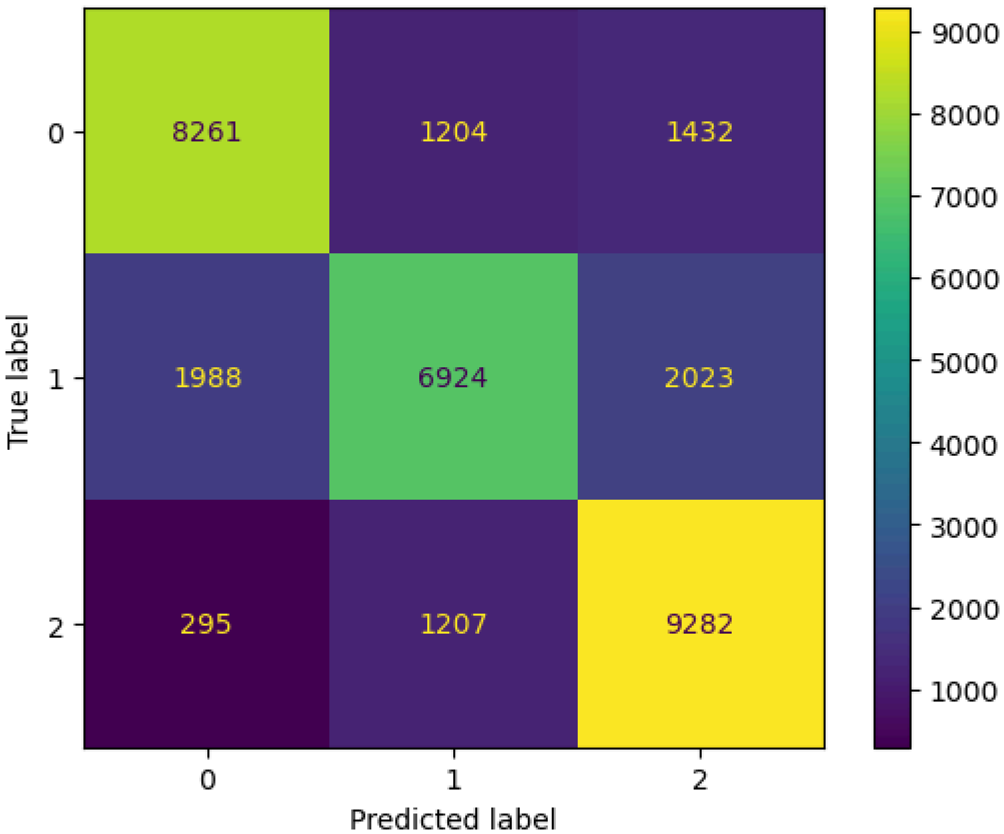
In [98]:
```
train_and_evaluate_model(LinearSVC())
```

```
              precision    recall  f1-score   support

           0       0.34      0.99      0.50     10897
           1       0.67      0.00      0.00     10935
           2       0.49      0.03      0.06     10784

    accuracy                           0.34     32616
   macro avg       0.50      0.34      0.19     32616
weighted avg       0.50      0.34      0.19     32616
```



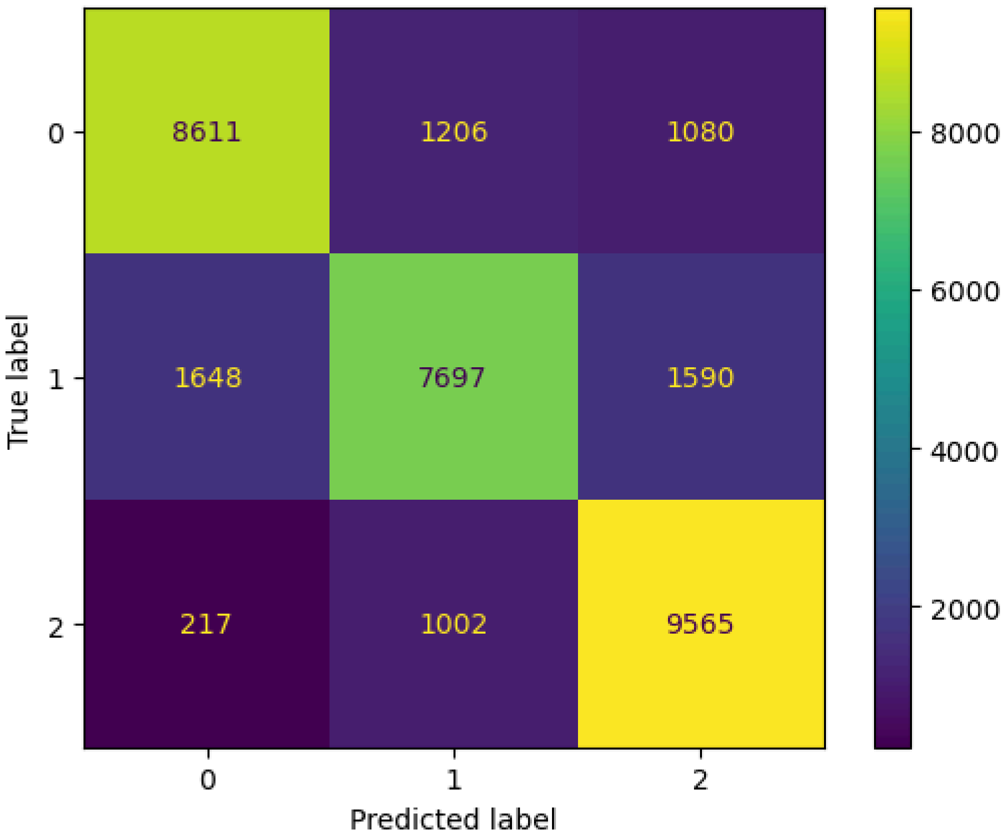
In [99]:
```
train_and_evaluate_model(GradientBoostingClassifier())
```

```
              precision    recall  f1-score   support

           0       0.78      0.76      0.77     10897
           1       0.74      0.63      0.68     10935
           2       0.73      0.86      0.79     10784

    accuracy                           0.75     32616
   macro avg       0.75      0.75      0.75     32616
weighted avg       0.75      0.75      0.75     32616
```



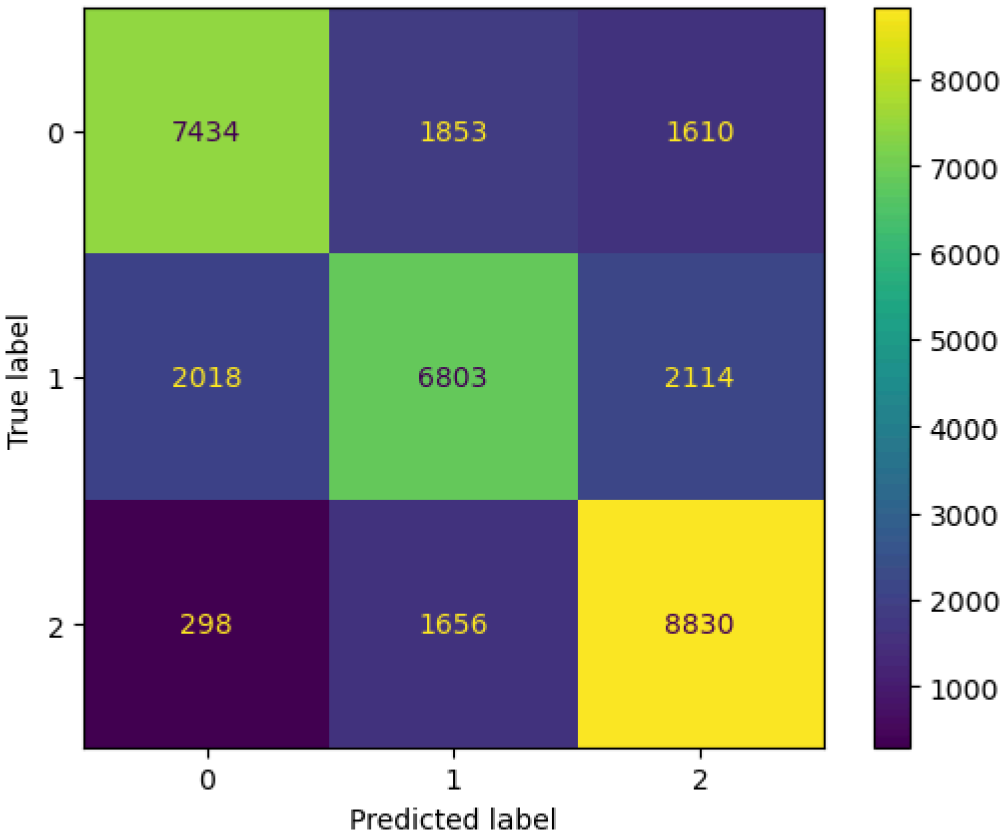
In [100]:
```
train_and_evaluate_model(HistGradientBoostingClassifier())
```

```
              precision    recall  f1-score   support

           0       0.82      0.79      0.81     10897
           1       0.78      0.70      0.74     10935
           2       0.78      0.89      0.83     10784

    accuracy                           0.79     32616
   macro avg       0.79      0.79      0.79     32616
weighted avg       0.79      0.79      0.79     32616
```



