

```
In [1]: 1 import pandas as pd  
2 import matplotlib.pyplot as plt  
3 import numpy as np  
4 import seaborn as sns  
5 import plotly.express as px  
6 import warnings  
7 warnings.filterwarnings("ignore")
```

```
In [2]: 1 #Reading the csv file:  
2 df = pd.read_csv(r'C:\Users\Public\gun-violence-data.csv')
```

```
In [3]: 1 #Data set columns and records count:  
2 print("Number of Columns :",len(df.columns))  
3 print("Number of Records :",len(df))
```

Number of Columns : 29
Number of Records : 239677

```
In [4]: 1 #Displaying first five records:  
2 df.head()
```

Out[4]:

	incident_id	date	state	city_or_county	address	n_killed	n_injured	url
0	461105	2013-01-01	Pennsylvania	McKeesport	1506 Versailles Avenue and Coursin Street	0	4	http://www.g...
1	460726	2013-01-01	California	Hawthorne	13500 block of Cerise Avenue	1	3	http://www.g...
2	478855	2013-01-01	Ohio	Lorain	1776 East 28th Street	1	3	http://www.g...
3	478925	2013-01-05	Colorado	Aurora	16000 block of East Ithaca Place	4	0	http://www.g...
4	478959	2013-01-07	North Carolina	Greensboro	307 Mourning Dove Terrace	2	2	http://www.g...

5 rows × 29 columns

```
In [5]: 1 # Data preprocessing  
2 df = df.dropna()  
3 df = df.drop_duplicates(keep=False)
```

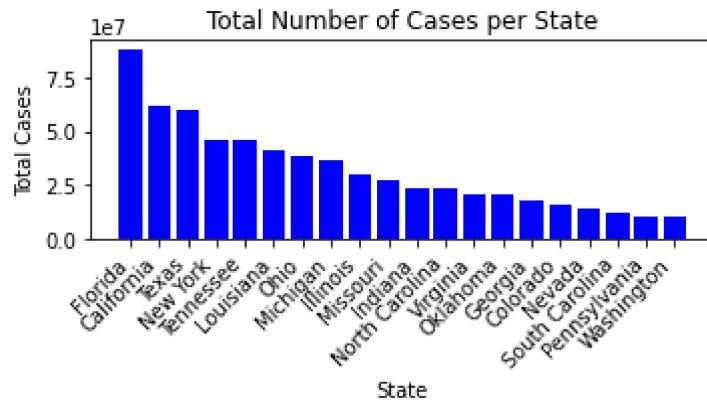
In [6]: 1 df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1059 entries, 36 to 239511
Data columns (total 29 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   incident_id      1059 non-null    int64  
 1   date              1059 non-null    object  
 2   state              1059 non-null    object  
 3   city_or_county    1059 non-null    object  
 4   address            1059 non-null    object  
 5   n_killed           1059 non-null    int64  
 6   n_injured          1059 non-null    int64  
 7   incident_url       1059 non-null    object  
 8   source_url         1059 non-null    object  
 9   incident_url_fields_missing 1059 non-null    bool   
 10  congressional_district 1059 non-null    float64 
 11  gun_stolen         1059 non-null    object  
 12  gun_type            1059 non-null    object  
 13  incident_characteristics 1059 non-null    object  
 14  latitude             1059 non-null    float64 
 15  location_description 1059 non-null    object  
 16  longitude            1059 non-null    float64 
 17  n_guns_involved     1059 non-null    float64 
 18  notes               1059 non-null    object  
 19  participant_age      1059 non-null    object  
 20  participant_age_group 1059 non-null    object  
 21  participant_gender    1059 non-null    object  
 22  participant_name      1059 non-null    object  
 23  participant_relationship 1059 non-null    object  
 24  participant_status     1059 non-null    object  
 25  participant_type       1059 non-null    object  
 26  sources              1059 non-null    object  
 27  state_house_district 1059 non-null    float64 
 28  state_senate_district 1059 non-null    float64 

dtypes: bool(1), float64(6), int64(3), object(19)
memory usage: 241.0+ KB
```

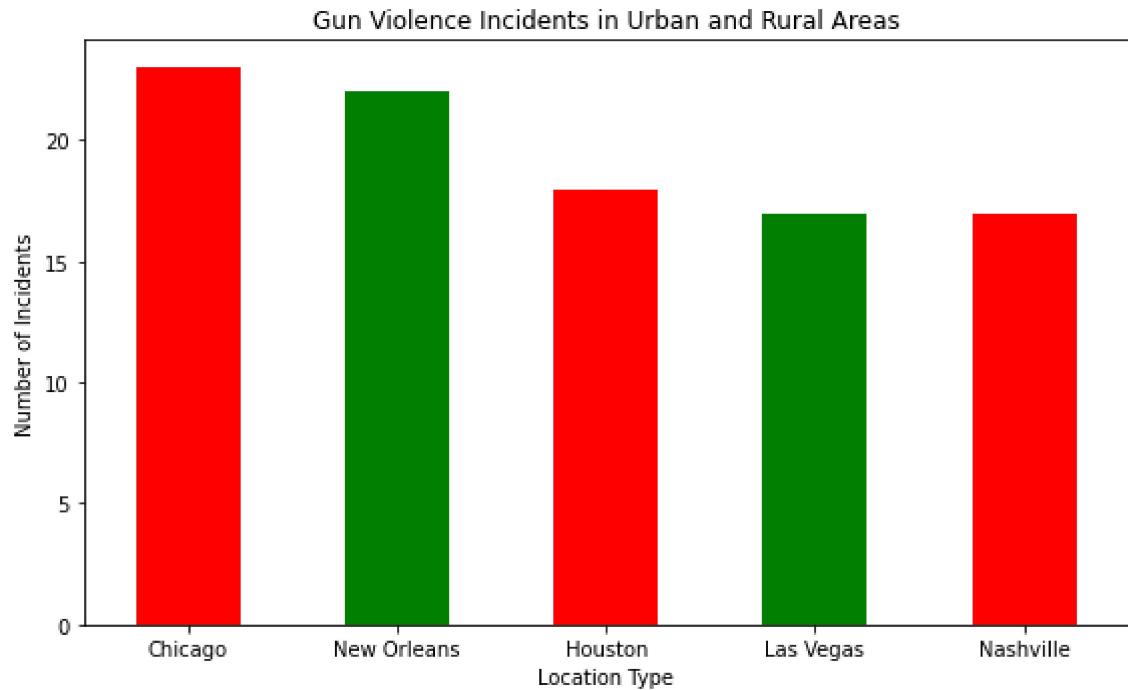
In [37]:

```
1 # How many cases have been registered in each state?
2 state_cases = df.groupby('state')[['incident_id']].sum().sort_values(ascending=True)
3
4 # Plotting the bar chart
5 plt.figure(figsize=(5, 3))
6 plt.bar(state_cases['state'], state_cases['incident_id'], color='blue')
7 plt.xlabel('State')
8 plt.ylabel('Total Cases')
9 plt.title('Total Number of Cases per State')
10 plt.xticks(rotation=45, ha='right') # Rotate x-axis labels for better readability
11 plt.tight_layout()
12
13 # Show the plot
14 plt.show()
```



In [8]: █

```
1 # Can you compare and contrast gun violence incidents between urban (ci
2 urban_vs_rural = df['city_or_county'].value_counts().head(5)
3
4 # Plotting the bar chart
5 plt.figure(figsize=(8, 5))
6 urban_vs_rural.plot(kind='bar', color=['red', 'green'])
7 plt.xlabel('Location Type')
8 plt.ylabel('Number of Incidents')
9 plt.title('Gun Violence Incidents in Urban and Rural Areas')
10 plt.xticks(rotation=0)
11 plt.tight_layout()
12
13 # Show the plot
14 plt.show()
```



```
In [9]: █ 1 #Determine if there's any correlation between the presence of specific
2 participant_statuses = {}
3
4 def participant_type_count(age_type):
5     if str(age_type) != 'nan':
6         ages = age_type.split("||")
7         if len(ages) == 1:
8             ages = ages[0].split("|")
9         for age in ages:
10             try:
11                 if age.split(':')[1] in participant_statuses.keys():
12                     participant_statuses[age.split(':')[1]] += 1
13                 else:
14                     participant_statuses[age.split(':')[1]] = 0
15             except:
16                 if age.split(':')[1] in participant_statuses.keys():
17                     participant_statuses[age.split(':')[1]] += 1
18                 else:
19                     participant_statuses[age.split(':')[1]] = 0
20
21
22 df['participant_status'].apply(participant_type_count);
23
24 participant_statuses = {k: v for k, v in sorted(participant_statuses.items(), key=lambda item: item[1], reverse=True)}
25 age_df = pd.DataFrame(participant_statuses.items(), columns = ['participant_status', 'Count'])
26 fig = px.bar(age_df, x='participant status', y='Count')
27 #fig.update_layout(xaxis_tickangle=45)
28 fig.show()
```

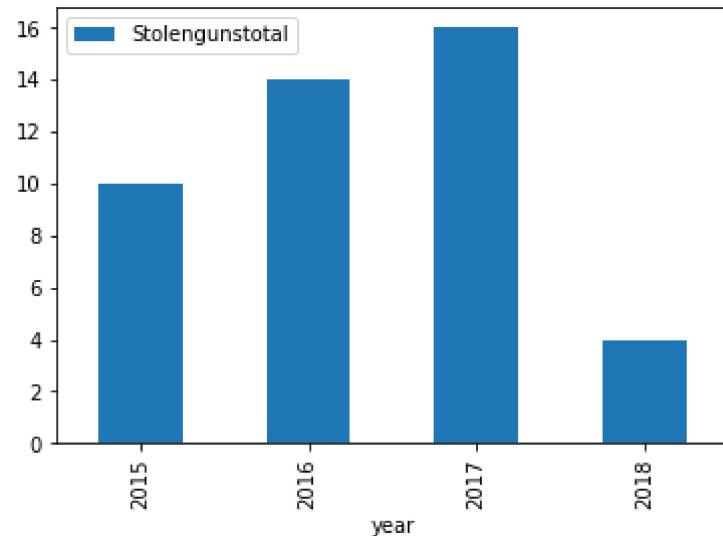
In [12]:

```
1 #Determine whether particular demographics are particularly susceptible
2 from collections import Counter
3 import re
4 from plotly.offline import download_plotlyjs, init_notebook_mode, plot,
5
6
7 total_incidents = []
8 for i, each_inc in enumerate(df['incident_characteristics'].fillna('Not
9     split_vals = [x for x in re.split('\|', each_inc) if len(x)>0]
10    total_incidents.append(split_vals)
11    if i == 0:
12        unique_incidents = Counter(split_vals)
13    else:
14        for x in split_vals:
15            unique_incidents[x] +=1
16
17 unique_incidents = pd.DataFrame.from_dict(unique_incidents, orient='in
18 colvals = unique_incidents[0].sort_values(ascending=False).index.values
19 find_val = lambda searchList, elem: [[i for i, x in enumerate(searchList)
20
21 a = np.zeros((df.shape[0], len(colvals)))
22 for i, incident in enumerate(total_incidents):
23     aval = find_val(colvals, incident)
24     a[i, np.array(aval)] = 1
25 incident = pd.DataFrame(a, index=df.index, columns=colvals)
26
27 prominent_incidents = incident.sum()[[4, 5, 6, 9, 10, 11, 13, 14, 15, 1
28                                         21, 23, 22, 24, 45, 51]]
29 fig = {
30     'data': [
31         {
32             'labels': prominent_incidents.index,
33             'values': prominent_incidents,
34             'type': 'pie',
35             'hoverinfo':'label+percent+name',
36             "domain": {"x": [0, .45]},
37         }
38     ],
39     'layout': {'title': 'Prominent Incidents of Gun Violence',
40               'showlegend': False, 'height':800, 'width':800}
41 }
42
43 iplot(fig)
```

In [13]:

```
1 # Determine whether cases using stolen guns differ from those involving
2 df['date']=pd.to_datetime(df['date'])
3 df['year'] = df['date'].dt.year
4 df['month']=df['date'].dt.month
5 df['gun_stolen'] = df['gun_stolen'].fillna('Null')
6
7 df['gun_stolen'] = df['gun_stolen'].str.replace(':::',',')
8 df['gun_stolen'] = df['gun_stolen'].str.replace('|',' ')
9 df['gun_stolen'] = df['gun_stolen'].str.replace(',',' ')
10 df['gun_stolen']= df['gun_stolen'].str.replace('\d+', ' ')
11
12
13 df['Stolenguns']=df['gun_stolen'].apply(lambda x: x.count('Stolen'))
14 df['stolenguns']=df['gun_stolen'].apply(lambda x: x.count('Stolen'))
15 df['Stolengunstotal'] = df['Stolenguns'] + df['stolenguns']
16
17 df_year_stolenguns = df[['year','Stolengunstotal']].groupby(['year'], as_index=False).sum()
18
19 df_year_stolenguns = df_year_stolenguns[df_year_stolenguns['Stolengunstotal'] > 0]
20 df_year_stolenguns[['year','Stolengunstotal']].set_index('year').plot(kind='bar')
```

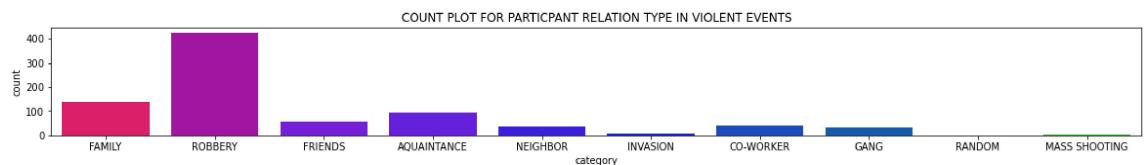
Out[13]: <AxesSubplot:xlabel='year'>



In [44]:

```
1 # To identify participant relation type in violent events
2 relation = df['participant_relationship']
3 relation = relation[relation.notnull()]
4 relation = relation.str.replace("[\d]", " ").str.upper()
5 relation1 = pd.DataFrame({"count": [len(relation[relation.str.contains("FAMILY"))],
6 len(relation[relation.str.contains("ROBBERY"))]),
7 len(relation[relation.str.contains("FRIENDS"))]),
8 len(relation[relation.str.contains("AQUAINTANCE"))]),
9 len(relation[relation.str.contains("NEIGHBOR"))]),
10 len(relation[relation.str.contains("INVASION"))]),
11 len(relation[relation.str.contains("CO-WORKER"))]),
12 len(relation[relation.str.contains("GANG"))]),
13 len(relation[relation.str.contains("RANDOM"))]),
14 len(relation[relation.str.contains("MASS SHOOTING"))]),
15 "category":["FAMILY", "ROBBERY", "FRIENDS", "AQUAINTANCE", "NEIGHBOR", "INVASION", "CO-WORKER", "GANG", "RANDOM", "MASS SHOOTING"]})
16 relation1
17 plt.figure(figsize=(20,2))
18 sns.barplot("category", "count", data=relation1, palette="prism")
19 plt.title("COUNT PLOT FOR PARTICPANT RELATION TYPE IN VIOLENT EVENTS")
```

Out[44]: Text(0.5, 1.0, 'COUNT PLOT FOR PARTICPANT RELATION TYPE IN VIOLENT EVENTS')

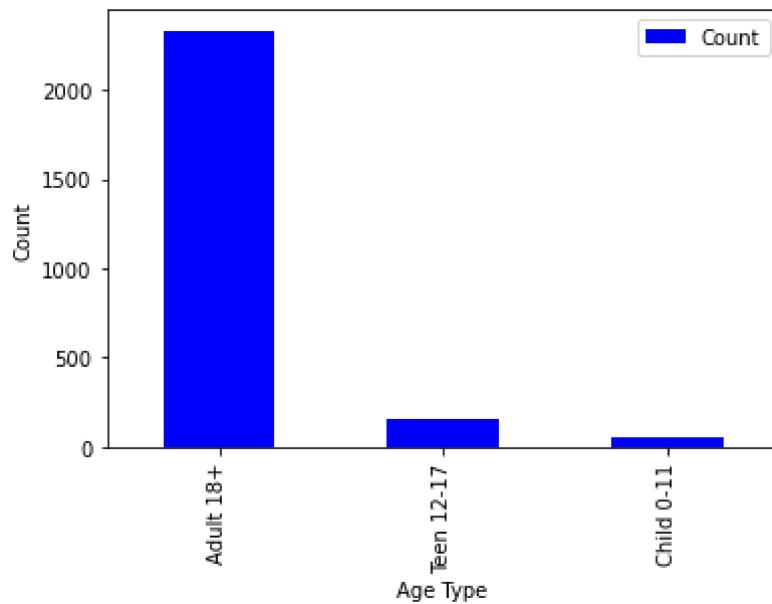


```
In [15]: ❶ 1 age_types = {}
2
3 def age_count(age_type):
4     if str(age_type) != 'nan':
5         ages = age_type.split("||")
6         if len(ages) == 1:
7             ages = ages[0].split("|")
8         for age in ages:
9             try:
10                 if age.split(':')[1] in age_types.keys():
11                     age_types[age.split(':')[1]] += 1
12                 else:
13                     age_types[age.split(':')[1]] = 0
14             except:
15                 if age.split(':')[1] in age_types.keys():
16                     age_types[age.split(':')[1]] += 1
17                 else:
18                     age_types[age.split(':')[1]] = 0
19
20
21 df['participant_age_group'].apply(age_count)
```

```
Out[15]: 36      None
83      None
101     None
181     None
200     None
...
239279  None
239297  None
239335  None
239506  None
239511  None
Name: participant_age_group, Length: 1059, dtype: object
```

In [16]:

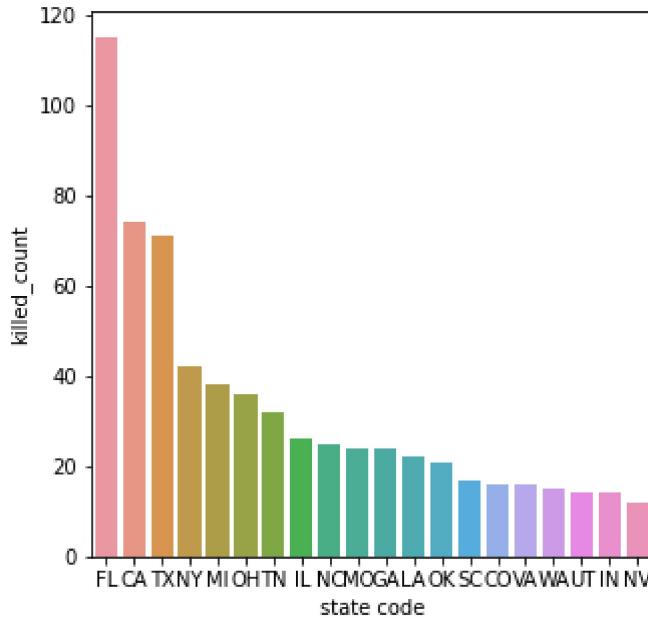
```
1 # Identify what particular ages are particularly engaged in these types
2 age_types = {k: v for k, v in sorted(age_types.items(), key=lambda item: item[1], reverse=True)}
3 age_df = pd.DataFrame(age_types.items(), columns = ['Age Type', 'Count'])
4 fig = px.bar(age_df, x='Age Type', y='Count')
5
6 age_df.plot(kind='bar', x='Age Type', y='Count', color='Blue')
7
8 # Add Labels and title
9 plt.xlabel('Age Type')
10 plt.ylabel('Count')
11 plt.show()
12 #fig.update_layout(xaxis_tickangle=45)
13 #fig.show()
```



In [31]:

```
1 # Find the overall amount of people murdered or killed in each state.
2 states = {'Alabama': 'AL', 'Alaska': 'AK', 'American Samoa': 'AS', 'Arizona': 'AZ', 'Arkansas': 'AR', 'California': 'CA', 'Colorado': 'CO', 'Connecticut': 'CT', 'Delaware': 'DE', 'Florida': 'FL', 'Georgia': 'GA', 'Hawaii': 'HI', 'Idaho': 'ID', 'Illinois': 'IL', 'Indiana': 'IN', 'Iowa': 'IA', 'Kansas': 'KS', 'Kentucky': 'KY', 'Louisiana': 'LA', 'Maine': 'ME', 'Maryland': 'MD', 'Massachusetts': 'MA', 'Michigan': 'MI', 'Minnesota': 'MN', 'Mississippi': 'MS', 'Missouri': 'MO', 'Montana': 'MT', 'Nebraska': 'NE', 'Nevada': 'NV', 'New Hampshire': 'NH', 'New Jersey': 'NJ', 'New Mexico': 'NM', 'New York': 'NY', 'North Carolina': 'NC', 'North Dakota': 'ND', 'Ohio': 'OH', 'Oklahoma': 'OK', 'Oregon': 'OR', 'Pennsylvania': 'PA', 'Rhode Island': 'RI', 'South Carolina': 'SC', 'South Dakota': 'SD', 'Tennessee': 'TN', 'Texas': 'TX', 'Utah': 'UT', 'Vermont': 'VT', 'Virginia': 'VA', 'Washington': 'WA', 'West Virginia': 'WV', 'Wisconsin': 'WI', 'Wyoming': 'WY'}
3
4 df['state code'] = df['state'].apply(lambda x : states[x])
5 df_out = df.groupby('state code')['n_killed'].sum().sort_values(ascending=True)
6 df_out.rename(columns={'n_killed': 'killed_count'}, inplace=True)
7 top_10_states = df_out.head(20)
8 plt.figure(figsize=(5,5))
9 sns.barplot(x='state code', y='killed_count', data=top_10_states)
```

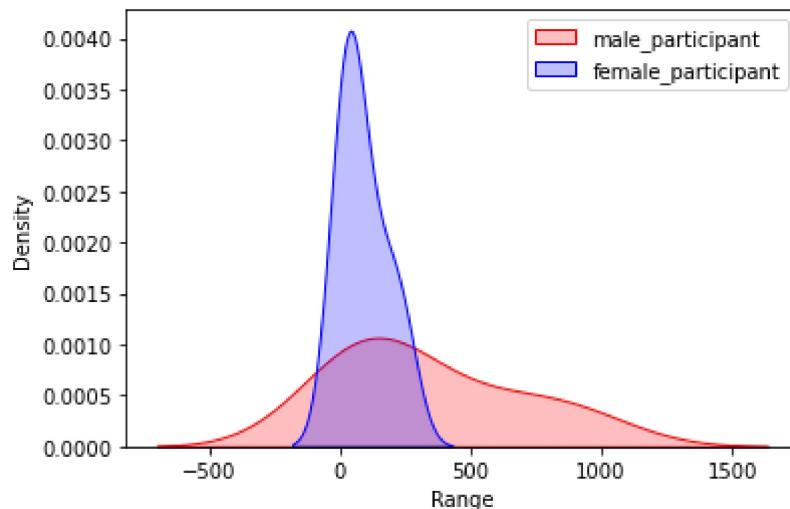
Out[31]: <AxesSubplot:xlabel='state code', ylabel='killed_count'>



In [18]:

```
1 # Identify which age group plays the biggest part in this violence.
2 df["participant_gender"] = df["participant_gender"].fillna("0::Unknown")
3
4 def gen(n) :
5     gen_rows = []
6     gen_row = str(n).split("||")
7     for i in gen_row :
8         g_row = str(i).split("::")
9         if len(g_row) > 1 :
10             gen_rows.append(g_row[1])
11
12     return gen_rows
13
14 gen_series = df.participant_gender.apply(gen)
15 df["total_participant"] = gen_series.apply(lambda x: len(x))
16 df["male_participant"] = gen_series.apply(lambda i: i.count("Male"))
17 df["female_participant"] = gen_series.apply(lambda i: i.count("Female"))
18 df["unknown_participant"] = gen_series.apply(lambda i: i.count("Unknown"))
19
20 genderwise_total = df[['total_participant', 'male_participant', 'female_participant']]
21 dp_gen_plot=sns.kdeplot(genderwise_total['male_participant'], shade=True)
22 dp_gen_plot=sns.kdeplot(genderwise_total['female_participant'], shade=True)
23 plt.legend()
24 plt.xlabel('Range')
25 #del(genderwise_total)
```

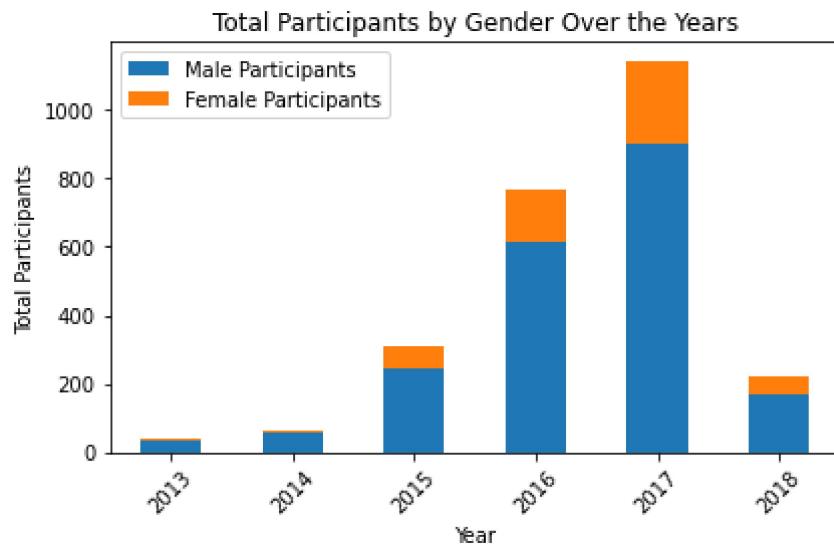
Out[18]: Text(0.5, 0, 'Range')



In [19]:

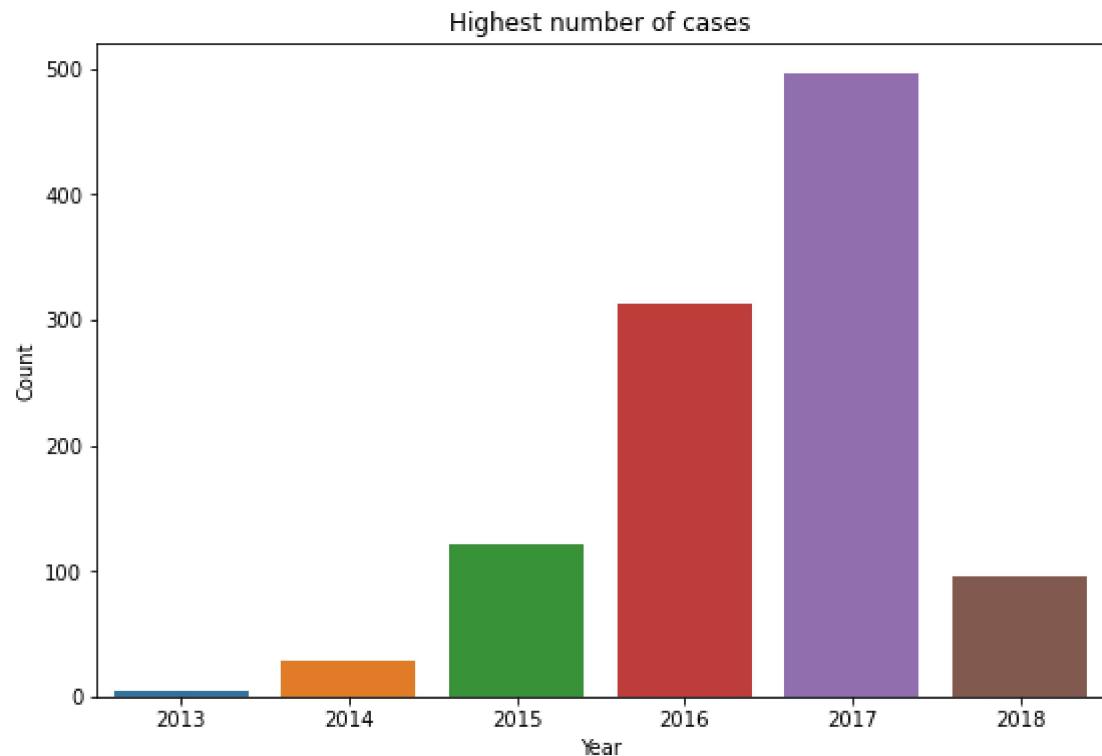
```
1 plt.figure(figsize=(10, 6))
2 genderwise_total[['male_participant', 'female_participant']].plot(kind=
3 plt.xlabel('Year')
4 plt.ylabel('Total Participants')
5 plt.title('Total Participants by Gender Over the Years')
6 plt.xticks(rotation=45)
7 plt.legend(['Male Participants', 'Female Participants'])
8 plt.tight_layout()
9 plt.show()
```

<Figure size 720x432 with 0 Axes>



In [20]:

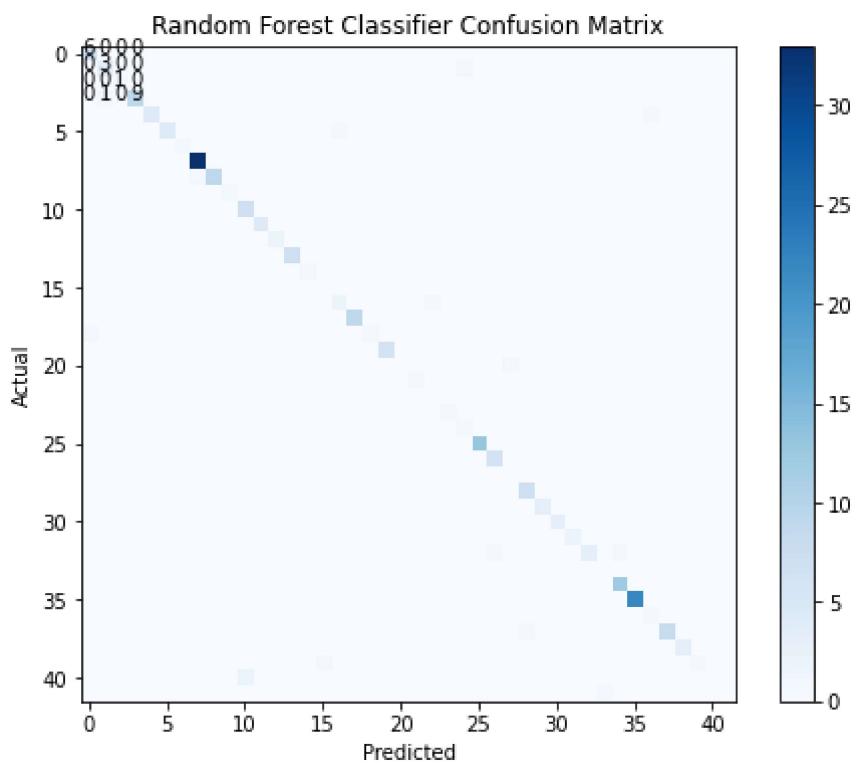
```
1 # In which year did the most cases occur?
2 df['date']=pd.to_datetime(df['date'])
3 df['year'] = df['date'].dt.year
4 df['month']=df['date'].dt.month
5
6
7 plt.figure(figsize=(9,6))
8 sns.countplot(x='year', data=df)
9 plt.xlabel('Year')
10 plt.ylabel('Count')
11 plt.title('Highest number of cases')
12
13 # Show the plot
14 plt.show()
```



In [21]:

```
1 from sklearn.ensemble import RandomForestClassifier
2 from sklearn.metrics import accuracy_score, confusion_matrix
3 from sklearn.model_selection import train_test_split
4
5 # Define features and target variable
6 X = df[['n_killed', 'n_injured', 'congressional_district', 'latitude',
7 y = df['state']
8
9 # Split data into train and test sets
10 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
11
12 # Initialize and train the Random Forest model
13 rf_model = RandomForestClassifier()
14 rf_model.fit(X_train, y_train)
15
16 # Make predictions
17 y_pred = rf_model.predict(X_test)
18
19 # Evaluate the model
20 accuracy = accuracy_score(y_test, y_pred)
21 print(f'Random Forest Classifier Accuracy: {accuracy:.2f}')
22
23 # Plot confusion matrix
24 cm = confusion_matrix(y_test, y_pred)
25 plt.figure(figsize=(8, 6))
26 plt.imshow(cm, cmap='Blues', interpolation='nearest')
27 plt.title('Random Forest Classifier Confusion Matrix')
28 plt.colorbar()
29 #plt.xticks(ticks=range(len(df['state'].unique()))), labels=df['state'].unique())
30 #plt.yticks(ticks=range(len(df['state'].unique()))), labels=df['state'].unique())
31 plt.xlabel('Predicted')
32 plt.ylabel('Actual')
33 for i in range(len(df['state'].head(5).unique())):
34     for j in range(len(df['state'].head(5).unique())):
35         plt.text(j, i, format(cm[i, j], 'd'), horizontalalignment="center")
36 plt.show()
```

Random Forest Classifier Accuracy: 0.93

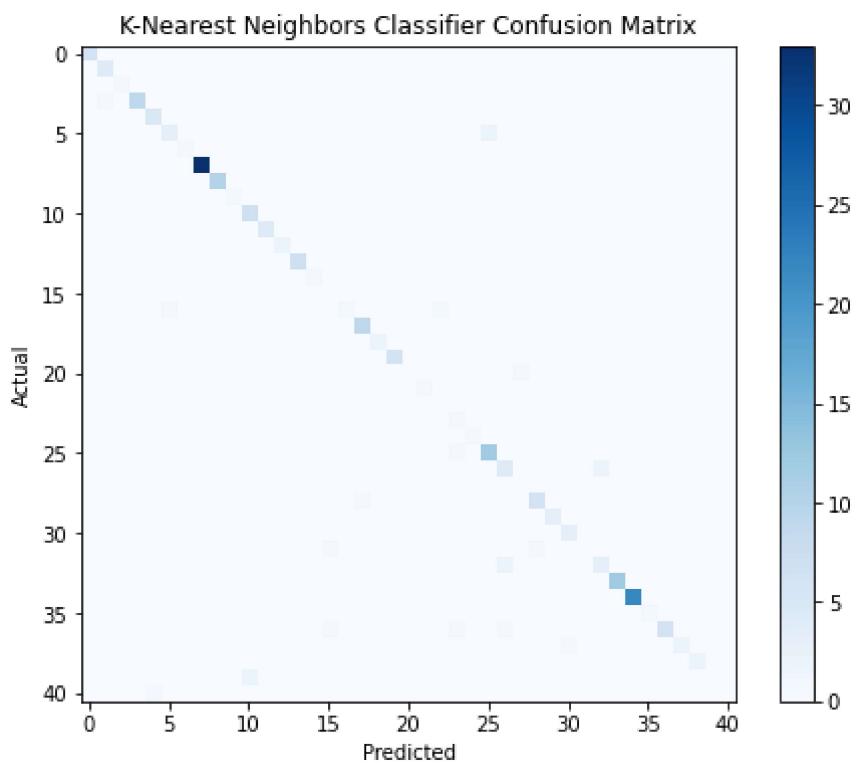


In [22]:

```
1 from sklearn.neighbors import KNeighborsClassifier
2
3 # Initialize and train the K-Nearest Neighbors model
4 knn_model = KNeighborsClassifier()
5 knn_model.fit(X_train, y_train)
6
7 # Make predictions
8 y_pred = knn_model.predict(X_test)
9
10 # Evaluate the model
11 accuracy = accuracy_score(y_test, y_pred)
12 print(f'K-Nearest Neighbors Classifier Accuracy: {accuracy:.2f}')
13
14 # Plot confusion matrix
15 cm = confusion_matrix(y_test, y_pred)
16 plt.figure(figsize=(8, 6))
17 plt.imshow(cm, cmap='Blues', interpolation='nearest')
18 plt.title('K-Nearest Neighbors Classifier Confusion Matrix')
19 plt.colorbar()
20 #plt.xticks(ticks=range(len(data['state'].unique()))), labels=data['stat
21 #plt.yticks(ticks=range(len(data['state'].unique()))), labels=data['stat
22 plt.xlabel('Predicted')
23 plt.ylabel('Actual')
24 for i in range(len(data['state'].head(5).unique())):
25     for j in range(len(data['state'].head(5).unique())):
26         plt.text(j, i, format(cm[i, j], 'd'), horizontalalignment="center",
27 plt.show()
28
```

K-Nearest Neighbors Classifier Accuracy: 0.90

```
-----
-
NameError: name 'data' is not defined                                     Traceback (most recent call last)
t)
~\AppData\Local\Temp\ipykernel_24236\4187023220.py in <module>
    22 plt.xlabel('Predicted')
    23 plt.ylabel('Actual')
--> 24 for i in range(len(data['state'].head(5).unique())):
    25     for j in range(len(data['state'].head(5).unique())):
    26         plt.text(j, i, format(cm[i, j], 'd'), horizontalalignment="center",
="center", color="white" if cm[i, j] > cm.max() / 2 else "black")
```



In [31]:

```
1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
3
4 # Select the relevant columns
5 data = df[['state', 'n_killed']]
6
7 # Group the data by state and calculate the total number of killings for each state
8 state_killed = data.groupby('state')['n_killed'].sum().reset_index()
9
10 # Convert the 'state' column into dummy variables (one-hot encoding)
11 state_dummies = pd.get_dummies(state_killed['state'], drop_first=True)
12
13 # Concatenate the dummy variables with the 'n_killed' column
14 X = pd.concat([state_dummies, state_killed['n_killed']], axis=1)
15
16 # Split the data into features (X) and target variable (y)
17 y = state_killed['n_killed']
18
19 # Initialize and train the Linear Regression model
20 model = LinearRegression()
21 model.fit(X, y)
22
23 # Print the coefficients
24 print('Intercept:', model.intercept_)
25 print('Coefficients:', model.coef_)
26
27 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
28 model = LinearRegression()
29 model.fit(X_train, y_train)
30 train_predictions = model.predict(X_train)
31
32 # Evaluate the model
33 #accuracy = accuracy_score(y_test, y_pred)
34 #print(f'Linear Regression Accuracy: {accuracy:.2f}')
35
36 # Evaluate the model on the training set
37 train_mae = mean_absolute_error(y_train, train_predictions)
38 train_mse = mean_squared_error(y_train, train_predictions)
39 train_r2 = r2_score(y_train, train_predictions)
40 print('Training Set Metrics:')
41 print('MAE:', train_mae)
42 print('MSE:', train_mse)
43 print('R-squared:', train_r2)
44
45 # Make predictions on the testing set
46 test_predictions = model.predict(X_test)
47
48 # Evaluate the model on the testing set
49 test_mae = mean_absolute_error(y_test, test_predictions)
50 test_mse = mean_squared_error(y_test, test_predictions)
51 test_r2 = r2_score(y_test, test_predictions)
52 print('\nTesting Set Metrics:')
53 print('MAE:', test_mae)
54 print('MSE:', test_mse)
```

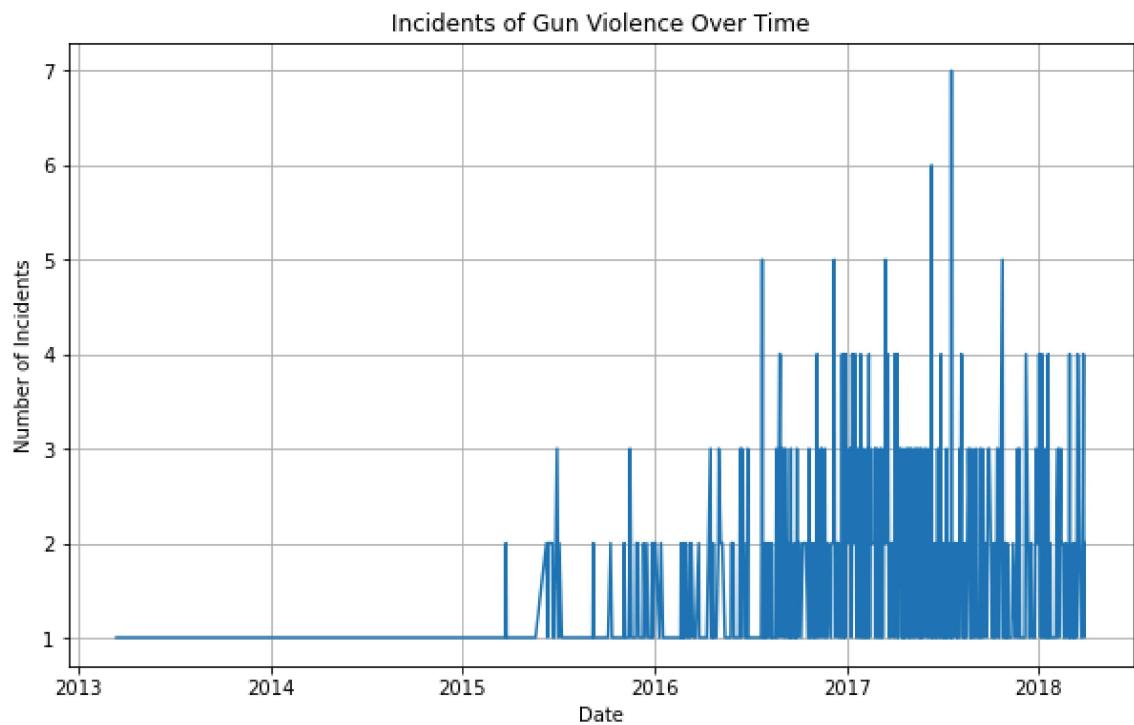
```
55 | print('R-squared:', test_r2)
```

```
Intercept: 0.00041373603639627277
Coefficients: [-2.89615225e-04 -4.13736036e-05 -2.89615225e-04 2.64791063
e-03
               2.48241622e-04 -1.24120811e-04 -3.30988829e-04 4.34422838e-03
               5.79230451e-04 -2.89615225e-04 1.59726988e-14 6.61977658e-04
               1.65494415e-04 -2.06868018e-04 -3.30988829e-04 -3.30988829e-04
               4.96483244e-04 -3.72362433e-04 -2.89615225e-04 -2.06868018e-04
               1.15846090e-03 8.27472073e-05 5.79230451e-04 -3.72362433e-04
               8.27472073e-05 -2.89615225e-04 4.13736037e-05 -8.27472073e-05
               1.32395532e-03 6.20604055e-04 -2.89615225e-04 1.07571369e-03
               4.55109640e-04 -8.27472073e-05 -1.24120811e-04 -3.30988829e-04
               2.89615225e-04 -4.13736036e-04 9.10219280e-04 2.52378982e-03
               1.65494415e-04 2.48241622e-04 2.06868018e-04 -2.48241622e-04
               -1.24120811e-04 -4.13736036e-04 9.99958626e-01]
Training Set Metrics:
MAE: 3.19776639946174e-15
MSE: 1.5254969233101717e-29
R-squared: 1.0

Testing Set Metrics:
MAE: 0.0007397303394362176
MSE: 1.4061917316493295e-06
R-squared: 0.9999999968646085
```

In [24]:

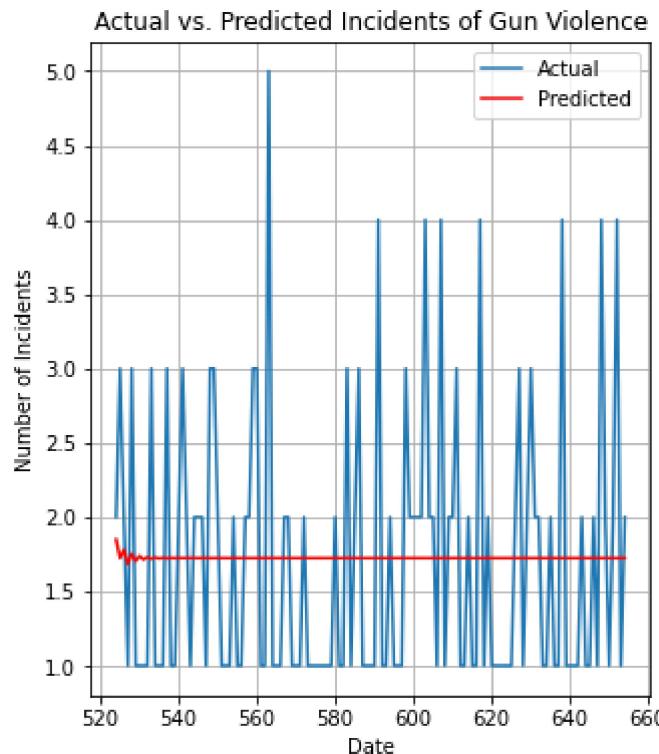
```
1 from statsmodels.tsa.arima.model import ARIMA
2 from sklearn.metrics import mean_squared_error
3
4 df['date'] = pd.to_datetime(df['date'])
5
6 # Group the data by date and count the number of incidents for each date
7 time_series_data = df.groupby('date').size().reset_index(name='incident_count')
8
9 # Set 'date' column as the index
10 time_series_data.set_index('date', inplace=True)
11
12 # Plot the time series data
13 plt.figure(figsize=(10, 6))
14 plt.plot(time_series_data.index, time_series_data['incident_count'])
15 plt.title('Incidents of Gun Violence Over Time')
16 plt.xlabel('Date')
17 plt.ylabel('Number of Incidents')
18 plt.grid(True)
19 plt.show()
```



In [25]:

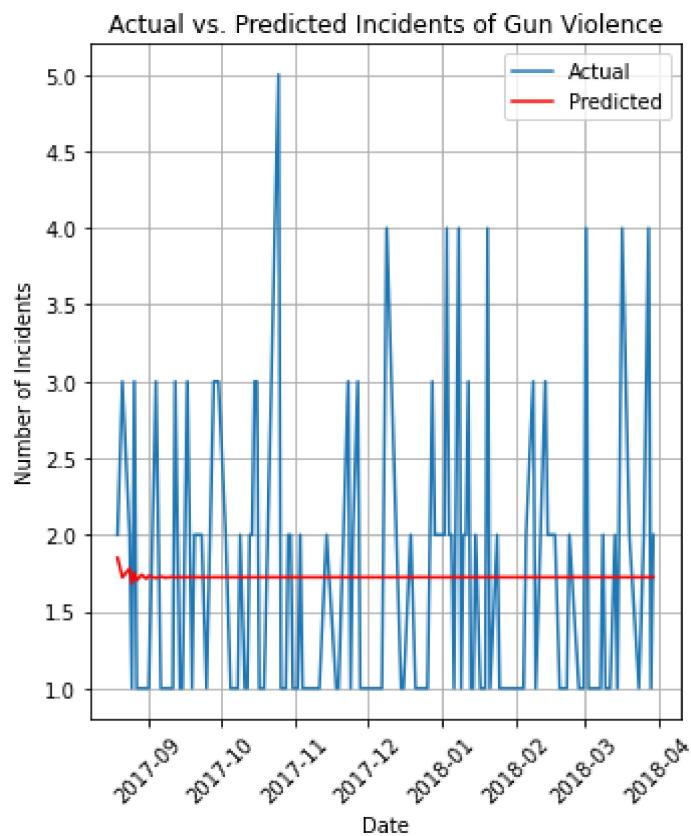
```
1 # Perform Time-Series Analysis
2 # Reset the index to ensure sequential indexing
3 time_series_data.reset_index(inplace=True)
4
5 # Split the data into training and testing sets
6 train_size = int(0.8 * len(time_series_data))
7 train_data = time_series_data.iloc[:train_size]
8 test_data = time_series_data.iloc[train_size:]
9
10 # Define and train the ARIMA model
11 order = (1, 1, 4) # Example order for ARIMA model (p, d, q)
12 model = ARIMA(train_data['incident_count'], order=order)
13 arima_model = model.fit()
14
15 # Make predictions for the testing set
16 predictions = arima_model.forecast(steps=len(test_data))
17
18 # Calculate Mean Squared Error (MSE)
19 mse = mean_squared_error(test_data['incident_count'], predictions)
20 print('Mean Squared Error (MSE):', mse)
21
22 # Plot the actual vs. predicted values
23 plt.figure(figsize=(5, 6))
24 plt.plot(test_data.index, test_data['incident_count'], label='Actual')
25 plt.plot(test_data.index, predictions, label='Predicted', color='red')
26 plt.title('Actual vs. Predicted Incidents of Gun Violence')
27 plt.xlabel('Date')
28 plt.ylabel('Number of Incidents')
29 plt.legend()
30 plt.grid(True)
31 plt.show()
```

Mean Squared Error (MSE): 0.84925056608664



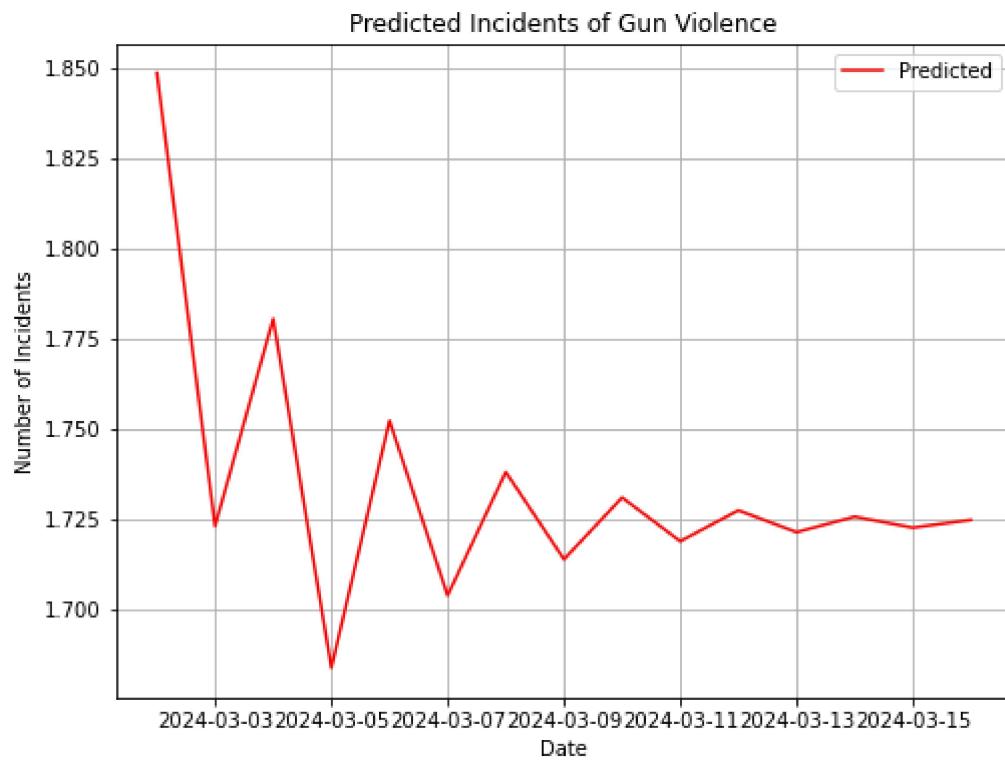
In [30]:

```
1 plt.figure(figsize=(5, 6))
2 plt.plot(test_data['date'], test_data['incident_count'], label='Actual')
3 plt.plot(test_data['date'], predictions, label='Predicted', color='red')
4 plt.title('Actual vs. Predicted Incidents of Gun Violence')
5 plt.xlabel('Date')
6 plt.ylabel('Number of Incidents')
7 plt.legend()
8 plt.grid(True)
9 plt.xticks(rotation=45) # Rotate x-axis labels for better readability
10 plt.tight_layout()
11 plt.show()
```



In [97]:

```
1 ## Total Crime Incidents Predictions For Future Days:  
2 today = pd.Timestamp.now().normalize()  
3  
4 # Define Future Dates  
5 future_dates = pd.date_range(start=today, periods=15, freq='D')  
6  
7 # Generate Forecast  
8 forecast = arima_model.forecast(steps=len(future_dates))  
9  
10 # Create DataFrame for Predictions  
11 predicted_df = pd.DataFrame({  
12     'Date': future_dates,  
13     'Predicted Incidents': forecast  
14 })  
15  
16 # Plot Predictions  
17 plt.figure(figsize=(8, 6))  
18 #plt.plot(time_series_data.index, time_series_data['incident_count'], l  
19 plt.plot(predicted_df['Date'], predicted_df['Predicted Incidents'], la  
20 plt.title('Predicted Incidents of Gun Violence')  
21 plt.xlabel('Date')  
22 plt.ylabel('Number of Incidents')  
23 plt.legend()  
24 plt.grid(True)  
25 plt.show()  
26  
27 # Display Predicted DataFrame  
28 print(predicted_df)  
29
```



	Date	Predicted Incidents
524	2024-03-02	1.848574
525	2024-03-03	1.723093
526	2024-03-04	1.780517
527	2024-03-05	1.683842
528	2024-03-06	1.752223
529	2024-03-07	1.703855
530	2024-03-08	1.738068
531	2024-03-09	1.713868
532	2024-03-10	1.730985
533	2024-03-11	1.718877
534	2024-03-12	1.727442
535	2024-03-13	1.721384
536	2024-03-14	1.725669
537	2024-03-15	1.722638
538	2024-03-16	1.724782