In [1]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
pd.set_option('display.max_columns', None)
```

In [2]:

```
data = pd.read_csv('/kaggle/input/crime-cast-forecasting-crime-categories/train.csv')
```

In [3]:

```
data.head()
```

Out[3]:

| | Location | Cross_Street | Latitude | Longitude | Date_Reported | Date_Occurred | Time_Occurred | Area_ID | Area_Name | Rep |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 4500 CARPENTER AV | NaN | 34.1522 | -118.3910 | 03/09/2020 12:00:00 AM | 03/06/2020 12:00:00 AM | 1800.0 | 15.0 | N Hollywood | |
| 1 | 45TH ST | ALAMEDA ST | 34.0028 | -118.2391 | 02/27/2020 12:00:00 AM | 02/27/2020 12:00:00 AM | 1345.0 | 13.0 | Newton | |
| 2 | 600 E MARTIN LUTHER KING JR BL | NaN | 34.0111 | -118.2653 | 08/21/2020 12:00:00 AM | 08/21/2020 12:00:00 AM | 605.0 | 13.0 | Newton | |
| 3 | 14900 ORO GRANDE ST | NaN | 34.2953 | -118.4590 | 11/08/2020 12:00:00 AM | 11/06/2020 12:00:00 AM | 1800.0 | 19.0 | Mission | |
| 4 | 7100 S VERMONT AV | NaN | 33.9787 | -118.2918 | 02/25/2020 12:00:00 AM | 02/25/2020 12:00:00 AM | 1130.0 | 12.0 | 77th Street | |

In [4]:

```
print(data['Weapon_Used_Code'].value_counts())
```

```
Weapon_Used_Code
400.0    3990
500.0     789
511.0     546
102.0     388
200.0     160
109.0     154
106.0     131
207.0     125
307.0      84
512.0      80
306.0      63
212.0      55
312.0      52
304.0      51
308.0      49
205.0      45
201.0      43
114.0      41
204.0      37
302.0      37
113.0      35
101.0      34
301.0      26
```

```
310.0      26
215.0      25
223.0      24
311.0      23
219.0      23
506.0      22
107.0      18
515.0      18
218.0      17
305.0      16
221.0      14
216.0      13
103.0      12
309.0      11
112.0       8
104.0       7
514.0       7
211.0       6
513.0       4
303.0       4
510.0       3
206.0       3
508.0       2
504.0       2
105.0       2
214.0       2
503.0       1
501.0       1
202.0       1
111.0       1
210.0       1
122.0       1
115.0       1
213.0       1
Name: count, dtype: int64
```

In [5]:

```
data['Weapon_Description'].value_counts()
```

Out[5]:

```
Weapon_Description
STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)    3990
UNKNOWN WEAPON/OTHER WEAPON                        789
VERBAL THREAT                                      546
HAND GUN                                           388
KNIFE WITH BLADE 6INCHES OR LESS                   160
SEMI-AUTOMATIC PISTOL                              154
UNKNOWN FIREARM                                    131
OTHER KNIFE                                        125
VEHICLE                                             84
MACE/PEPPER SPRAY                                   80
ROCK/THROWN OBJECT                                  63
BOTTLE                                              55
PIPE/METAL PIPE                                     52
CLUB/BAT                                            51
STICK                                               49
KITCHEN KNIFE                                       45
KNIFE WITH BLADE OVER 6 INCHES IN LENGTH            43
AIR PISTOL/REVOLVER/RIFLE/BB GUN                    41
FOLDING KNIFE                                       37
BLUNT INSTRUMENT                                    37
SIMULATED GUN                                       35
REVOLVER                                            34
BELT FLAILING INSTRUMENT/CHAIN                      26
CONCRETE BLOCK/BRICK                                26
MACHETE                                             25
UNKNOWN TYPE CUTTING INSTRUMENT                     24
HAMMER                                              23
SCREWDRIVER                                         23
FIRE                                                22
```

```
OTHER FIREARM                                     18
PHYSICAL PRESENCE                                 18
OTHER CUTTING INSTRUMENT                          17
FIXED OBJECT                                      16
GLASS                                             14
SCISSORS                                          13
RIFLE                                             12
BOARD                                             11
TOY GUN                                            8
SHOTGUN                                            7
TIRE IRON                                          7
AXE                                                6
STUN GUN                                           4
BRASS KNUCKLES                                     4
SCALDING LIQUID                                    3
SWITCH BLADE                                       3
MARTIAL ARTS WEAPONS                               2
DEMAND NOTE                                        2
SAWED OFF RIFLE/SHOTGUN                            2
ICE PICK                                           2
CAUSTIC CHEMICAL/POISON                            1
BOMB THREAT                                        1
BOWIE KNIFE                                        1
STARTER PISTOL/REVOLVER                            1
RAZOR BLADE                                        1
HECKLER & KOCH 93 SEMIAUTOMATIC ASSAULT RIFLE      1
ASSAULT WEAPON/UZI/AK47/ETC                        1
CLEAVER                                            1
Name: count, dtype: int64
```

In [6]:

```
data[['Weapon_Used_Code', 'Weapon_Description']].value_counts()
```

Out[6]:

```
Weapon_Used_Code  Weapon_Description
400.0             STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)    3990
500.0             UNKNOWN WEAPON/OTHER WEAPON                        789
511.0             VERBAL THREAT                                      546
102.0             HAND GUN                                           388
200.0             KNIFE WITH BLADE 6INCHES OR LESS                   160
109.0             SEMI-AUTOMATIC PISTOL                              154
106.0             UNKNOWN FIREARM                                    131
207.0             OTHER KNIFE                                        125
307.0             VEHICLE                                             84
512.0             MACE/PEPPER SPRAY                                   80
306.0             ROCK/THROWN OBJECT                                  63
212.0             BOTTLE                                              55
312.0             PIPE/METAL PIPE                                     52
304.0             CLUB/BAT                                            51
308.0             STICK                                               49
205.0             KITCHEN KNIFE                                       45
201.0             KNIFE WITH BLADE OVER 6 INCHES IN LENGTH            43
114.0             AIR PISTOL/REVOLVER/RIFLE/BB GUN                    41
302.0             BLUNT INSTRUMENT                                    37
204.0             FOLDING KNIFE                                       37
113.0             SIMULATED GUN                                       35
101.0             REVOLVER                                            34
310.0             CONCRETE BLOCK/BRICK                                26
301.0             BELT FLAILING INSTRUMENT/CHAIN                      26
215.0             MACHETE                                             25
223.0             UNKNOWN TYPE CUTTING INSTRUMENT                     24
219.0             SCREWDRIVER                                         23
311.0             HAMMER                                              23
506.0             FIRE                                                22
515.0             PHYSICAL PRESENCE                                   18
107.0             OTHER FIREARM                                       18
218.0             OTHER CUTTING INSTRUMENT                            17
305.0             FIXED OBJECT                                        16
221.0             GLASS                                               14
216.0             SCISSORS                                            13
```

```
103.0            RIFLE                                              12
309.0            BOARD                                              11
112.0            TOY GUN                                             8
514.0            TIRE IRON                                           7
104.0            SHOTGUN                                             7
211.0            AXE                                                 6
513.0            STUN GUN                                            4
303.0            BRASS KNUCKLES                                      4
510.0            SCALDING LIQUID                                     3
206.0            SWITCH BLADE                                        3
504.0            DEMAND NOTE                                         2
105.0            SAWED OFF RIFLE/SHOTGUN                             2
508.0            MARTIAL ARTS WEAPONS                                2
214.0            ICE PICK                                            2
115.0            ASSAULT WEAPON/UZI/AK47/ETC                         1
111.0            STARTER PISTOL/REVOLVER                             1
122.0            HECKLER & KOCH 93 SEMIAUTOMATIC ASSAULT RIFLE       1
501.0            BOMB THREAT                                         1
503.0            CAUSTIC CHEMICAL/POISON                             1
202.0            BOWIE KNIFE                                         1
210.0            RAZOR BLADE                                         1
213.0            CLEAVER                                             1
Name: count, dtype: int64
```

In [7]:

```
data[['Status_Description', 'Status']].value_counts()
```

Out[7]:

```
Status_Description  Status
Invest Cont         IC        15236
Adult Other         AO         2597
Adult Arrest        AA         2054
Juv Arrest          JA           70
Juv Other           JO           43
Name: count, dtype: int64
```

In [8]:

```
data['Status'].value_counts()
```

Out[8]:

```
Status
IC    15236
AO     2597
AA     2054
JA       70
JO       43
Name: count, dtype: int64
```

In [9]:

```
data['Status_Description'].value_counts()
```

Out[9]:

```
Status_Description
Invest Cont     15236
Adult Other      2597
Adult Arrest     2054
Juv Arrest         70
Juv Other          43
Name: count, dtype: int64
```

In [10]:

```
data[['Premise_Description', 'Premise_Code']].value_counts()
```

Out[10]:

```
Premise_Description                         Premise_Code
STREET                                      101.0           5033
```

```
STREET                                          101.0          5033
SINGLE FAMILY DWELLING                          501.0          3379
MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)    502.0          2491
PARKING LOT                                     108.0          1437
SIDEWALK                                        102.0           978
                                                               ...
FRAT HOUSE/SORORITY/DORMITORY                   508.0             1
FACTORY                                         302.0             1
SKATEBOARD FACILITY/SKATEBOARD PARK*            736.0             1
MTA - PURPLE LINE - PERSHING SQUARE             917.0             1
RECORD-CD MUSIC/COMPUTER GAME STORE             225.0             1
Name: count, Length: 216, dtype: int64
```

In [11]:

```
data['Premise_Code'].value_counts()
```

Out[11]:

```
Premise_Code
101.0    5033
501.0    3379
502.0    2491
108.0    1437
102.0     978
         ...
214.0       1
909.0       1
896.0       1
744.0       1
250.0       1
Name: count, Length: 217, dtype: int64
```

In [12]:

```
data['Premise_Description'].value_counts()
```

Out[12]:

```
Premise_Description
STREET                                          5033
SINGLE FAMILY DWELLING                          3379
MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)    2491
PARKING LOT                                     1437
SIDEWALK                                         978
                                                ...
BUS DEPOT/TERMINAL, OTHER THAN MTA                 1
MTA - RED LINE - HOLLYWOOD/WESTERN                 1
MTA - SILVER LINE - ROSECRANS                      1
HIGH-RISE BUILDING                                 1
COMPUTER SERVICES/REPAIRS/SALES                    1
Name: count, Length: 216, dtype: int64
```

In [13]:

```
data[['Area_Name', 'Area_ID']].value_counts()
```

Out[13]:

```
Area_Name    Area_ID
77th Street  12.0       1345
Pacific      14.0       1157
Central      1.0        1156
Southwest    3.0        1130
Southeast    18.0       1067
N Hollywood  15.0       1065
Hollywood    6.0        1014
Newton       13.0        999
Olympic      20.0        960
Wilshire     7.0         943
Rampart      2.0         931
West LA      8.0         910
Van Nuys     9.0         902
Harbor       5.0         872
```

```
Harbor       5.0          872
Mission      19.0         870
Northeast    11.0         839
Topanga      21.0         792
West Valley  10.0         790
Devonshire   17.0         769
Hollenbeck   4.0          755
Foothill     16.0         734
Name: count, dtype: int64
```

In [14]:

```
data['Area_Name'].value_counts()
```

Out[14]:

```
Area_Name
77th Street    1345
Pacific        1157
Central        1156
Southwest      1130
Southeast      1067
N Hollywood    1065
Hollywood      1014
Newton          999
Olympic         960
Wilshire        943
Rampart         931
West LA         910
Van Nuys        902
Harbor          872
Mission         870
Northeast       839
Topanga         792
West Valley     790
Devonshire      769
Hollenbeck      755
Foothill        734
Name: count, dtype: int64
```

In [15]:

```
data['Area_ID'].value_counts()
```

Out[15]:

```
Area_ID
12.0    1345
14.0    1157
1.0     1156
3.0     1130
18.0    1067
15.0    1065
6.0     1014
13.0     999
20.0     960
7.0      943
2.0      931
8.0      910
9.0      902
5.0      872
19.0     870
11.0     839
21.0     792
10.0     790
17.0     769
4.0      755
16.0     734
Name: count, dtype: int64
```

In [16]:

```
test_data = pd.read_csv('/kaggle/input/crime-cast-forecasting-crime-categories/test.csv')
```

In [17]:

```
print(test_data[['Weapon_Used_Code', 'Weapon_Description']].value_counts())
print(test_data['Weapon_Description'].value_counts())
print(test_data['Weapon_Used_Code'].value_counts())
```

```
Weapon_Used_Code  Weapon_Description
400.0             STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)    1003
500.0             UNKNOWN WEAPON/OTHER WEAPON                        208
511.0             VERBAL THREAT                                      110
102.0             HAND GUN                                            98
200.0             KNIFE WITH BLADE 6INCHES OR LESS                    50
106.0             UNKNOWN FIREARM                                     38
109.0             SEMI-AUTOMATIC PISTOL                               34
207.0             OTHER KNIFE                                         32
307.0             VEHICLE                                             28
212.0             BOTTLE                                              18
512.0             MACE/PEPPER SPRAY                                   17
308.0             STICK                                               16
306.0             ROCK/THROWN OBJECT                                  16
304.0             CLUB/BAT                                            15
114.0             AIR PISTOL/REVOLVER/RIFLE/BB GUN                    14
312.0             PIPE/METAL PIPE                                     14
204.0             FOLDING KNIFE                                       10
311.0             HAMMER                                              10
302.0             BLUNT INSTRUMENT                                     9
223.0             UNKNOWN TYPE CUTTING INSTRUMENT                      9
205.0             KITCHEN KNIFE                                        8
219.0             SCREWDRIVER                                          7
101.0             REVOLVER                                             7
201.0             KNIFE WITH BLADE OVER 6 INCHES IN LENGTH             7
218.0             OTHER CUTTING INSTRUMENT                             6
215.0             MACHETE                                              6
301.0             BELT FLAILING INSTRUMENT/CHAIN                       5
309.0             BOARD                                                4
515.0             PHYSICAL PRESENCE                                    4
113.0             SIMULATED GUN                                        4
310.0             CONCRETE BLOCK/BRICK                                 3
505.0             EXPLOXIVE DEVICE                                     3
506.0             FIRE                                                 3
221.0             GLASS                                                3
216.0             SCISSORS                                             3
107.0             OTHER FIREARM                                        3
303.0             BRASS KNUCKLES                                       3
513.0             STUN GUN                                             2
104.0             SHOTGUN                                              2
112.0             TOY GUN                                              2
305.0             FIXED OBJECT                                         1
507.0             LIQUOR/DRUGS                                         1
103.0             RIFLE                                                1
514.0             TIRE IRON                                            1
510.0             SCALDING LIQUID                                      1
115.0             ASSAULT WEAPON/UZI/AK47/ETC                          1
503.0             CAUSTIC CHEMICAL/POISON                              1
206.0             SWITCH BLADE                                         1
208.0             RAZOR                                                1
213.0             CLEAVER                                              1
214.0             ICE PICK                                             1
217.0             SWORD                                                1
516.0             DOG/ANIMAL (SIC ANIMAL ON)                           1
Name: count, dtype: int64
Weapon_Description
STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)    1003
UNKNOWN WEAPON/OTHER WEAPON                        208
VERBAL THREAT                                      110
HAND GUN                                            98
KNIFE WITH BLADE 6INCHES OR LESS                    50
UNKNOWN FIREARM                                     38
SEMI-AUTOMATIC PISTOL                               34
OTHER KNIFE                                         32
VEHICLE                                             28
```