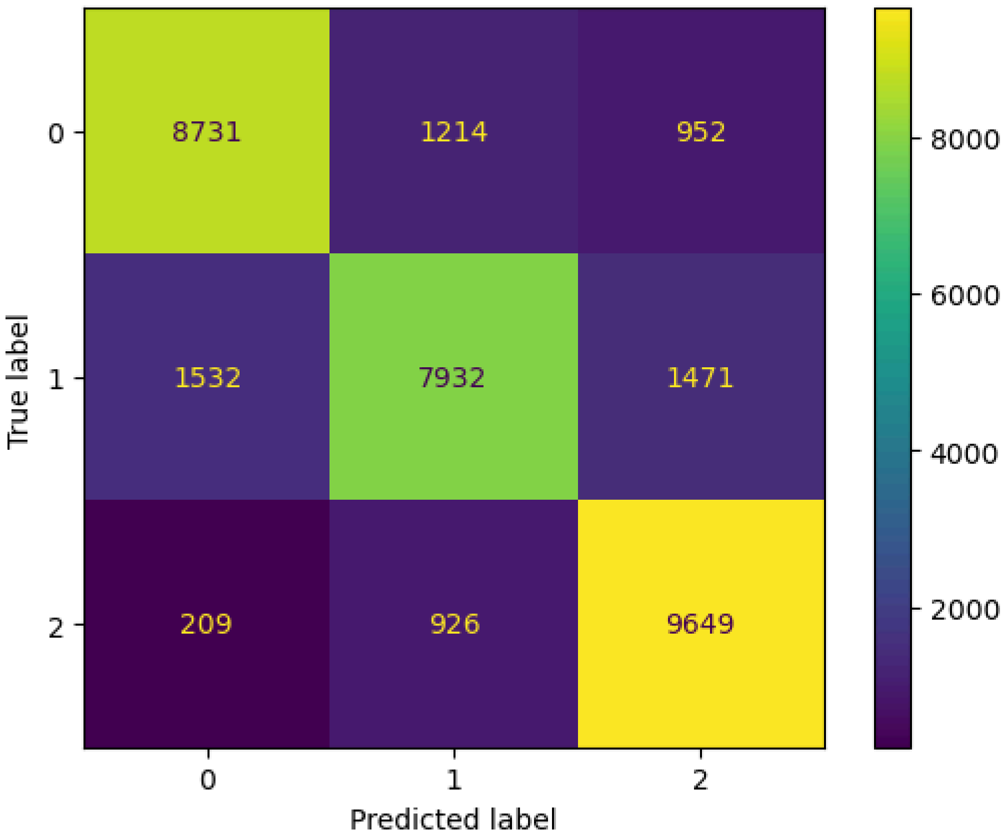
In [101]:
```
train_and_evaluate_model(AdaBoostClassifier())
```

```
              precision    recall  f1-score   support

           0       0.76      0.68      0.72     10897
           1       0.66      0.62      0.64     10935
           2       0.70      0.82      0.76     10784

    accuracy                           0.71     32616
   macro avg       0.71      0.71      0.71     32616
weighted avg       0.71      0.71      0.71     32616
```



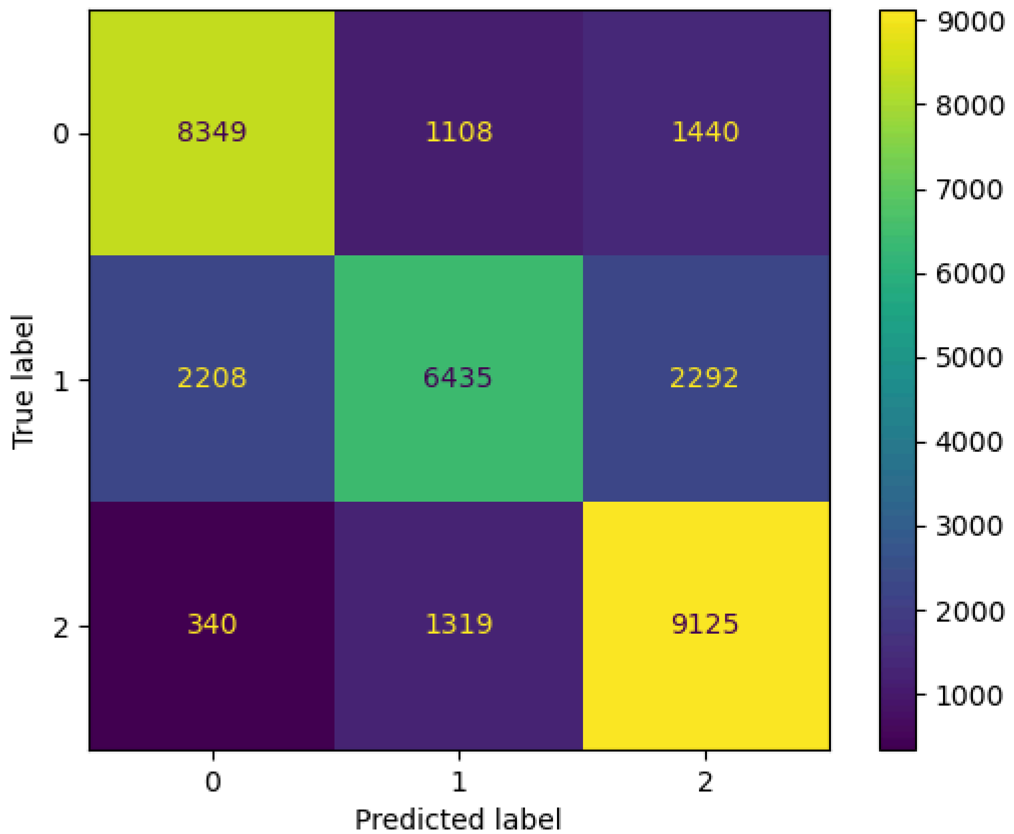
In [102]:
```
train_and_evaluate_model(XGBClassifier())
```

```
              precision    recall  f1-score   support

           0       0.83      0.80      0.82     10897
           1       0.79      0.73      0.76     10935
           2       0.80      0.89      0.84     10784

    accuracy                           0.81     32616
   macro avg       0.81      0.81      0.81     32616
weighted avg       0.81      0.81      0.81     32616
```



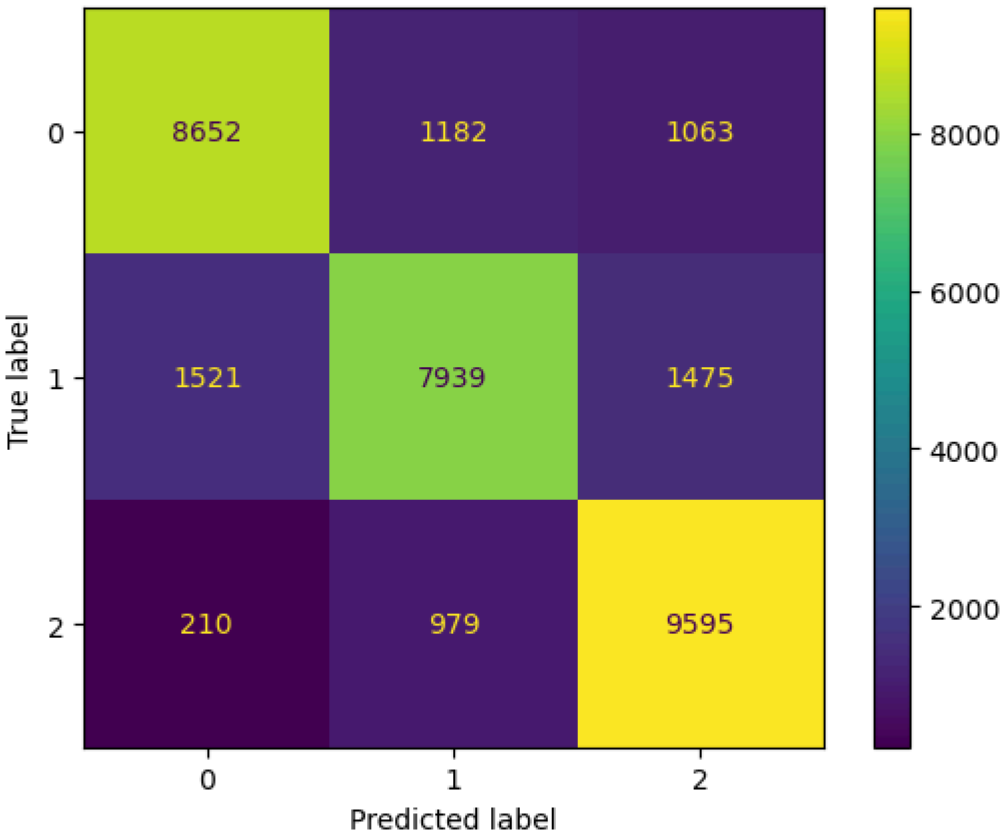
In [103]:
```
train_and_evaluate_model(XGBRFClassifier())
```

```
              precision    recall  f1-score   support

           0       0.77      0.77      0.77     10897
           1       0.73      0.59      0.65     10935
           2       0.71      0.85      0.77     10784

    accuracy                           0.73     32616
   macro avg       0.73      0.73      0.73     32616
weighted avg       0.73      0.73      0.73     32616
```