```
BOTTLE                                            18
MACE/PEPPER SPRAY                                 17
STICK                                             16
ROCK/THROWN OBJECT                                16
CLUB/BAT                                          15
PIPE/METAL PIPE                                   14
AIR PISTOL/REVOLVER/RIFLE/BB GUN                  14
FOLDING KNIFE                                     10
HAMMER                                            10
BLUNT INSTRUMENT                                   9
UNKNOWN TYPE CUTTING INSTRUMENT                    9
KITCHEN KNIFE                                      8
SCREWDRIVER                                        7
REVOLVER                                           7
KNIFE WITH BLADE OVER 6 INCHES IN LENGTH           7
MACHETE                                            6
OTHER CUTTING INSTRUMENT                           6
BELT FLAILING INSTRUMENT/CHAIN                     5
SIMULATED GUN                                      4
PHYSICAL PRESENCE                                  4
BOARD                                              4
CONCRETE BLOCK/BRICK                               3
EXPLOXIVE DEVICE                                   3
OTHER FIREARM                                      3
BRASS KNUCKLES                                     3
GLASS                                              3
FIRE                                               3
SCISSORS                                           3
TOY GUN                                            2
SHOTGUN                                            2
STUN GUN                                           2
CAUSTIC CHEMICAL/POISON                            1
SWITCH BLADE                                       1
ASSAULT WEAPON/UZI/AK47/ETC                        1
CLEAVER                                            1
SWORD                                              1
TIRE IRON                                          1
FIXED OBJECT                                       1
DOG/ANIMAL (SIC ANIMAL ON)                         1
LIQUOR/DRUGS                                       1
RAZOR                                              1
ICE PICK                                           1
SCALDING LIQUID                                    1
RIFLE                                              1
Name: count, dtype: int64
Weapon_Used_Code
400.0    1003
500.0     208
511.0     110
102.0      98
200.0      50
106.0      38
109.0      34
207.0      32
307.0      28
212.0      18
512.0      17
308.0      16
306.0      16
304.0      15
312.0      14
114.0      14
204.0      10
311.0      10
302.0       9
223.0       9
205.0       8
219.0       7
101.0       7
201.0       7
215.0       6
218.0       6
```

```
301.0       5
113.0       4
515.0       4
309.0       4
310.0       3
505.0       3
107.0       3
303.0       3
221.0       3
506.0       3
216.0       3
112.0       2
104.0       2
513.0       2
503.0       1
206.0       1
115.0       1
213.0       1
217.0       1
514.0       1
305.0       1
516.0       1
507.0       1
208.0       1
214.0       1
510.0       1
103.0       1
Name: count, dtype: int64
```

### Data Cleaning: Dropping Redundant Columns

**In the initial dataset, I identified four columns that contained redundant information. These columns were:**

1. **Weapon_Used_Code**
2. **Status_Description**
3. **Premise_Description**
4. **Area_Name**

**Each of these columns had a corresponding column that provided the same information in a different format:**

- `Weapon_Description` **and** `Weapon_Used_Code`
- `Status_Description` **and** `Status`
- `Premise_Description` **and** `Premise_Code`
- `Area_Name` **and** `Area_ID`

**To streamline our dataset and ensure that I focus on the most relevant information for our analysis, I decided to drop the columns** `Weapon_Description`**,** `Status_Description`**,** `Premise_Description`**, and** `Area_Name`**.**

**This decision was made based on the following reasons:**

1. **Redundancy: Each dropped column had a corresponding column that conveyed the same information. By maintaining only one version of the information, we ensure the integrity and clarity of our dataset.**
2. **Efficiency: Reducing the number of columns simplifies the dataset, making it easier to handle and analyze. This can improve the performance of data processing tasks and the interpretability of analysis results.**

**The resulting cleaned dataset retains the most relevant columns, which are:**

- **Weapon_Used_Code**
- **Status**
- **Premise_Code**
- **Area_ID**

**This cleaned dataset is now more concise and focused, setting a solid foundation for accurate and efficient analysis.**

### Data Cleaning: Dropping Columns with Missing Values

I identified that the `Cross_Street` column had 16,000 null values. Due to the high proportion of missing data and its limited relevance to my analysis, I decided to drop this column to maintain the dataset's integrity and quality.

In [18]:

```
data['Cross_Street'].isnull().sum()
```

Out[18]:

```
16552
```

In [19]:

```
data = data.drop('Weapon_Description', axis=1)
data = data.drop('Status_Description', axis=1)
data = data.drop('Premise_Description', axis=1)
data = data.drop('Area_Name', axis=1)
data = data.drop('Cross_Street', axis=1)
```

In [20]:

```
data['Victim_Age'].value_counts()
```

Out[20]:

```
Victim_Age
 0.0     4828
 30.0     448
 31.0     446
 26.0     442
 29.0     425
         ...
 98.0       2
-2.0        2
 92.0       2
 96.0       2
 94.0       2
Name: count, Length: 100, dtype: int64
```

In [21]:

```
data['Victim_Age'].unique()
```

Out[21]:

```
array([75., 41., 67., 61.,  0., 50., 68., 22., 31., 46., 72., 26., 38.,
       37., 42., 40., 53., 60., 29., 13., 33., 27., 15., 23., 74., 63.,
       78., 51., 44., 34., 69., 36., 52., 25., 49., 48., 32., 18., 35.,
       24., 39., 16., 28., 47., 30., 64., 76.,  5., 58., 45., 57., 19.,
       55., 54., 21., 65., 17., 20., 77., 82., 56., -2., 84., 59., 43.,
        7., 70., 66., 62., 14., 80., 71., 81., 96., 12., 11.,  4., 83.,
       10.,  8.,  6., 88., 86., 73.,  9., 87., 85., 93., 95., 99., 79.,
        3.,  2., 91., 92., 90., 89., 98., -1., 94.])
```

## Data Cleaning: Handling Invalid Values in `Victim_Age`

I identified that the `Victim_Age` column contained invalid values such as -1 and -2. These values are not plausible for representing ages, so I replaced them with 0 to ensure data consistency and accuracy.

In [22]:

```
data['Victim_Age'].replace([-1, -2], 0, inplace=True)
```

In [23]:

```
data['Victim_Age'].value_counts()
```

Out[23]:

```
Victim_Age
0.0     4834
30.0     448
31.0     446
26.0     442
29.0     425
        ...
93.0       5
92.0       2
96.0       2
98.0       2
94.0       2
Name: count, Length: 98, dtype: int64
```

### Data Cleaning: Handling Missing Values in `Weapon_Used_Code`

**I found that the `Weapon_Used_Code` column contained some missing values. To address this, I replaced the missing values with 0 to maintain data consistency and avoid potential issues during analysis.**

In [24]:

```
data['Weapon_Used_Code'] = data[['Weapon_Used_Code']].fillna(0)
```

### Data Cleaning: Handling Missing Values in `Victim_Sex` and `Victim_Descent`

**I identified missing values in the `Victim_Sex` and `Victim_Descent` columns. To address this, I replaced the missing values with 'Unknown' to maintain data integrity and ensure completeness for subsequent analysis.**

In [25]:

```
data['Victim_Sex'].unique()
```

Out[25]:

```
array(['M', 'X', 'F', nan, 'H'], dtype=object)
```

In [26]:

```
data['Victim_Descent'].unique()
```

Out[26]:

```
array(['W', 'H', 'B', 'X', nan, 'O', 'A', 'K', 'C', 'F', 'I', 'J', 'Z',
       'V', 'P', 'D', 'U', 'G'], dtype=object)
```

In [27]:

```
data['Victim_Sex'] = data[['Victim_Sex']].fillna('Unknown')
data['Victim_Descent'] = data['Victim_Descent'].fillna('Unknown')
```

In [28]:

```
l = []
for i in range(20000):
    l.append((str(data['Modus_Operandi'][i]).split()))

s = set()
for i in l:
    for j in i:
        s.add(j)
print(len(list(s))) # including np.nan
```

```
482
```

**There are 482 unique `Modus Operandi`, or Modes of Operation , but this is including the null values as well. So the Actual Number is 482-1 = 481. I made one hot encoded vectors of each row consisting of `Modus_Operandi` sequence. Then dropped the original Modus_Operandi Column and concatenated the**

`modus_operandi_encoded` to our data.

In [29]:

```
modus_operandi_encoded = data['Modus_Operandi'].str.get_dummies(sep=' ')
```

In [30]:

```
data = pd.concat([data, modus_operandi_encoded], axis=1)
data = data.drop('Modus_Operandi', axis=1)
```

## Data Cleaning: Processing Date Columns

I processed the `Date_Reported` and `Date_Occurred` columns to remove unnecessary time information and convert them into a proper datetime format. This ensures the dates are correctly interpreted and simplifies date-based analysis.

1. **Remove Time Information**: The `12:00:00 AM` time was removed from both date columns to clean up the data.
2. **Convert to Datetime**: Both columns were converted to `datetime` objects for better handling and analysis.

In [31]:

```
data['Date_Reported'] = (data['Date_Reported'].str.replace(' 12:00:00 AM', ''))
data['Date_Occurred'] = (data['Date_Occurred'].str.replace(' 12:00:00 AM', ''))
data['Date_Reported'] = pd.to_datetime(data['Date_Reported'], format='%m/%d/%Y')
data['Date_Occurred'] = pd.to_datetime(data['Date_Occurred'], format='%m/%d/%Y')
```

In [32]:

```
data['Date_Reported'][0] - data['Date_Occurred'][0]
```

Out[32]:

```
Timedelta('3 days 00:00:00')
```

## Data Cleaning: Additional Transformations and Calculations

I performed additional transformations and calculations on the date columns to extract meaningful features and drop unnecessary columns.

1. **Calculate Reporting Delay:** I calculated the delay between the date the incident occurred and the date it was reported. This new feature, `Reported_Delay`, is measured in days. The average reporting delay was also computed.
2. **Extract Month and Day**: I extracted the month and day from the `Date_Occurred` column to create new features `Month_Occurred` and `Day_Occurred`.
3. **Drop Date Columns**: After extracting the necessary information, I dropped the `Date_Occurred` and `Date_Reported` columns as they were no longer needed.

These steps helped in creating useful features for analysis and ensured that the dataset remains clean and focused on relevant information.

In [33]:

```
data['Reported_Delay'] = (data['Date_Reported'] - data['Date_Occurred']).dt.days
print("Average Reporting Delay:", data['Reported_Delay'].mean())
```

```
Average Reporting Delay: 22.12
```

In [34]:

```
data['Month_Occurred'] = data['Date_Occurred'].dt.month
data['Day_Occurred'] = data['Date_Occurred'].dt.day
```

In [35]:

```
data.drop(['Date_Occurred', 'Date_Reported'], axis=1, inplace=True)
```

## Data Cleaning: Encoding Categorical Columns

**To prepare the dataset for machine learning algorithms, I encoded the categorical columns using `LabelEncoder`. This transformation converts categorical values into numerical values, making them suitable for model training.**

**The columns encoded were:**

- `Location`
- `Victim_Sex`
- `Victim_Descent`
- `Status`

**These columns were selected because they contain categorical data that need to be converted into a numeric format for the algorithms to process effectively.**

In [36]:

```
data
```

Out[36]:

| | Location | Latitude | Longitude | Time_Occurred | Area_ID | Reporting_District_no | Part 1-2 | Victim_Age | Victim_Sex | Vict |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 4500 CARPENTER AV | 34.1522 | -118.3910 | 1800.0 | 15.0 | 1563.0 | 1.0 | 75.0 | M | |
| **1** | 45TH ST | 34.0028 | -118.2391 | 1345.0 | 13.0 | 1367.0 | 1.0 | 41.0 | M | |
| **2** | 600 E MARTIN LUTHER KING JR BL | 34.0111 | -118.2653 | 605.0 | 13.0 | 1343.0 | 2.0 | 67.0 | M | |
| **3** | 14900 ORO GRANDE ST | 34.2953 | -118.4590 | 1800.0 | 19.0 | 1924.0 | 1.0 | 61.0 | M | |
| **4** | 7100 S VERMONT AV | 33.9787 | -118.2918 | 1130.0 | 12.0 | 1245.0 | 1.0 | 0.0 | X | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **19995** | 5100 W ADAMS BL | 34.0334 | -118.3523 | 700.0 | 3.0 | 303.0 | 2.0 | 51.0 | M | |
| **19996** | 16900 ROSCOE BL | 34.2212 | -118.5011 | 259.0 | 10.0 | 1008.0 | 1.0 | 0.0 | M | |
| **19997** | 1000 S SHENANDOAH ST | 34.0571 | -118.3815 | 1400.0 | 8.0 | 849.0 | 1.0 | 42.0 | M | |
| **19998** | 300 W SEPULVEDA ST | 33.7451 | -118.2835 | 600.0 | 5.0 | 558.0 | 2.0 | 76.0 | F | |
| **19999** | DALTON AV | 34.0037 | -118.3034 | 1800.0 | 3.0 | 397.0 | 1.0 | 0.0 | Unknown | |

**20000 rows × 498 columns**

In [37]:

```
lb = LabelEncoder()
columns_to_encode = ['Location', 'Victim_Sex', 'Victim_Descent', 'Status', 'Area_ID', 'P
remise_Code', 'Reporting_District_no', 'Weapon_Used_Code']
for col in columns_to_encode:
    data[col] = lb.fit_transform(data[col])
```

In [38]:

```
data
```

Out[38]:

| | Location | Latitude | Longitude | Time_Occurred | Area_ID | Reporting_District_no | Part 1-2 | Victim_Age | Victim_Sex | Victim_De |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7238 | 34.1522 | -118.3910 | 1800.0 | 14 | 775 | 1.0 | 75.0 | 2 | |
| **1** | 7300 | 34.0028 | -118.2391 | 1345.0 | 12 | 647 | 1.0 | 41.0 | 2 | |
| **2** | 8525 | 34.0111 | -118.2653 | 605.0 | 12 | 633 | 2.0 | 67.0 | 2 | |
| **3** | 2879 | 34.2953 | -118.4590 | 1800.0 | 18 | 972 | 1.0 | 61.0 | 2 | |
| **4** | 9584 | 33.9787 | -118.2918 | 1130.0 | 11 | 596 | 1.0 | 0.0 | 4 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **19995** | 7868 | 34.0334 | -118.3523 | 700.0 | 2 | 96 | 2.0 | 51.0 | 2 | |
| **19996** | 3555 | 34.2212 | -118.5011 | 259.0 | 9 | 471 | 1.0 | 0.0 | 2 | |
| **19997** | 441 | 34.0571 | -118.3815 | 1400.0 | 7 | 395 | 1.0 | 42.0 | 2 | |
| **19998** | 5975 | 33.7451 | -118.2835 | 600.0 | 4 | 246 | 2.0 | 76.0 | 0 | |
| **19999** | 11453 | 34.0037 | -118.3034 | 1800.0 | 2 | 149 | 1.0 | 0.0 | 3 | |

**20000 rows × 498 columns**

In [39]:

```
data['Time_Occurred'] = data['Time_Occurred'].astype(int)
data['Part 1-2'] = data['Part 1-2'].astype(int)
data['Victim_Age'] = data['Victim_Age'].astype(int)
```

In [40]:

```
data
```

Out[40]:

| | Location | Latitude | Longitude | Time_Occurred | Area_ID | Reporting_District_no | Part 1-2 | Victim_Age | Victim_Sex | Victim_De |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7238 | 34.1522 | -118.3910 | 1800 | 14 | 775 | 1 | 75 | 2 | |
| **1** | 7300 | 34.0028 | -118.2391 | 1345 | 12 | 647 | 1 | 41 | 2 | |
| **2** | 8525 | 34.0111 | -118.2653 | 605 | 12 | 633 | 2 | 67 | 2 | |
| **3** | 2879 | 34.2953 | -118.4590 | 1800 | 18 | 972 | 1 | 61 | 2 | |
| **4** | 9584 | 33.9787 | -118.2918 | 1130 | 11 | 596 | 1 | 0 | 4 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **19995** | 7868 | 34.0334 | -118.3523 | 700 | 2 | 96 | 2 | 51 | 2 | |
| **19996** | 3555 | 34.2212 | -118.5011 | 259 | 9 | 471 | 1 | 0 | 2 | |
| **19997** | 441 | 34.0571 | -118.3815 | 1400 | 7 | 395 | 1 | 42 | 2 | |
| **19998** | 5975 | 33.7451 | -118.2835 | 600 | 4 | 246 | 2 | 76 | 0 | |
| **19999** | 11453 | 34.0037 | -118.3034 | 1800 | 2 | 149 | 1 | 0 | 3 | |

**20000 rows × 498 columns**

In [41]:

```
data['Location'].value_counts()
```

Out[41]:

```
Location
9255     33
9947     32
12261    31
9257     31
9950     30
         ..
5575      1
10982     1
11872     1
12316     1
11453     1
Name: count, Length: 12399, dtype: int64
```

In [42]:

```
for i in range(20000):
    if data['Location'][i] == 9255:
        print(data.loc[i, ['Location', 'Latitude', 'Longitude']])
```