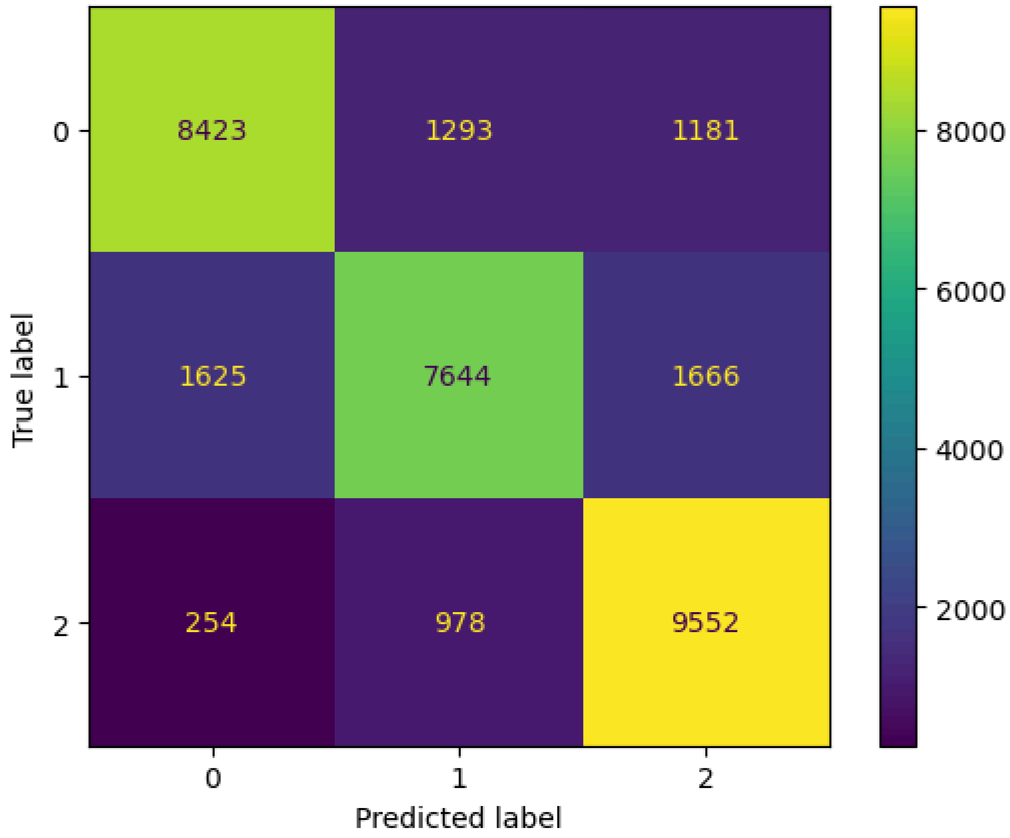
In [104]:
```
train_and_evaluate_model(CatBoostClassifier(silent=True))
```

```
              precision    recall  f1-score   support

           0       0.83      0.79      0.81     10897
           1       0.79      0.73      0.75     10935
           2       0.79      0.89      0.84     10784

    accuracy                           0.80     32616
   macro avg       0.80      0.80      0.80     32616
weighted avg       0.80      0.80      0.80     32616
```



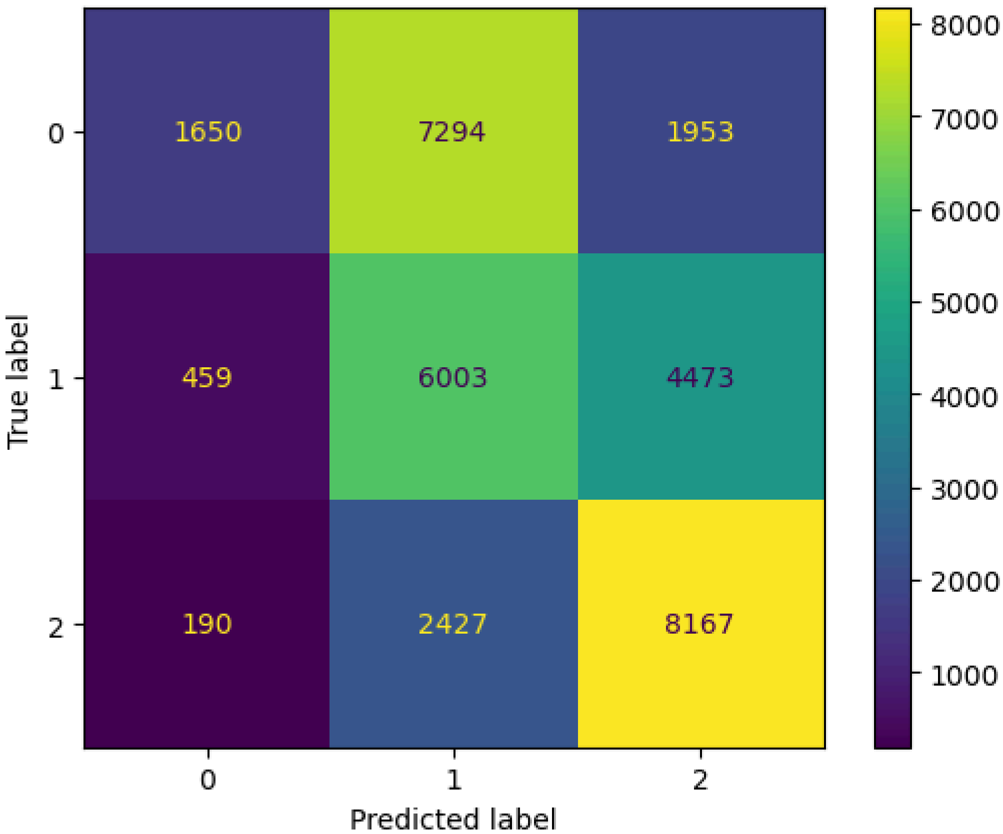
In [105]:
```
train_and_evaluate_model(LGBMClassifier())
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.007383 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 3661
[LightGBM] [Info] Number of data points in the train set: 76101, number o
f used features: 18
[LightGBM] [Info] Start training from score -1.099598
[LightGBM] [Info] Start training from score -1.101099
[LightGBM] [Info] Start training from score -1.095149
              precision    recall  f1-score   support

           0       0.82      0.77      0.79     10897
           1       0.77      0.70      0.73     10935
           2       0.77      0.89      0.82     10784

    accuracy                           0.79     32616
   macro avg       0.79      0.79      0.78     32616
weighted avg       0.79      0.79      0.78     32616
```



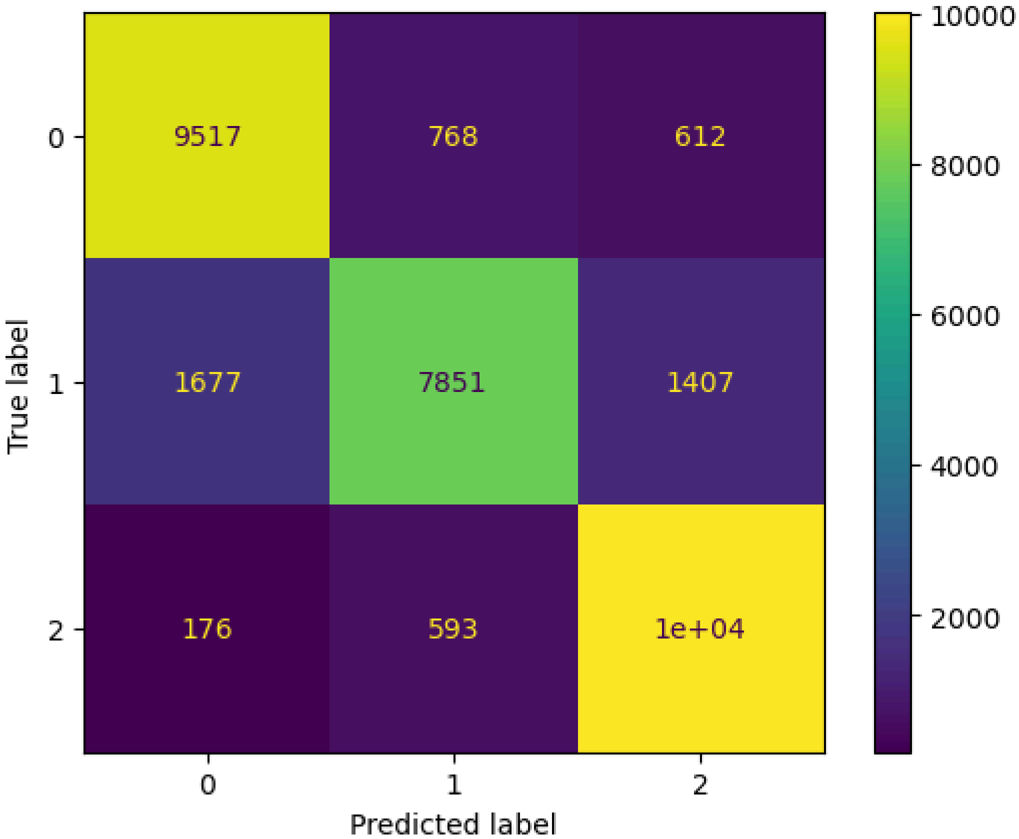
In [106]:
```
train_and_evaluate_model(MLPClassifier())
```

```
              precision    recall  f1-score   support

           0       0.72      0.15      0.25     10897
           1       0.38      0.55      0.45     10935
           2       0.56      0.76      0.64     10784

    accuracy                           0.49     32616
   macro avg       0.55      0.49      0.45     32616
weighted avg       0.55      0.49      0.45     32616
```



In [107]:
```
train_and_evaluate_model(VotingClassifier(estimators=[
    ('RF',RandomForestClassifier()),
    ('KNN',KNeighborsClassifier()),
    ('HIST',HistGradientBoostingClassifier())
],voting='hard'))
```

```
              precision    recall  f1-score   support

           0       0.84      0.87      0.85     10897
           1       0.85      0.72      0.78     10935
           2       0.83      0.93      0.88     10784

    accuracy                           0.84     32616
   macro avg       0.84      0.84      0.84     32616
weighted avg       0.84      0.84      0.84     32616
```



Checking score of models

Baseline Models Performance Comparison

In [108]:
```
model_perfs = pd.DataFrame({'Model': model_names, 'Accuracy': accuracy_scor
model_perfs
```

Out[108]:

	Model	Accuracy	Precision	Recall	F1
0	VotingClassifier(estimators=[('RF', RandomFore...	0.839557	0.839557	0.839557	0.839557
1	(DecisionTreeClassifier(max_features='sqrt', r...	0.839465	0.839465	0.839465	0.839465
2	(ExtraTreeClassifier(random_state=1036040382),...	0.821069	0.821069	0.821069	0.821069
3	(DecisionTreeClassifier(random_state=136957480...	0.813006	0.813006	0.813006	0.813006
4	XGBClassifier(base_score=None, booster=None, c...	0.806721	0.806721	0.806721	0.806721
5	<catboost.core.CatBoostClassifier object at 0x...	0.802857	0.802857	0.802857	0.802857
6	HistGradientBoostingClassifier()	0.793261	0.793261	0.793261	0.793261
7	LGBMClassifier()	0.785473	0.785473	0.785473	0.785473
8	KNeighborsClassifier()	0.762203	0.762203	0.762203	0.762203
9	([DecisionTreeRegressor(criterion='friedman_ms...	0.750153	0.750153	0.750153	0.750153
10	DecisionTreeClassifier()	0.747087	0.747087	0.747087	0.747087
11	XGBRFClassifier(base_score=None, booster=None,...	0.733045	0.733045	0.733045	0.733045
12	(DecisionTreeClassifier(max_depth=1, random_st...	0.707230	0.707230	0.707230	0.707230
13	RidgeClassifier()	0.635670	0.635670	0.635670	0.635670
14	MLPClassifier()	0.485038	0.485038	0.485038	0.485038
15	BernoulliNB()	0.471118	0.471118	0.471118	0.471118
16	PassiveAggressiveClassifier()	0.409124	0.409124	0.409124	0.409124
17	LinearSVC()	0.341090	0.341090	0.341090	0.341090
18	LogisticRegression()	0.334130	0.334130	0.334130	0.334130
19	GaussianNB()	0.334100	0.334100	0.334100	0.334100
20	SGDClassifier()	0.330605	0.330605	0.330605	0.330605

Hyperparameter Tuning using RandomizedSearchCV

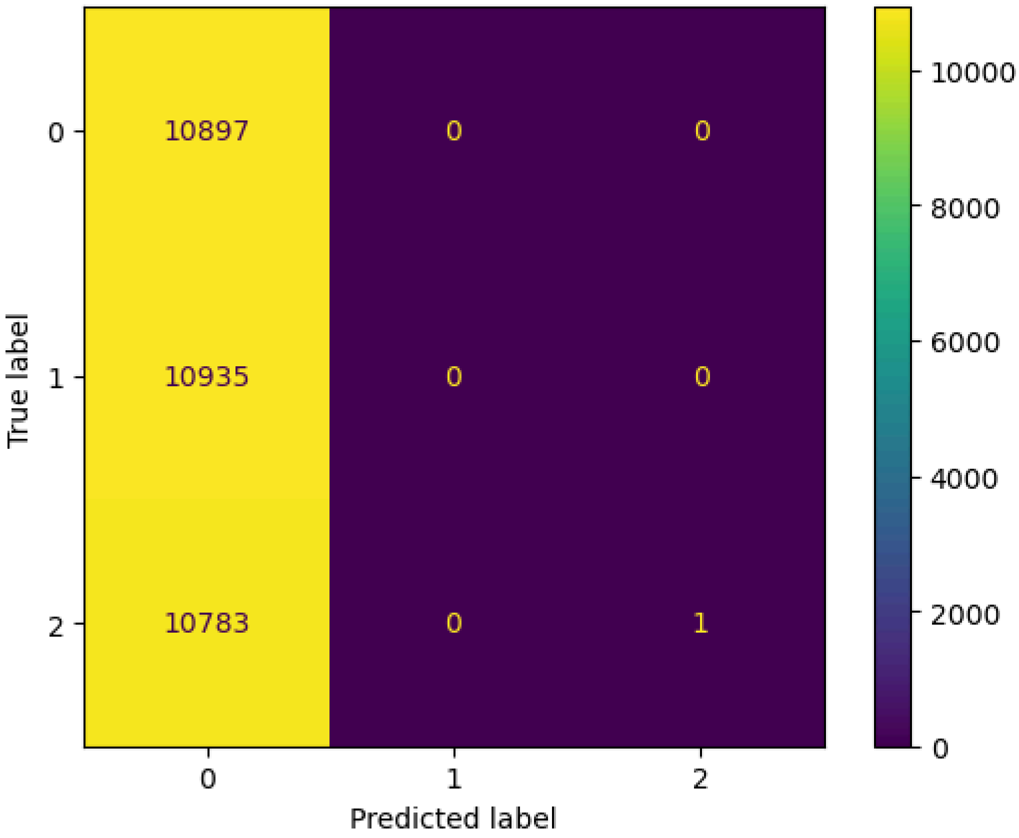
In [109]:
```
param_grid = {'learning_rate': [0.2,0.4,0.5,0.8,1.0],
              'loss': ['auto', 'binary_crossentropy', 'categorical_crossent
grid_hgb = RandomizedSearchCV(HistGradientBoostingClassifier(),param_grid,(
train_and_evaluate_model(grid_hgb)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END .......................learning_rate=0.4, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.4, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.4, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.4, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.4, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.5, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.5, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.5, loss=auto; total ti
me=   0.0s
[CV] END .......................learning_rate=0.5, loss=auto; total ti
me=   0.0s
```