```
Location         9255
Latitude      34.0412
Longitude   -118.2436
Name: 569, dtype: object
Location         9255
Latitude      34.0636
Longitude   -118.2979
Name: 785, dtype: object
Location         9255
Latitude      33.7613
Longitude   -118.2819
Name: 2638, dtype: object
Location         9255
Latitude      34.0672
Longitude   -118.2985
Name: 4054, dtype: object
Location         9255
Latitude      34.0423
Longitude   -118.2452
Name: 4170, dtype: object
Location         9255
Latitude      34.0657
Longitude   -118.2825
Name: 5232, dtype: object
Location         9255
Latitude       34.046
Longitude   -118.2509
Name: 5406, dtype: object
Location         9255
Latitude      34.0421
Longitude   -118.2469
Name: 6071, dtype: object
Location         9255
Latitude      34.0601
Longitude   -118.2761
Name: 6781, dtype: object
Location        9255
Latitude     34.0446
Longitude   -118.249
Name: 6893, dtype: object
Location        9255
Latitude     34.0466
Longitude   -118.252
Name: 7069, dtype: object
Location         9255
Latitude      34.0343
Longitude   -118.2054
Name: 9705, dtype: object
Location         9255
```

```
Location         9255
Latitude      34.0394
Longitude   -118.2405
Name: 9826, dtype: object
Location        9255
Latitude     34.0446
Longitude   -118.249
Name: 10872, dtype: object
Location         9255
Latitude       34.062
Longitude   -118.2804
Name: 11570, dtype: object
Location         9255
Latitude      34.0435
Longitude   -118.2471
Name: 11756, dtype: object
Location         9255
Latitude      34.0593
Longitude   -118.2749
Name: 11769, dtype: object
Location         9255
Latitude      34.0453
Longitude   -118.2499
Name: 12176, dtype: object
Location       9255
Latitude     34.039
Longitude   -118.24
Name: 12810, dtype: object
Location         9255
Latitude      34.0382
Longitude   -118.2384
Name: 13686, dtype: object
Location         9255
Latitude      34.0428
Longitude   -118.2461
Name: 15124, dtype: object
Location        9255
Latitude     34.0446
Longitude   -118.249
Name: 15283, dtype: object
Location         9255
Latitude      34.0428
Longitude   -118.2461
Name: 15819, dtype: object
Location         9255
Latitude      34.0429
Longitude   -118.2462
Name: 16558, dtype: object
Location         9255
Latitude      34.0474
Longitude   -118.2531
Name: 16675, dtype: object
Location         9255
Latitude      34.0453
Longitude   -118.2499
Name: 17156, dtype: object
Location         9255
Latitude      34.0435
Longitude   -118.2471
Name: 17689, dtype: object
Location         9255
Latitude      34.0585
Longitude   -118.2724
Name: 17832, dtype: object
Location         9255
Latitude      34.0403
Longitude   -118.2421
Name: 18127, dtype: object
Location         9255
Latitude      34.0435
Longitude   -118.2471
Name: 18298, dtype: object
Location         9255
```

```
Latitude      34.0417
Longitude   -118.2444
Name: 18594, dtype: object
Location         9255
Latitude      34.0439
Longitude   -118.2479
Name: 18627, dtype: object
Location        9255
Latitude     34.0466
Longitude   -118.252
Name: 19971, dtype: object
```

In [43]:

```
data = data.drop(['Latitude', 'Longitude'], axis=1)
```

**Applying Same Preprocessing steps to test.csv as well**

In [44]:

```
test_data = test_data.drop('Weapon_Description', axis=1)
test_data = test_data.drop('Status_Description', axis=1)
test_data = test_data.drop('Premise_Description', axis=1)
test_data = test_data.drop('Area_Name', axis=1)
test_data = test_data.drop('Cross_Street', axis=1)
```

In [45]:

```
test_data['Victim_Age'].replace([-1, -2], 0, inplace=True)
test_data['Weapon_Used_Code'] = test_data[['Weapon_Used_Code']].fillna(0)
test_data['Victim_Sex'] = test_data[['Victim_Sex']].fillna('Unknown')
test_data['Victim_Descent'] = test_data['Victim_Descent'].fillna('Unknown')
```

In [46]:

```
train_data = pd.read_csv('/kaggle/input/crime-cast-forecasting-crime-categories/train.csv
')
```

In [47]:

```
def get_unique_modus_operandi(column):
    split_values = column.dropna().str.split()
    flattened_list = [item for sublist in split_values for item in sublist]
    unique_modus_operandi = list(set(flattened_list))
    return unique_modus_operandi

unique_modus_train = get_unique_modus_operandi(train_data['Modus_Operandi'])

train_modus_encoded = train_data['Modus_Operandi'].str.get_dummies(sep=' ')
for modus in unique_modus_train:
    if modus not in train_modus_encoded.columns:
        train_modus_encoded[modus] = 0

test_modus_encoded = pd.DataFrame(columns=train_modus_encoded.columns)
test_modus_encoded = test_modus_encoded.reindex(test_data.index, fill_value=0)

for index, row in test_data.iterrows():
    if isinstance(row['Modus_Operandi'], str):
        test_modus_list = row['Modus_Operandi'].split()
        for modus in test_modus_list:
            if modus in test_modus_encoded.columns:
                test_modus_encoded.at[index, modus] = 1

test_data = pd.concat([test_data, test_modus_encoded], axis=1)
```

In [48]:

```
test_data = test_data.drop('Modus_Operandi', axis=1)
```

In [49]:

```
test_data['Date_Reported'] = (test_data['Date_Reported'].str.replace(' 12:00:00 AM', '')
)
test_data['Date_Occurred'] = (test_data['Date_Occurred'].str.replace(' 12:00:00 AM', '')
)
test_data['Date_Reported'] = pd.to_datetime(test_data['Date_Reported'], format='%m/%d/%Y
')
test_data['Date_Occurred'] = pd.to_datetime(test_data['Date_Occurred'], format='%m/%d/%Y
')

test_data['Reported_Delay'] = (test_data['Date_Reported'] - test_data['Date_Occurred']).
dt.days
print("Average Reporting Delay:", test_data['Reported_Delay'].mean())
```

```
Average Reporting Delay: 20.8666
```

In [50]:

```
test_data['Month_Occurred'] = test_data['Date_Occurred'].dt.month
test_data['Day_Occurred'] = test_data['Date_Occurred'].dt.day
```

In [51]:

```
test_data.drop(['Date_Occurred', 'Date_Reported'], axis=1, inplace=True)
```

In [52]:

```
lb = LabelEncoder()
columns_to_encode = ['Location', 'Victim_Sex', 'Victim_Descent', 'Status', 'Area_ID', 'P
remise_Code', 'Reporting_District_no', 'Weapon_Used_Code']
for col in columns_to_encode:
    test_data[col] = lb.fit_transform(test_data[col])
```

In [53]:

```
test_data['Time_Occurred'] = test_data['Time_Occurred'].astype(int)
test_data['Part 1-2'] = test_data['Part 1-2'].astype(int)
test_data['Victim_Age'] = test_data['Victim_Age'].astype(int)
```

In [54]:

```
test_data = test_data.drop(['Latitude', 'Longitude'], axis=1)
```

In [55]:

```
test_data.shape, data.shape
```

Out[55]:

```
((5000, 495), (20000, 496))
```

In [56]:

```
X = data.drop('Crime_Category', axis=1)
y = data['Crime_Category']
```

**Dataset appears to be imbalanced**

In [57]:

```
data['Crime_Category'].value_counts()
```

Out[57]:

```
Crime_Category
Property Crimes                    11666
Violent Crimes                      4767
Crimes against Public Order         1808
Fraud and White-Collar Crimes       1355
Crimes against Persons               225
Other Crimes                         179
```

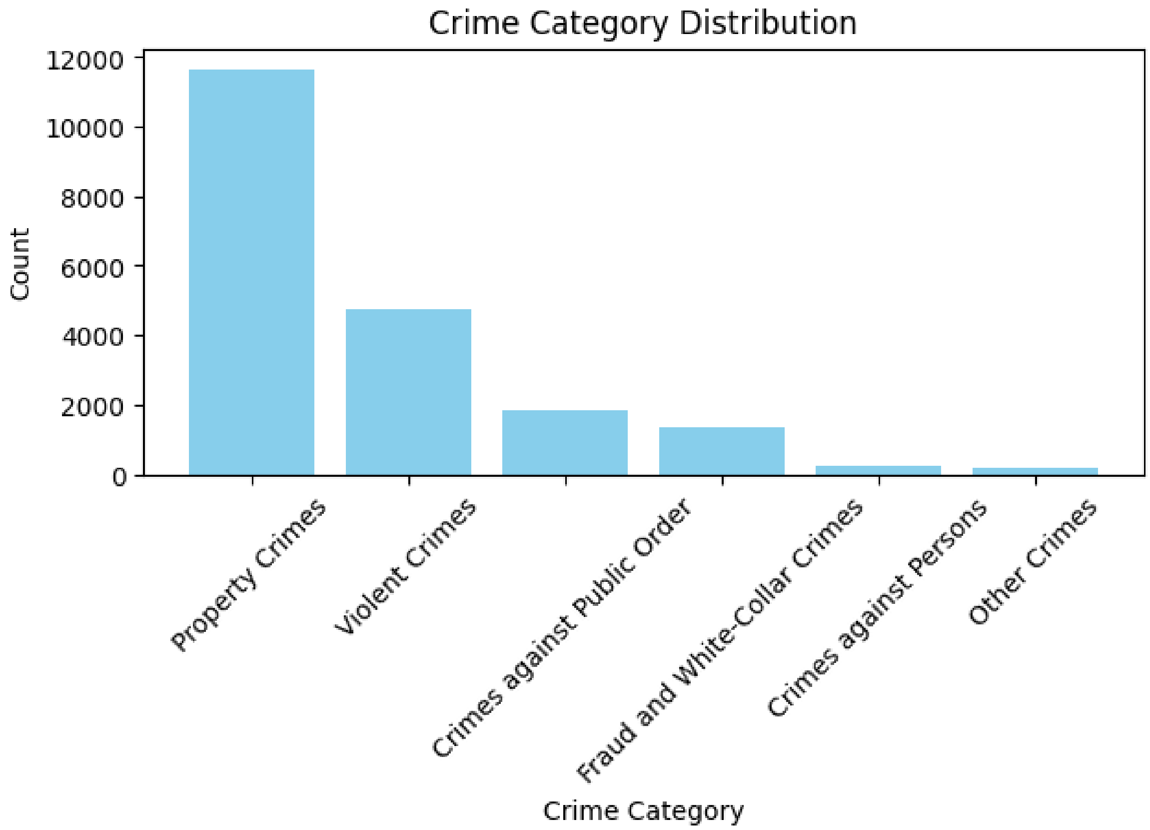
```
Other Crimes                  179
Name: count, dtype: int64
```

In [58]:

```python
import matplotlib.pyplot as plt

crime_categories = ['Property Crimes', 'Violent Crimes', 'Crimes against Public Order', '
Fraud and White-Collar Crimes', 'Crimes against Persons', 'Other Crimes']
crime_counts = [11666, 4767, 1808, 1355, 225, 179]

plt.figure(figsize=(7, 3))
plt.bar(crime_categories, crime_counts, color='skyblue')
plt.xlabel('Crime Category')
plt.ylabel('Count')
plt.title('Crime Category Distribution')
plt.xticks(rotation=45)
plt.show()
```




In [59]:

```python
X.shape, y.shape
```

Out[59]:

```
((20000, 495), (20000,))
```

In [60]:

```python
from sklearn.model_selection import train_test_split
```

**SPLITTING**

In [61]:

```python
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.25, random_state=40,
stratify=y)
```

In [62]:

```python
X_train.shape, X_val.shape, y_train.shape, y_val.shape
```

Out[62]:

((15000, 495), (5000, 495), (15000,), (5000,))

In [63]:

```
from sklearn.dummy import DummyClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score, confusion_matr
ix, ConfusionMatrixDisplay
```

In [64]:

```
def eval_model(X_train, X_val, y_train, y_val, estimator):
    estimator.fit(X_train, y_train)
    y_train_pred = estimator.predict(X_train)
    y_val_pred = estimator.predict(X_val)
    print(estimator,"'s Performance:")
    print()
    print("Training Accuracy: ", accuracy_score(y_train, y_train_pred))
    print("Validation Accuracy: ", accuracy_score(y_val, y_val_pred))
    print()
    print("Training Recall: ", recall_score(y_train, y_train_pred, average='weighted'))
    print("Validation Recall: ", recall_score(y_val, y_val_pred, average='weighted'))
    print()
    print("Training Precision: ", precision_score(y_train, y_train_pred, average='weight
ed', zero_division=0))
    print("Validation Precision: ", precision_score(y_val, y_val_pred, average='weighted
', zero_division=0))
    print()
    cm = confusion_matrix(y_val, y_val_pred)
    disp = ConfusionMatrixDisplay(cm)
    disp.plot()
```

**BASELINE MODEL**

In [65]:

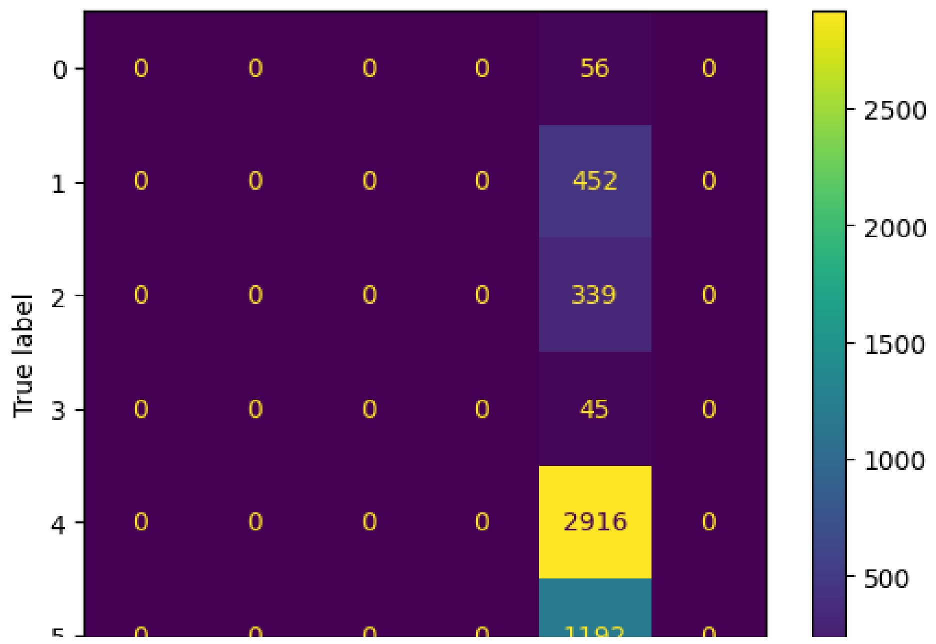
```
dummy_clf = DummyClassifier(random_state=42)
eval_model(X_train, X_val, y_train, y_val, dummy_clf)
```

```
DummyClassifier(random_state=42) 's Performance:

Training Accuracy:  0.5833333333333334
Validation Accuracy:  0.5832

Training Recall:  0.5833333333333334
Validation Recall:  0.5832

Training Precision:  0.34027777777777778
Validation Precision:  0.34012224
```




### LOGISTIC REGRESSION

In [66]:

```
'''from sklearn.linear_model import LogisticRegression
lr_clf = LogisticRegression(max_iter=100000, random_state=42)
eval_model(X_train, X_val, y_train, y_val, lr_clf)

/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: Convergenc
eWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of f AND g EVALUATIONS EXCEEDS LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
LogisticRegression(max_iter=100000, random_state=42) 's Performance:

Training Accuracy:  0.8655333333333334
Validation Accuracy:  0.8646

Training Recall:  0.8655333333333334
Validation Recall:  0.8646

Training Precision:  0.8468340093141288
Validation Precision:  0.8415426977473839'''
```

Out[66]:

```
"from sklearn.linear_model import LogisticRegression\nlr_clf = LogisticRegression(max_ite
r=100000, random_state=42)\neval_model(X_train, X_val, y_train, y_val, lr_clf)\n\n/opt/co
nda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarnin
g: lbfgs failed to converge (status=1):\nSTOP: TOTAL NO. of f AND g EVALUATIONS EXCEEDS L
IMIT.\n\nIncrease the number of iterations (max_iter) or scale the data as shown in:\n
https://scikit-learn.org/stable/modules/preprocessing.html\nPlease also refer to the docu
mentation for alternative solver options:\n    https://scikit-learn.org/stable/modules/li
near_model.html#logistic-regression\n  n_iter_i = _check_optimize_result(\nLogisticRegres
sion(max_iter=100000, random_state=42) 's Performance:\n\nTraining Accuracy:  0.865533333
3333334\nValidation Accuracy:  0.8646\n\nTraining Recall:  0.8655333333333334\nValidation
Recall:  0.8646\n\nTraining Precision:  0.8468340093141288\nValidation Precision:  0.8415
426977473839"
```

In [67]:

```
'''from sklearn.linear_model import LogisticRegression
lr_clf = LogisticRegression(max_iter=1000, random_state=42)
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
lr_pipe = Pipeline([('scaling', StandardScaler()), ('lr_clf', lr_clf)])
eval_model(X_train, X_val, y_train, y_val, lr_pipe)'''
```

Out[67]:

```
"from sklearn.linear_model import LogisticRegression\nlr_clf = LogisticRegression(max_ite
r=1000, random_state=42)\nfrom sklearn.preprocessing import StandardScaler\nfrom sklearn.
pipeline import Pipeline\nlr_pipe = Pipeline([('scaling', StandardScaler()), ('lr_clf', l
r_clf)])\neval_model(X_train, X_val, y_train, y_val, lr_pipe)"
```

### Logistic Regression Cross Validation

In [68]:

```
'''from sklearn.model_selection import cross_val_score
lr_cv_acc = cross_val_score(lr_pipe, X, y, cv=10, scoring='accuracy')
```

```
lr_cv_recall = cross_val_score(lr_pipe, X, y, cv=10, scoring='recall_weighted')
lr_cv_precision = cross_val_score(lr_pipe, X, y, cv=10, scoring='precision_weighted')

print(f'Logistic Regression Cross Val Scores: {round(lr_cv_acc.mean(), 2)} +/- {round(lr_cv_acc.std(), 2)}')
print(f'Logistic Regression Cross Val Scores: {round(lr_cv_recall.mean(), 2)} +/- {round(lr_cv_recall.std(), 2)}')
print(f'Logistic Regression Cross Val Scores: {round(lr_cv_precision.mean(), 2)} +/- {round(lr_cv_precision.std(), 2)}')'''
```

Out[68]:

```
"from sklearn.model_selection import cross_val_score\nlr_cv_acc = cross_val_score(lr_pipe, X, y, cv=10, scoring='accuracy')\nlr_cv_recall = cross_val_score(lr_pipe, X, y, cv=10, scoring='recall_weighted')\nlr_cv_precision = cross_val_score(lr_pipe, X, y, cv=10, scoring='precision_weighted')\n\nprint(f'Logistic Regression Cross Val Scores: {round(lr_cv_acc.mean(), 2)} +/- {round(lr_cv_acc.std(), 2)}')\nprint(f'Logistic Regression Cross Val Scores: {round(lr_cv_recall.mean(), 2)} +/- {round(lr_cv_recall.std(), 2)}')\nprint(f'Logistic Regression Cross Val Scores: {round(lr_cv_precision.mean(), 2)} +/- {round(lr_cv_precision.std(), 2)}')"
```

#### Decision Tree

In [69]:

```
'''from sklearn.tree import DecisionTreeClassifier
dt_clf = DecisionTreeClassifier(criterion='entropy')
dt_pipe = Pipeline([('scaling', StandardScaler()), ('dt_clf', dt_clf)])
eval_model(X_train, X_val, y_train, y_val, dt_pipe)'''
```

Out[69]:

```
"from sklearn.tree import DecisionTreeClassifier\ndt_clf = DecisionTreeClassifier(criterion='entropy')\ndt_pipe = Pipeline([('scaling', StandardScaler()), ('dt_clf', dt_clf)])\neval_model(X_train, X_val, y_train, y_val, dt_pipe)"
```

#### Decision Tree Grid Search

In [70]:

```
'''from sklearn.model_selection import GridSearchCV

param_grid = {
    'max_depth': [None, 10, 20, 30, 40, 50],
    'min_samples_split': [2, 10, 20],
    'min_samples_leaf': [1, 5, 10],
    'max_features': [None, 'sqrt', 'log2'],
    'ccp_alpha': [0.0, 0.01, 0.1]
}

dt_grid_search = GridSearchCV(estimator=dt_clf, param_grid=param_grid, cv=5, scoring='accuracy')
dt_grid_search.fit(X_train, y_train)'''

'''best_params = dt_grid_search.best_params_
best_model = dt_grid_search.best_estimator_
print("Best parameters found: ", best_params)
eval_model(X_train, X_val, y_train, y_val, best_model)

Output:
Best parameters found:  {'ccp_alpha': 0.0, 'max_depth': 20, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_split': 20}
DecisionTreeClassifier(criterion='entropy', max_depth=20, min_samples_split=20) 's Performance:

Training Accuracy:  0.97
Validation Accuracy:  0.94

Training Recall:  0.97
Validation Recall:  0.94
```

```
Training Precision:  0.97
Validation Precision:  0.94'''
```

Out[70]:

```
'best_params = dt_grid_search.best_params_\nbest_model = dt_grid_search.best_estimator_\n
print("Best parameters found: ", best_params)\neval_model(X_train, X_val, y_train, y_val,
best_model)\n\nOutput:\nBest parameters found:  {\'ccp_alpha\': 0.0, \'max_depth\': 20, \
'max_features\': None, \'min_samples_leaf\': 1, \'min_samples_split\': 20}\nDecisionTreeC
lassifier(criterion=\'entropy\', max_depth=20, min_samples_split=20) \'s Performance:\n\n
Training Accuracy:  0.97\nValidation Accuracy:  0.94\n\nTraining Recall:  0.97\nValidatio
n Recall:  0.94\n\nTraining Precision:  0.97\nValidation Precision:  0.94'
```

In [71]:

```
'''dt_clf_gini = DecisionTreeClassifier(max_depth=30, max_features=None, min_samples_leaf
=5, min_samples_split=20)
eval_model(X_train, X_val, y_train, y_val, dt_clf_gini)'''
```

Out[71]:

```
'dt_clf_gini = DecisionTreeClassifier(max_depth=30, max_features=None, min_samples_leaf=5
, min_samples_split=20)\neval_model(X_train, X_val, y_train, y_val, dt_clf_gini)'
```

In [72]:

```
'''from sklearn.neighbors import KNeighborsClassifier
knn_clf = KNeighborsClassifier()
knn_pipe = Pipeline([('scaling', StandardScaler()), ('knn_clf', knn_clf)])
eval_model(X_train, X_val, y_train, y_val, knn_pipe)'''
```

Out[72]:

```
"from sklearn.neighbors import KNeighborsClassifier\nknn_clf = KNeighborsClassifier()\nkn
n_pipe = Pipeline([('scaling', StandardScaler()), ('knn_clf', knn_clf)])\neval_model(X_tr
ain, X_val, y_train, y_val, knn_pipe)"
```

In [73]:

```
'''param_grid = {
    'n_neighbors': [5, 7, 9,],
    'weights': ['uniform', 'distance'],
    'algorithm': ['auto', 'ball_tree', 'kd_tree'],
    'leaf_size': [10, 30, 50],
    'metric': ['euclidean', 'minkowski']
}

knn_grid_search = GridSearchCV(estimator=knn_clf, param_grid=param_grid, scoring='accurac
y')
knn_grid_search.fit(X_train, y_train)

best_params = knn_grid_search.best_params_
best_model = knn_grid_search.best_estimator_
print("Best parameters found: ", best_params)
eval_model(X_train, X_val, y_train, y_val, best_model)

Output:
Best parameters found:  {'algorithm': 'auto', 'leaf_size': 10, 'metric': 'euclidean', 'n_
neighbors': 9, 'weights': 'distance'}
KNeighborsClassifier(leaf_size=10, metric='euclidean', n_neighbors=9,
                     weights='distance') 's Performance:
Training Accuracy:  1.0
Validation Accuracy:  0.58025
'''
```

Out[73]:

```
'param_grid = {\n    \'n_neighbors\': [5, 7, 9,],\n    \'weights\': [\'uniform\', \'dista
nce\'],\n    \'algorithm\': [\'auto\', \'ball_tree\', \'kd_tree\'],\n    \'leaf_size\': [
10, 30, 50],\n    \'metric\': [\'euclidean\', \'minkowski\']\n}\n\nknn_grid_search = Grid
SearchCV(estimator=knn_clf, param_grid=param_grid, scoring=\'accuracy\')\nknn_grid_search
.fit(X_train, y_train)\n\nbest_params = knn_grid_search.best_params_\nbest_model = knn_gr
id_search.best_estimator_\nprint("Best parameters found: ", best_params)\neval_model(X_tr
ain, X_val, y_train, y_val, best_model)\n\nOutput:\nBest parameters found:  {\'algorithm
```

```
ain, X_val, y_train, y_val, best_model)\n\nOutput: \nBest parameters found: {\'algorithm
\': \'auto\', \'leaf_size\': 10, \'metric\': \'euclidean\', \'n_neighbors\': 9, \'weights
\': \'distance\'}\nKNeighborsClassifier(leaf_size=10, metric=\'euclidean\', n_neighbors=9
,\n                     weights=\'distance\') \'s Performance:\nTraining Accuracy:  1.0\n
Validation Accuracy:  0.58025\n'
```

In [74]:

```
'''from sklearn.ensemble import RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=300, random_state=42)
eval_model(X_train, X_val, y_train, y_val, rf_clf)'''
```

Out[74]:

```
'from sklearn.ensemble import RandomForestClassifier\nrf_clf = RandomForestClassifier(n_e
stimators=300, random_state=42)\neval_model(X_train, X_val, y_train, y_val, rf_clf)'
```

In [75]:

```
'''param_grid = {
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
}

grid_search_rf = GridSearchCV(estimator=rf_clf, param_grid=param_grid, n_jobs=-1, verbose
=2, scoring='accuracy')
grid_search_rf.fit(X_train, y_train)

print(f"Best parameters found: {grid_search_rf.best_params_}")
print(f"Best cross-validation score: {grid_search_rf.best_score_:.2f}")
Output:
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best parameters found: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5}
Best cross-validation score: 0.95'''
```

Out[75]:

```
'param_grid = {\n    \'max_depth\': [10, 20, 30, None],\n    \'min_samples_split\': [2, 5
, 10],\n    \'min_samples_leaf\': [1, 2, 4],\n}\n\ngrid_search_rf = GridSearchCV(estimato
r=rf_clf, param_grid=param_grid, n_jobs=-1, verbose=2, scoring=\'accuracy\')\ngrid_search
_rf.fit(X_train, y_train)\n\nprint(f"Best parameters found: {grid_search_rf.best_params_}
")\nprint(f"Best cross-validation score: {grid_search_rf.best_score_:.2f}")\nOutput:\nFit
ting 5 folds for each of 36 candidates, totalling 180 fits\nBest parameters found: {\'max
_depth\': None, \'min_samples_leaf\': 1, \'min_samples_split\': 5}\nBest cross-validation
score: 0.95'
```

In [76]:

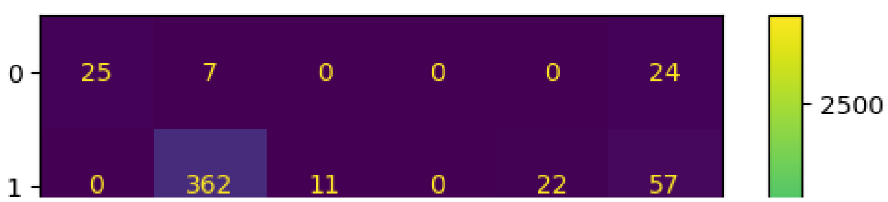
```
from sklearn.ensemble import RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=300, max_depth=None, min_samples_leaf=1, mi
n_samples_split=5,random_state=42)
eval_model(X_train, X_val, y_train, y_val, rf_clf)
```

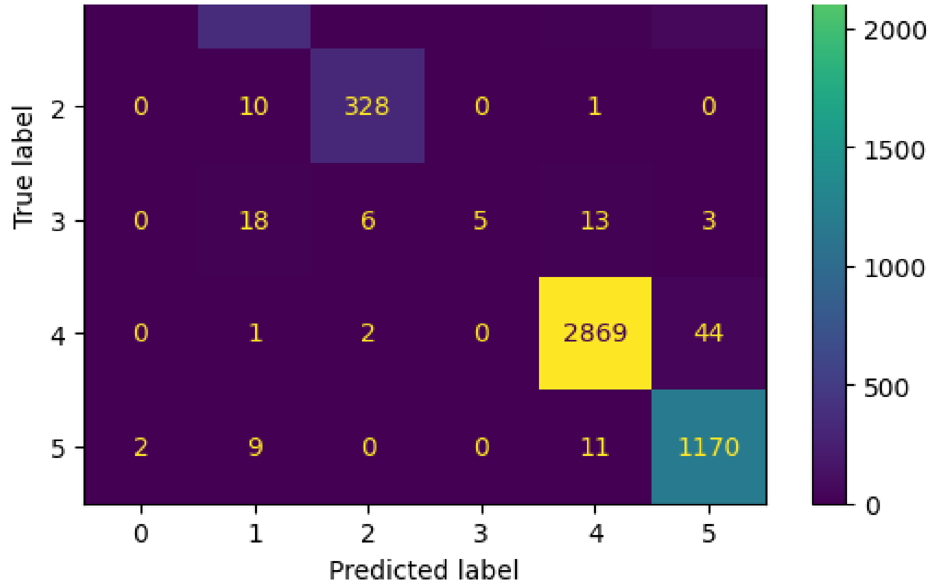
```
RandomForestClassifier(min_samples_split=5, n_estimators=300, random_state=42) 's Perform
ance:

Training Accuracy:  0.9950666666666667
Validation Accuracy:  0.9518

Training Recall:  0.9950666666666667
Validation Recall:  0.9518

Training Precision:  0.995092767059309
Validation Precision:  0.952553493368948
```






In [77]:

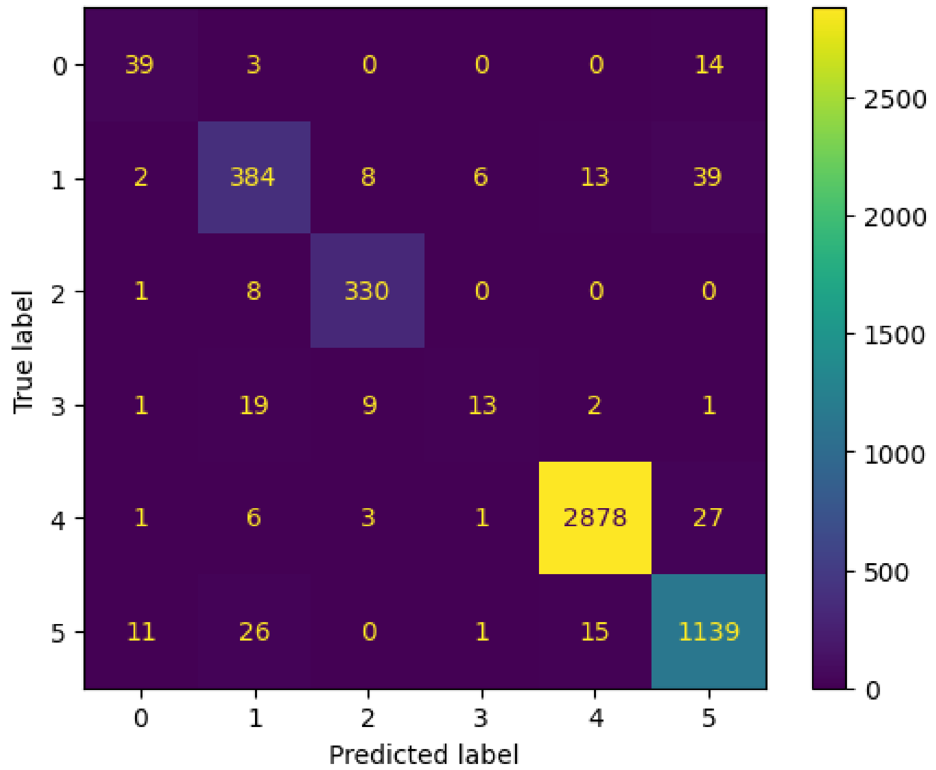
```
from sklearn.ensemble import GradientBoostingClassifier
gb_clf = GradientBoostingClassifier(n_estimators=300, min_samples_split=5, random_state=
42)
eval_model(X_train, X_val, y_train, y_val, gb_clf)
```

```
GradientBoostingClassifier(min_samples_split=5, n_estimators=300,
                           random_state=42) 's Performance:

Training Accuracy:  0.9860666666666666
Validation Accuracy:  0.9566

Training Recall:  0.9860666666666666
Validation Recall:  0.9566

Training Precision:  0.9861691888768132
Validation Precision:  0.9550274419843306
```




In [78]:

```
prediction = gb_clf.predict(test_data)
```

In [79]:

In [79]:

```
final_prediction = pd.DataFrame({'ID': range(1, len(prediction) + 1), 'Crime_Category': prediction})
final_prediction.to_csv('gb_sixth_submission.csv', index=False)
```