In [110]:
```
param_grid = {'penalty': ['l1','l2','elasticnet'],
              'C': [0.001,0.01,0.1,0.5],
              'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
              'multi_class': ['ovr', 'multinomial'],
              'l1_ratio': [0.2,0.5,0.8]
             }

grid_lr = RandomizedSearchCV(LogisticRegression(),param_grid,verbose=2,cv=
train_and_evaluate_model(grid_lr)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END C=0.1, l1_ratio=0.5, multi_class=multinomial, penalty=l2, solver
=liblinear; total time=   0.0s
[CV] END C=0.1, l1_ratio=0.5, multi_class=multinomial, penalty=l2, solver
=liblinear; total time=   0.0s
[CV] END C=0.1, l1_ratio=0.5, multi_class=multinomial, penalty=l2, solver
=liblinear; total time=   0.0s
[CV] END C=0.1, l1_ratio=0.5, multi_class=multinomial, penalty=l2, solver
=liblinear; total time=   0.0s
[CV] END C=0.1, l1_ratio=0.5, multi_class=multinomial, penalty=l2, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=l2, solver=lbfgs;
total time=   0.4s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=l2, solver=lbfgs;
total time=   0.4s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=l2, solver=lbfgs;
total time=   0.5s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=l2, solver=lbfgs;
total time=   0.4s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=l2, solver=lbfgs;
total time=   0.4s
[CV] END C=0.5, l1_ratio=0.8, multi_class=multinomial, penalty=l1, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=multinomial, penalty=l1, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=multinomial, penalty=l1, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=multinomial, penalty=l1, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=multinomial, penalty=l1, solver
=liblinear; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=sag; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=sag; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=sag; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=sag; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=sag; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=l1, solver=sag; t
otal time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=l1, solver=sag; t
otal time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=l1, solver=sag; t
otal time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=l1, solver=sag; t
otal time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=l1, solver=sag; t
otal time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
```

```
[CV] END C=0.5, l1_ratio=0.5, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.5, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.5, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.5, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.5, l1_ratio=0.5, multi_class=ovr, penalty=elasticnet, solver
=liblinear; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=newton-cg; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=newton-cg; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=newton-cg; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=newton-cg; total time=   0.0s
[CV] END C=0.01, l1_ratio=0.8, multi_class=ovr, penalty=elasticnet, solve
r=newton-cg; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.2, multi_class=multinomial, penalty=l1, solv
er=sag; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.2, multi_class=multinomial, penalty=l1, solv
er=sag; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.2, multi_class=multinomial, penalty=l1, solv
er=sag; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.2, multi_class=multinomial, penalty=l1, solv
er=sag; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.2, multi_class=multinomial, penalty=l1, solv
er=sag; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.8, multi_class=multinomial, penalty=elasticn
et, solver=lbfgs; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.8, multi_class=multinomial, penalty=elasticn
et, solver=lbfgs; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.8, multi_class=multinomial, penalty=elasticn
et, solver=lbfgs; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.8, multi_class=multinomial, penalty=elasticn
et, solver=lbfgs; total time=   0.0s
[CV] END C=0.001, l1_ratio=0.8, multi_class=multinomial, penalty=elasticn
et, solver=lbfgs; total time=   0.0s
              precision    recall  f1-score   support

           0       0.33      1.00      0.50     10897
           1       0.00      0.00      0.00     10935
           2       1.00      0.00      0.00     10784

    accuracy                           0.33     32616
   macro avg       0.44      0.33      0.17     32616
weighted avg       0.44      0.33      0.17     32616
```

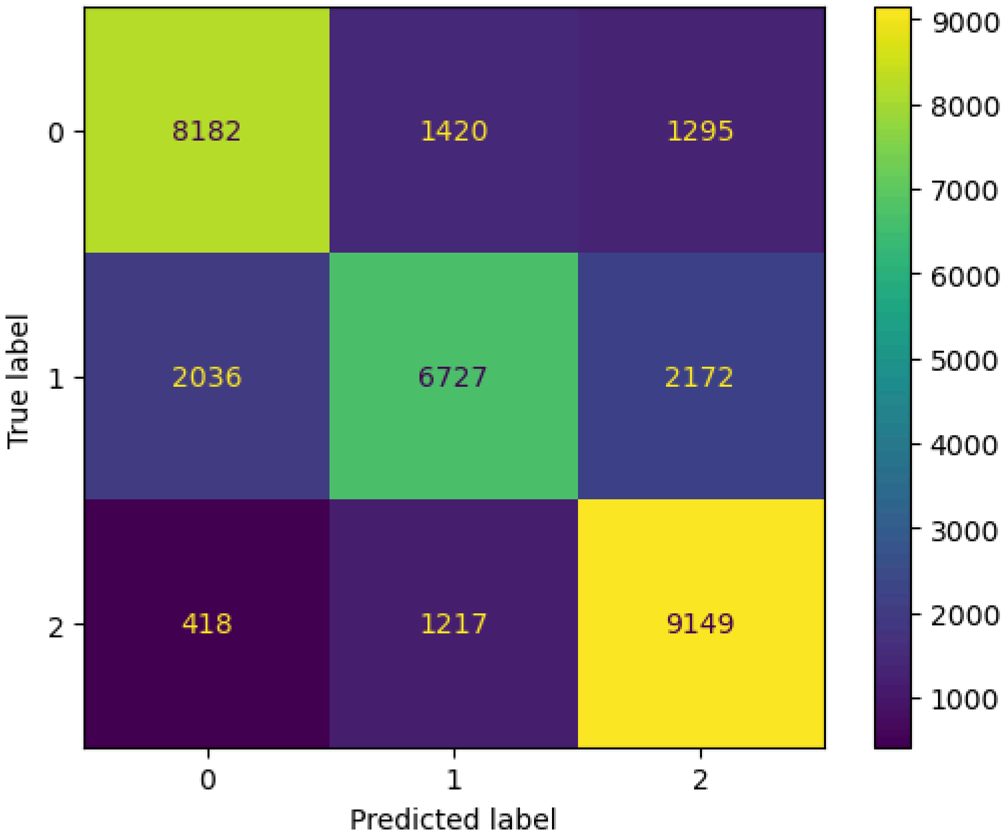


10897
0
0
10935
0
0
10783
0
1
True label
Predicted label
0
1
2
0
1
2
10000
8000
6000
4000
2000
0

In [111]:
```
param_grid = {'criterion': ['gini','entropy'],
              'max_features': ['sqrt','log2'],
              'max_depth': [2,12,38,68,98,128,201]
             }

grid_dt = RandomizedSearchCV(DecisionTreeClassifier(),param_grid,verbose=4
train_and_evaluate_model(grid_dt)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV 1/5] END criterion=entropy, max_depth=12, max_features=sqrt;, score=
0.737 total time=   0.4s
[CV 2/5] END criterion=entropy, max_depth=12, max_features=sqrt;, score=
0.731 total time=   0.5s
[CV 3/5] END criterion=entropy, max_depth=12, max_features=sqrt;, score=
0.735 total time=   0.4s
[CV 4/5] END criterion=entropy, max_depth=12, max_features=sqrt;, score=
0.731 total time=   0.4s
[CV 5/5] END criterion=entropy, max_depth=12, max_features=sqrt;, score=
0.718 total time=   0.4s
[CV 1/5] END criterion=gini, max_depth=2, max_features=sqrt;, score=0.616
total time=   0.0s
[CV 2/5] END criterion=gini, max_depth=2, max_features=sqrt;, score=0.625
total time=   0.0s
[CV 3/5] END criterion=gini, max_depth=2, max_features=sqrt;, score=0.617
total time=   0.0s
[CV 4/5] END criterion=gini, max_depth=2, max_features=sqrt;, score=0.653
total time=   0.0s
[CV 5/5] END criterion=gini, max_depth=2, max_features=sqrt;, score=0.559
total time=   0.0s
[CV 1/5] END criterion=entropy, max_depth=12, max_features=log2;, score=
0.728 total time=   0.4s
[CV 2/5] END criterion=entropy, max_depth=12, max_features=log2;, score=
0.725 total time=   0.4s
[CV 3/5] END criterion=entropy, max_depth=12, max_features=log2;, score=
0.735 total time=   0.4s
[CV 4/5] END criterion=entropy, max_depth=12, max_features=log2;, score=
0.733 total time=   0.4s
[CV 5/5] END criterion=entropy, max_depth=12, max_features=log2;, score=
0.724 total time=   0.4s
[CV 1/5] END criterion=entropy, max_depth=201, max_features=log2;, score=
0.730 total time=   0.8s
[CV 2/5] END criterion=entropy, max_depth=201, max_features=log2;, score=
0.735 total time=   0.7s
[CV 3/5] END criterion=entropy, max_depth=201, max_features=log2;, score=
0.734 total time=   0.7s
[CV 4/5] END criterion=entropy, max_depth=201, max_features=log2;, score=
0.737 total time=   0.7s
[CV 5/5] END criterion=entropy, max_depth=201, max_features=log2;, score=
0.729 total time=   0.7s
[CV 1/5] END criterion=entropy, max_depth=2, max_features=sqrt;, score=0.
629 total time=   0.0s
[CV 2/5] END criterion=entropy, max_depth=2, max_features=sqrt;, score=0.
592 total time=   0.0s
[CV 3/5] END criterion=entropy, max_depth=2, max_features=sqrt;, score=0.
593 total time=   0.0s
[CV 4/5] END criterion=entropy, max_depth=2, max_features=sqrt;, score=0.
655 total time=   0.1s
[CV 5/5] END criterion=entropy, max_depth=2, max_features=sqrt;, score=0.
609 total time=   0.0s
[CV 1/5] END criterion=entropy, max_depth=68, max_features=sqrt;, score=
0.739 total time=   0.7s
[CV 2/5] END criterion=entropy, max_depth=68, max_features=sqrt;, score=
0.731 total time=   0.7s
[CV 3/5] END criterion=entropy, max_depth=68, max_features=sqrt;, score=
0.735 total time=   0.7s
[CV 4/5] END criterion=entropy, max_depth=68, max_features=sqrt;, score=
0.725 total time=   0.8s
[CV 5/5] END criterion=entropy, max_depth=68, max_features=sqrt;, score=
0.732 total time=   0.7s
```

```
[CV 1/5] END criterion=entropy, max_depth=128, max_features=log2;, score=
0.730 total time=   0.7s
[CV 2/5] END criterion=entropy, max_depth=128, max_features=log2;, score=
0.725 total time=   0.7s
[CV 3/5] END criterion=entropy, max_depth=128, max_features=log2;, score=
0.737 total time=   0.8s
[CV 4/5] END criterion=entropy, max_depth=128, max_features=log2;, score=
0.732 total time=   0.7s
[CV 5/5] END criterion=entropy, max_depth=128, max_features=log2;, score=
0.723 total time=   0.8s
[CV 1/5] END criterion=gini, max_depth=98, max_features=sqrt;, score=0.74
1 total time=   0.5s
[CV 2/5] END criterion=gini, max_depth=98, max_features=sqrt;, score=0.73
5 total time=   0.5s
[CV 3/5] END criterion=gini, max_depth=98, max_features=sqrt;, score=0.73
9 total time=   0.5s
[CV 4/5] END criterion=gini, max_depth=98, max_features=sqrt;, score=0.72
6 total time=   0.5s
[CV 5/5] END criterion=gini, max_depth=98, max_features=sqrt;, score=0.72
5 total time=   0.6s
[CV 1/5] END criterion=entropy, max_depth=38, max_features=sqrt;, score=
0.729 total time=   0.8s
[CV 2/5] END criterion=entropy, max_depth=38, max_features=sqrt;, score=
0.731 total time=   0.7s
[CV 3/5] END criterion=entropy, max_depth=38, max_features=sqrt;, score=
0.733 total time=   0.8s
[CV 4/5] END criterion=entropy, max_depth=38, max_features=sqrt;, score=
0.734 total time=   0.7s
[CV 5/5] END criterion=entropy, max_depth=38, max_features=sqrt;, score=
0.718 total time=   0.8s
[CV 1/5] END criterion=gini, max_depth=12, max_features=log2;, score=0.73
5 total time=   0.3s
[CV 2/5] END criterion=gini, max_depth=12, max_features=log2;, score=0.73
4 total time=   0.3s
[CV 3/5] END criterion=gini, max_depth=12, max_features=log2;, score=0.73
8 total time=   0.3s
[CV 4/5] END criterion=gini, max_depth=12, max_features=log2;, score=0.73
2 total time=   0.3s
[CV 5/5] END criterion=gini, max_depth=12, max_features=log2;, score=0.72
8 total time=   0.3s
              precision    recall  f1-score   support

           0       0.77      0.75      0.76     10897
           1       0.72      0.62      0.66     10935
           2       0.73      0.85      0.78     10784

    accuracy                           0.74     32616
   macro avg       0.74      0.74      0.73     32616
weighted avg       0.74      0.74      0.73     32616
```



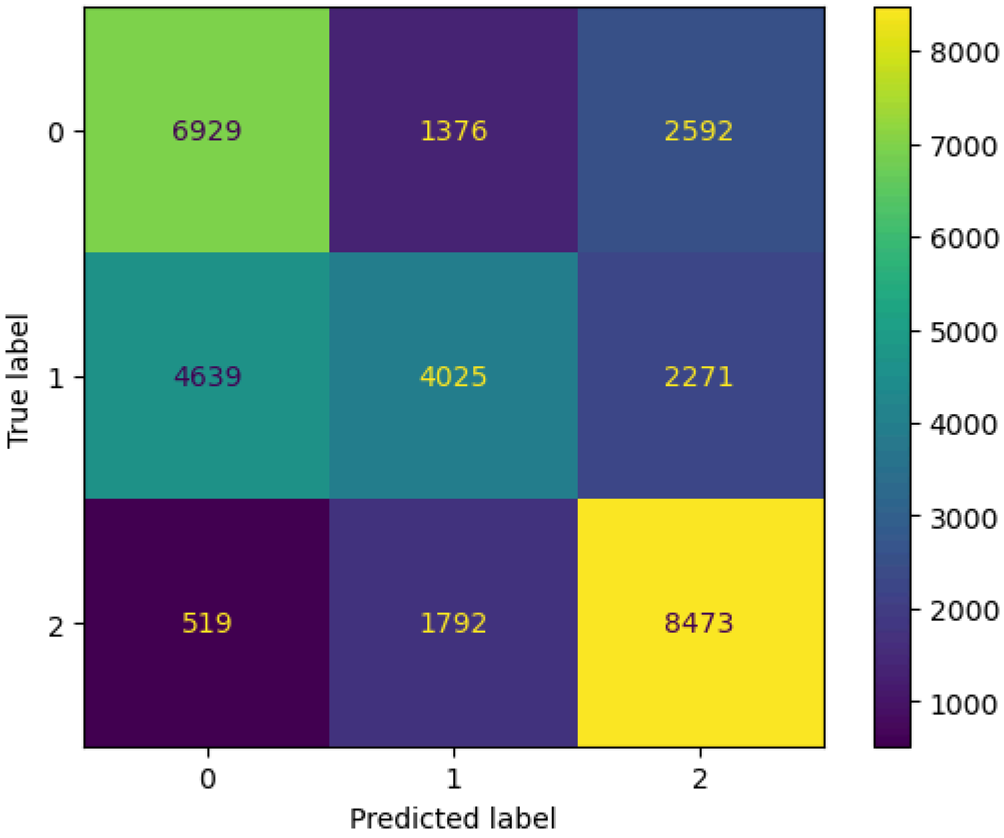
In [112]:
```
param_grid = {'boosting_type': ['gbdt','dart','goss','rf'],
              'learning_rate': np.linspace(0,1,6)[1:],
              'n_estimators': [200,500,600,1000],
              'importance_type': ['split','gain'],
              'min_split_gain': [0.68,0.79,0.87,1]}

grid_lgbm = RandomizedSearchCV(LGBMClassifier(),param_grid,verbose=3)
train_and_evaluate_model(grid_lgbm)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead
of testing was 0.012778 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 3660
[LightGBM] [Info] Number of data points in the train set: 60880, numbe
r of used features: 18
[LightGBM] [Info] Start training from score -1.099615
[LightGBM] [Info] Start training from score -1.101096
[LightGBM] [Info] Start training from score -1.095136
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
-inf
[LightGBM] [Warning] No further splits with positive gain, best gain:
```

In [113]:
```
param_grid = {'alpha': np.linspace(0,1,6),
              'binarize': np.linspace(0,1,5),
              'fit_prior': [True,False]
             }

grid_bnb = RandomizedSearchCV(BernoulliNB(),param_grid,verbose=3,cv=5)
train_and_evaluate_model(grid_bnb)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV 1/5] END alpha=1.0, binarize=0.5, fit_prior=False;, score=0.480 total
time=   0.0s
[CV 2/5] END alpha=1.0, binarize=0.5, fit_prior=False;, score=0.481 total
time=   0.0s
[CV 3/5] END alpha=1.0, binarize=0.5, fit_prior=False;, score=0.477 total
time=   0.0s
[CV 4/5] END alpha=1.0, binarize=0.5, fit_prior=False;, score=0.480 total
time=   0.0s
[CV 5/5] END alpha=1.0, binarize=0.5, fit_prior=False;, score=0.479 total
time=   0.0s
[CV 1/5] END alpha=0.8, binarize=1.0, fit_prior=False;, score=0.599 total
time=   0.0s
[CV 2/5] END alpha=0.8, binarize=1.0, fit_prior=False;, score=0.592 total
time=   0.0s
[CV 3/5] END alpha=0.8, binarize=1.0, fit_prior=False;, score=0.600 total
time=   0.0s
[CV 4/5] END alpha=0.8, binarize=1.0, fit_prior=False;, score=0.600 total
time=   0.0s
[CV 5/5] END alpha=0.8, binarize=1.0, fit_prior=False;, score=0.589 total
time=   0.0s
[CV 1/5] END alpha=0.4, binarize=0.5, fit_prior=False;, score=0.480 total
time=   0.0s
[CV 2/5] END alpha=0.4, binarize=0.5, fit_prior=False;, score=0.481 total
time=   0.0s
[CV 3/5] END alpha=0.4, binarize=0.5, fit_prior=False;, score=0.477 total
time=   0.0s
[CV 4/5] END alpha=0.4, binarize=0.5, fit_prior=False;, score=0.480 total
time=   0.0s
[CV 5/5] END alpha=0.4, binarize=0.5, fit_prior=False;, score=0.479 total
time=   0.0s
[CV 1/5] END alpha=0.6000000000000001, binarize=0.0, fit_prior=True;, sco
re=0.473 total time=   0.0s
[CV 2/5] END alpha=0.6000000000000001, binarize=0.0, fit_prior=True;, sco
re=0.475 total time=   0.0s
[CV 3/5] END alpha=0.6000000000000001, binarize=0.0, fit_prior=True;, sco
re=0.470 total time=   0.0s
[CV 4/5] END alpha=0.6000000000000001, binarize=0.0, fit_prior=True;, sco
re=0.472 total time=   0.0s
[CV 5/5] END alpha=0.6000000000000001, binarize=0.0, fit_prior=True;, sco
re=0.471 total time=   0.0s
[CV 1/5] END alpha=0.0, binarize=0.25, fit_prior=False;, score=0.333 tota
l time=   0.0s
[CV 2/5] END alpha=0.0, binarize=0.25, fit_prior=False;, score=0.333 tota
l time=   0.0s
[CV 3/5] END alpha=0.0, binarize=0.25, fit_prior=False;, score=0.333 tota
l time=   0.0s
[CV 4/5] END alpha=0.0, binarize=0.25, fit_prior=False;, score=0.333 tota
l time=   0.0s
[CV 5/5] END alpha=0.0, binarize=0.25, fit_prior=False;, score=0.333 tota
l time=   0.0s
[CV 1/5] END alpha=0.6000000000000001, binarize=0.5, fit_prior=False;, sc
ore=0.480 total time=   0.0s
[CV 2/5] END alpha=0.6000000000000001, binarize=0.5, fit_prior=False;, sc
ore=0.481 total time=   0.0s
[CV 3/5] END alpha=0.6000000000000001, binarize=0.5, fit_prior=False;, sc
ore=0.477 total time=   0.0s
[CV 4/5] END alpha=0.6000000000000001, binarize=0.5, fit_prior=False;, sc
ore=0.480 total time=   0.0s
[CV 5/5] END alpha=0.6000000000000001, binarize=0.5, fit_prior=False;, sc
ore=0.479 total time=   0.0s
```

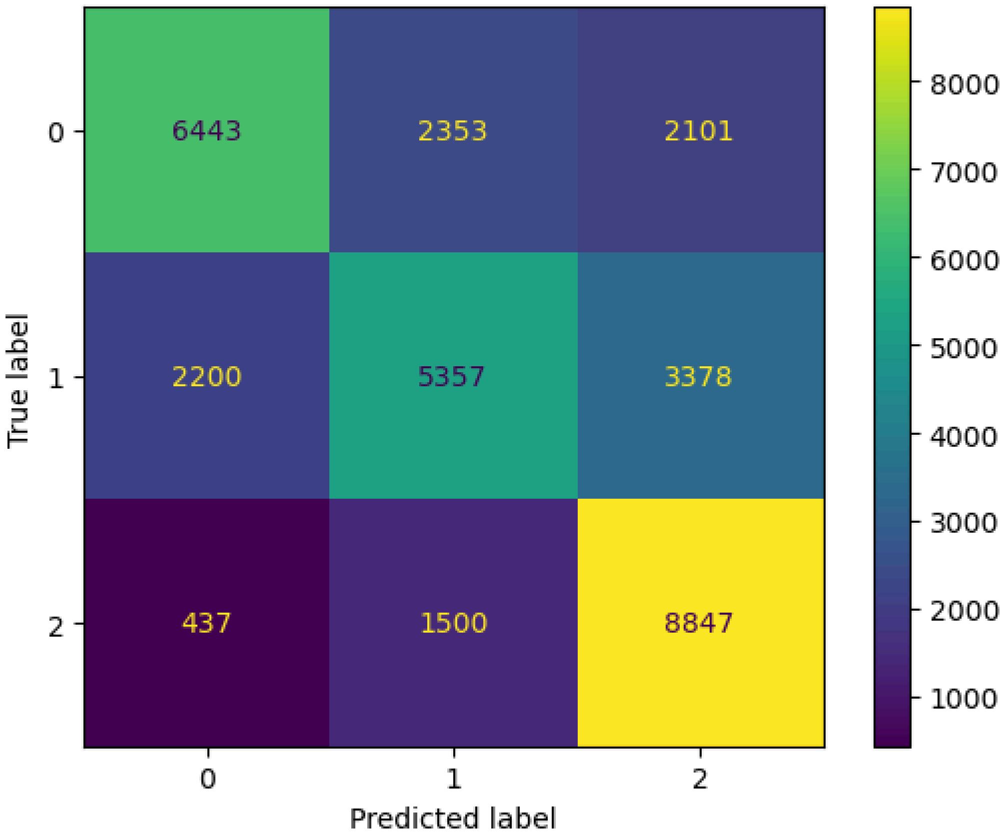
```
[CV 1/5] END alpha=0.8, binarize=0.75, fit_prior=False;, score=0.485 tota
l time=   0.0s
[CV 2/5] END alpha=0.8, binarize=0.75, fit_prior=False;, score=0.486 tota
l time=   0.0s
[CV 3/5] END alpha=0.8, binarize=0.75, fit_prior=False;, score=0.483 tota
l time=   0.0s
[CV 4/5] END alpha=0.8, binarize=0.75, fit_prior=False;, score=0.487 tota
l time=   0.0s
[CV 5/5] END alpha=0.8, binarize=0.75, fit_prior=False;, score=0.484 tota
l time=   0.0s
[CV 1/5] END alpha=0.8, binarize=0.25, fit_prior=True;, score=0.475 total
time=   0.0s
[CV 2/5] END alpha=0.8, binarize=0.25, fit_prior=True;, score=0.476 total
time=   0.0s
[CV 3/5] END alpha=0.8, binarize=0.25, fit_prior=True;, score=0.472 total
time=   0.0s
[CV 4/5] END alpha=0.8, binarize=0.25, fit_prior=True;, score=0.476 total
time=   0.0s
[CV 5/5] END alpha=0.8, binarize=0.25, fit_prior=True;, score=0.474 total
time=   0.0s
[CV 1/5] END alpha=0.0, binarize=0.75, fit_prior=True;, score=0.333 total
time=   0.0s
[CV 2/5] END alpha=0.0, binarize=0.75, fit_prior=True;, score=0.333 total
time=   0.0s
[CV 3/5] END alpha=0.0, binarize=0.75, fit_prior=True;, score=0.333 total
time=   0.0s
[CV 4/5] END alpha=0.0, binarize=0.75, fit_prior=True;, score=0.333 total
time=   0.0s
[CV 5/5] END alpha=0.0, binarize=0.75, fit_prior=True;, score=0.333 total
time=   0.0s
[CV 1/5] END alpha=0.2, binarize=0.25, fit_prior=True;, score=0.475 total
time=   0.0s
[CV 2/5] END alpha=0.2, binarize=0.25, fit_prior=True;, score=0.476 total
time=   0.0s
[CV 3/5] END alpha=0.2, binarize=0.25, fit_prior=True;, score=0.472 total
time=   0.0s
[CV 4/5] END alpha=0.2, binarize=0.25, fit_prior=True;, score=0.476 total
time=   0.0s
[CV 5/5] END alpha=0.2, binarize=0.25, fit_prior=True;, score=0.474 total
time=   0.0s
              precision    recall  f1-score   support

           0       0.57      0.64      0.60     10897
           1       0.56      0.37      0.44     10935
           2       0.64      0.79      0.70     10784

    accuracy                           0.60     32616
   macro avg       0.59      0.60      0.58     32616
weighted avg       0.59      0.60      0.58     32616
```


6929
1376
2592
4639
4025
2271
519
1792
8473
0
1
2
True label
Predicted label
8000
7000
6000
5000
4000
3000
2000
1000

In [114]:
```
param_grid = {'alpha': np.linspace(0,1,5),
              'fit_intercept': [True,False],
              'positive': [True,False],
              'solver': ['svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'sa

grid_ridge = RandomizedSearchCV(RidgeClassifier(),param_grid,verbose=2,cv=
train_and_evaluate_model(grid_ridge)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END alpha=1.0, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=1.0, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=1.0, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=1.0, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=1.0, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.0, fit_intercept=False, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.0, fit_intercept=False, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.0, fit_intercept=False, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.0, fit_intercept=False, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.0, fit_intercept=False, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.5, fit_intercept=True, positive=True, solver=lsqr; total
time=   0.0s
[CV] END alpha=0.5, fit_intercept=True, positive=True, solver=lsqr; total
time=   0.0s
[CV] END alpha=0.5, fit_intercept=True, positive=True, solver=lsqr; total
time=   0.0s
[CV] END alpha=0.5, fit_intercept=True, positive=True, solver=lsqr; total
time=   0.0s
[CV] END alpha=0.5, fit_intercept=True, positive=True, solver=lsqr; total
time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=False, solver=cholesk
y; total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=False, solver=cholesk
y; total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=False, solver=cholesk
y; total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=False, solver=cholesk
y; total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=False, solver=cholesk
y; total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=False, positive=True, solver=cholesky;
total time=   0.0s
```

```
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=sparse_cg;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=sparse_cg;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=sparse_cg;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=sparse_cg;
total time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=True, solver=sparse_cg;
total time=   0.0s
[CV] END alpha=0.75, fit_intercept=True, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.75, fit_intercept=True, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.75, fit_intercept=True, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.75, fit_intercept=True, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.75, fit_intercept=True, positive=True, solver=svd; total
time=   0.0s
[CV] END alpha=0.25, fit_intercept=True, positive=False, solver=saga; tot
al time=   3.2s
[CV] END alpha=0.25, fit_intercept=True, positive=False, solver=saga; tot
al time=   3.2s
[CV] END alpha=0.25, fit_intercept=True, positive=False, solver=saga; tot
al time=   2.4s
[CV] END alpha=0.25, fit_intercept=True, positive=False, solver=saga; tot
al time=   3.2s
[CV] END alpha=0.25, fit_intercept=True, positive=False, solver=saga; tot
al time=   2.8s
[CV] END alpha=0.25, fit_intercept=False, positive=False, solver=svd; tot
al time=   0.1s
[CV] END alpha=0.25, fit_intercept=False, positive=False, solver=svd; tot
al time=   0.0s
[CV] END alpha=0.25, fit_intercept=False, positive=False, solver=svd; tot
al time=   0.0s
[CV] END alpha=0.25, fit_intercept=False, positive=False, solver=svd; tot
al time=   0.0s
[CV] END alpha=0.25, fit_intercept=False, positive=False, solver=svd; tot
al time=   0.0s
              precision    recall  f1-score   support

           0       0.71      0.59      0.65     10897
           1       0.58      0.49      0.53     10935
           2       0.62      0.82      0.70     10784

    accuracy                           0.63     32616
   macro avg       0.64      0.63      0.63     32616
weighted avg       0.64      0.63      0.63     32616
```



Optimized Models Performance Comparison

In [115]:
```
model_perfs = pd.DataFrame({'Model': model_names, 'Accuracy': accuracy_sco
model_perfs
```

Out[115]:

	Model	Accuracy	Precision	Recall	F1
0	VotingClassifier(estimators=[('RF', RandomFore...	0.839557	0.839557	0.839557	0.839557
1	(DecisionTreeClassifier(max_features='sqrt', r...	0.839465	0.839465	0.839465	0.839465
2	RandomizedSearchCV(estimator=LGBMClassifier(),...	0.828888	0.828888	0.828888	0.828888
3	(ExtraTreeClassifier(random_state=1036040382),...	0.821069	0.821069	0.821069	0.821069
4	(DecisionTreeClassifier(random_state=136957480...	0.813006	0.813006	0.813006	0.813006
5	XGBClassifier(base_score=None, booster=None, c...	0.806721	0.806721	0.806721	0.806721
6	<catboost.core.CatBoostClassifier object at 0x...	0.802857	0.802857	0.802857	0.802857
7	HistGradientBoostingClassifier()	0.793261	0.793261	0.793261	0.793261
8	LGBMClassifier()	0.785473	0.785473	0.785473	0.785473
9	KNeighborsClassifier()	0.762203	0.762203	0.762203	0.762203
10	([DecisionTreeRegressor(criterion='friedman_ms...	0.750153	0.750153	0.750153	0.750153
11	DecisionTreeClassifier()	0.747087	0.747087	0.747087	0.747087
12	RandomizedSearchCV(cv=5, estimator=DecisionTre...	0.737613	0.737613	0.737613	0.737613
13	XGBRFClassifier(base_score=None, booster=None,...	0.733045	0.733045	0.733045	0.733045
14	(DecisionTreeClassifier(max_depth=1, random_st...	0.707230	0.707230	0.707230	0.707230
15	RidgeClassifier()	0.635670	0.635670	0.635670	0.635670
16	RandomizedSearchCV(cv=5, estimator=RidgeClassi...	0.633033	0.633033	0.633033	0.633033
17	RandomizedSearchCV(cv=5, estimator=BernoulliNB...	0.595628	0.595628	0.595628	0.595628
18	MLPClassifier()	0.485038	0.485038	0.485038	0.485038
19	BernoulliNB()	0.471118	0.471118	0.471118	0.471118
20	PassiveAggressiveClassifier()	0.409124	0.409124	0.409124	0.409124
21	LinearSVC()	0.341090	0.341090	0.341090	0.341090
22	RandomizedSearchCV(cv=5, estimator=LogisticReg...	0.334130	0.334130	0.334130	0.334130
23	LogisticRegression()	0.334130	0.334130	0.334130	0.334130
24	GaussianNB()	0.334100	0.334100	0.334100	0.334100
25	SGDClassifier()	0.330605	0.330605	0.330605	0.330605

Before evaluating the best model after hyperparameter tuning, let's first understand the initial performance of the models. Looking at the accuracy, precision, recall, and F1-score metrics, the best model initially seems to be the VotingClassifier and the DecisionTreeClassifier. Both models achieved the highest scores across all the mentioned metrics.

Now, after hyperparameter tuning, the scores remain the same for the VotingClassifier and DecisionTreeClassifier. The other models show similar performance as well.

Evaluation of the Best Model (VotingClassifier):

Accuracy: 83.96% Precision: 83.96% Recall: 83.96% F1 Score: 83.96% Why is it the Best Model?

Consistency: The VotingClassifier demonstrates consistency in performance across all metrics, indicating a balanced and robust model.

Ensemble Advantage: The VotingClassifier is an ensemble model, combining the strengths of multiple base models. This often leads to better generalization and performance.

Hyperparameter Tuning: Even after hyperparameter tuning, the VotingClassifier maintains its high scores, suggesting that the initial configuration was already effective.

DecisionTreeClassifier Contribution: Given that the DecisionTreeClassifier is one of the base models in the ensemble, its individual performance contributes significantly to the overall success of the VotingClassifier.

Practical Considerations: Depending on the nature of your problem and the importance of precision, recall, or overall accuracy, you might prioritize different models. In this case, the

In [ ]:

In [ ]: