Calgary Crime Data Analysis and Neural Network Prediction

The aim of this project is to use the Crime and Disorder Data provided by the City of Calgary's data website to analyze the data and predict the number of crimes that will occur in the future. The data is from 2018 to 2024 and contains the number of crimes that occurred in Calgary for each month. After throughly analyzing the data, I will be building a neural network model and optimizing it to predict the number of crimes that will occur in the future.

Data Dictionary

Column Name	Description
Community Name	The name of the community in Calgary
Category	The type of crime that occurred
Crime Count	The number of crimes that occurred in that month
Year	The year the crime occurred
Month	The month the crime occurred

Strategy

1. Loading the data and understanding the data
2. Data Preprocessing - cleaing the data and preparing it for analysis
3. Exploratory Data Analysis - Analyzing the data to understand the trends and patterns
4. Building a Neural Network Model
5. Optimizing the model
6. Training the model
7. Predicting the number of crimes that will occur in the future

In [ ]:
```
#Importing the Libraries import
numpy as np import
matplotlib.pyplot as plt import
pandas as pd import seaborn as
sns
```

In [ ]:
```
#Loading the dataset df =
pd.read_csv('/content/Community_Crime_Statistics_20240522.csv')
df.head()
```

Out[ ]:

	Community	Category	Crime Count	Year	Month
0	01B	Assault (Non-domestic)	1	2022	11
1	01B	Break & Enter - Commercial	1	2019	6
2	01B	Break & Enter - Commercial	1	2019	8
3	01B	Break & Enter - Commercial	2	2020	3
4	01B	Break & Enter - Commercial	2	2020	7

Here the is the representation of first 5 records of the data, which gives a brief informaton about the data. Since the dataset is alphabetically sorted by the community name, the data is not in a chronological order.

Data Preprocessing

In [ ]:
```
#shape of the dataset df.shape
```

Out[ ]:
```
(70661, 5)
```

Here we have bearly 70661 records and 5 columns. Therefore, we have enough data for preparing an analysis and developing a model for prediction.

In [ ]:
```
#checking for missing values
df.isnull().sum()
```

Out[ ]:
```
Community      0 Category
 0
 Crime Count    0
 Year           0
 Month          0
 dtype: int64
```

The dataset is pretty clean and does not have any missing values.

In [ ]:
```
#checking for the datatypes
df.dtypes
```

Out[ ]:
```
Community      object Category
 object
 Crime Count     int64
 Year            int64
 Month           int64
 dtype: object
```

Making sure that the columns have correct datatype, before I proceed with the analysis.

In [ ]:
```
#Descriptive statistics
df.describe()
```

Out[ ]:

	Crime Count	Year	Month
count	70661.000000	70661.000000	70661.000000

mean	2.855748	2020.618616	6.369242
std	3.664965	1.825330	3.451445
min	1.000000	2018.000000	1.000000
25%	1.000000	2019.000000	3.000000
50%	2.000000	2021.000000	6.000000
75%	3.000000	2022.000000	9.000000
max	111.000000	2024.000000	12.000000

Exploratory Data Analysis

In the exploraotry data analysis, I will be analyzing the data to understand the trends and patterns in the data. Through this analysis, I will be able to understand the data better and build a better model for prediction.

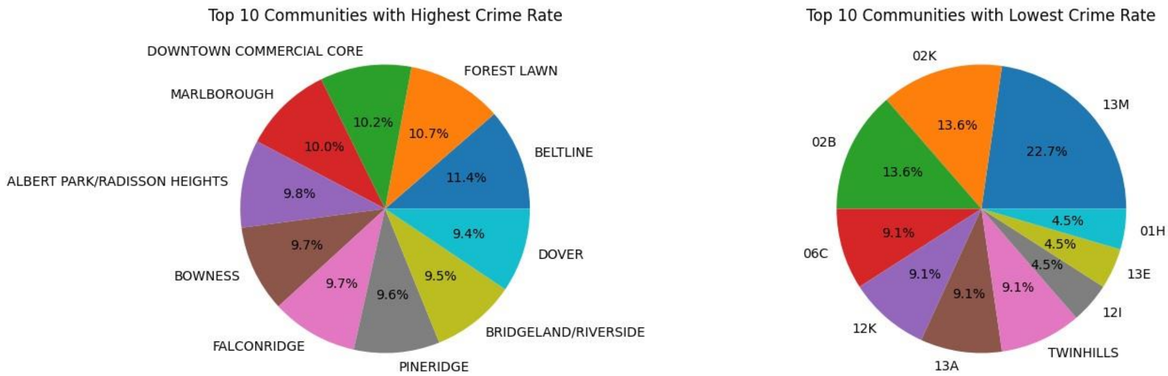
Community Distribution

In [ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 5))

#Top 10 Communities with Highest Crime Rate
df['Community'].value_counts().head(10).plot.pie(autopct='%1.1f%%', ax = ax[0])
ax[0].set_title('Top 10 Communities with Highest Crime Rate') ax[0].set_ylabel('')

#Top 10 Communities with Lowest Crime Rate
df['Community'].value_counts().tail(10).plot.pie(autopct='%1.1f%%', ax = ax[1])
ax[1].set_title('Top 10 Communities with Lowest Crime Rate') ax[1].set_ylabel('')
```

Out[ ]:
```
Text(0, 0.5, '')
```



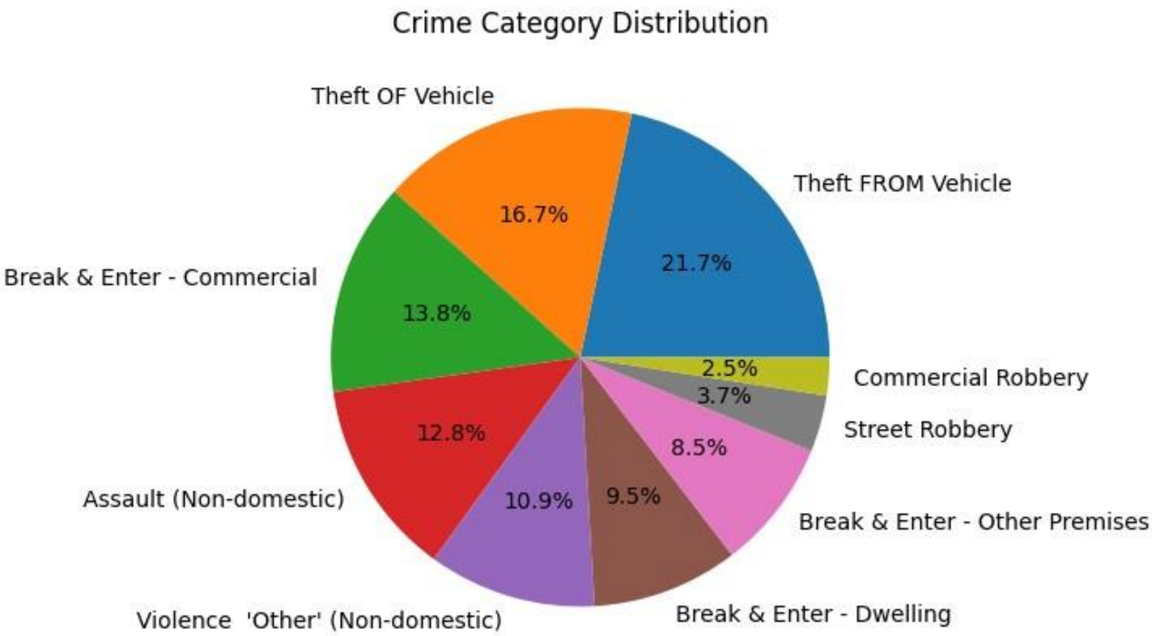
These pie charts show the distribution of crimes in each community. The first pie chart shows the top 10 most dangerous communities in Calgary. The second pie chart shows the distribution of top 10 safest communities in Calgary. In the first pie chart, Beltline is the most dangerous community in Calgary with 11.4% of the top crimes in number, followed by Forest Lawn with 10.7% and Downtown Commercial Core with 10.2%. In the second pie chart, the safest community is 13M with 22.7% of the least crimes in number, followed by 02K with 13.6% and 02B with 13.6%.

This is note that all these observations are without any bias and completely based on the data from the city of Calgary website.

Crime Category Distribution

```
In [ ]: plt.figure(figsize=(5, 5))
        df['Category'].value_counts().plot.pie(autopct='%1.1f%%')
        plt.title('Crime Category Distribution') plt.ylabel('')
```

```
Out[ ]:  Text(0, 0.5, '')
```

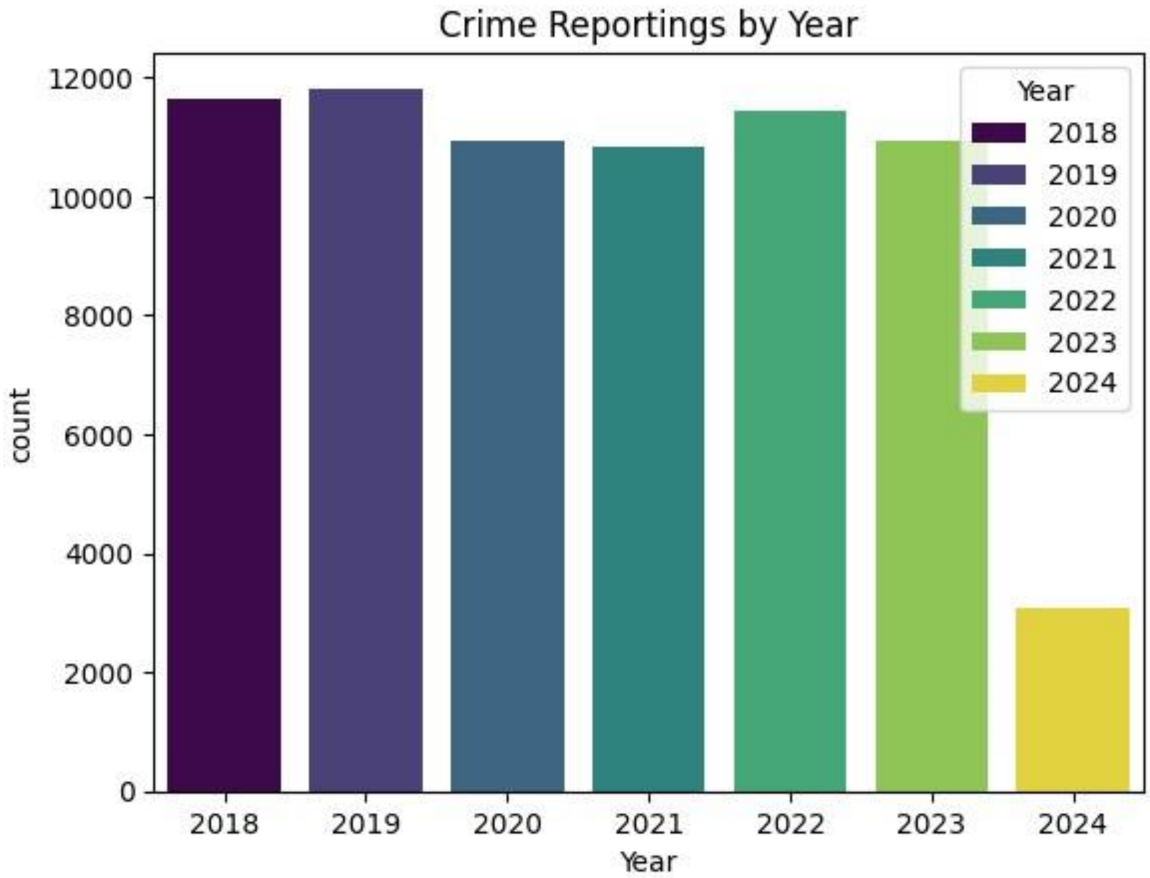


This graph shows the distribution of crimes in each category by the number of crimes. The top crime category is Theft from Vehicle with 21.7% of the total crimes, followed by Theft of Vehicle with 16.7% and Break and Enter - Commercial with 13.8%. The least crime category inc;udes commerical or street robbery.

Crime Reportings Over the Years

```
In [ ]:( sns.countplot(x = 'Year', data = df, hue = 'Year', palette='viridis').set_title
```

```
Out[ ]: Text(0.5, 1.0, 'Crime Reportings by Year')
```



This bar graph shows the distribution of number of crimes reported in the year. The year 2019 had the highest reportings of crimes followed by 2022 and 2018. The crime reportings in 2024 are less due to limited data till April 2024.

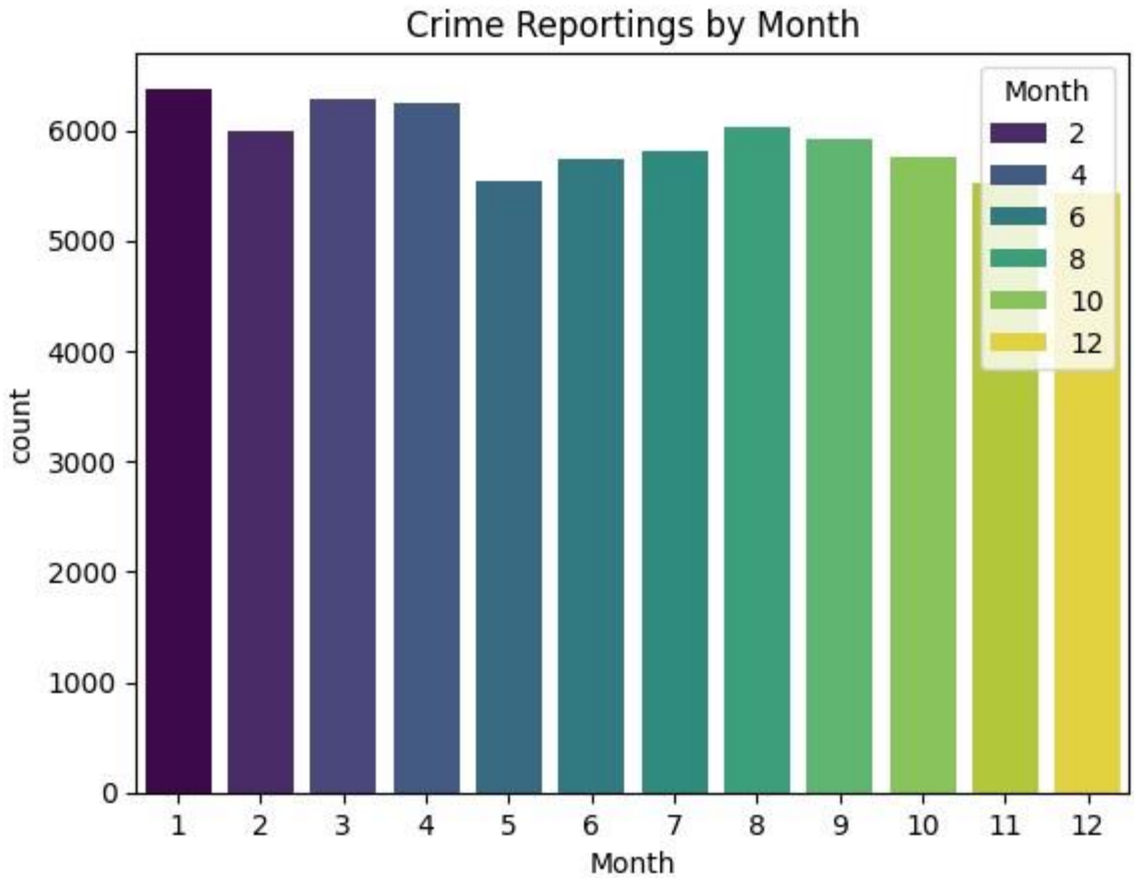
Crime Reportings by Month

In [ ]:

```
sns.countplot(x = 'Month', data = df, hue = 'Month', palette='viridis').set_tit
```

Out[ ]:

```
Text(0.5, 1.0, 'Crime Reportings by Month')
```

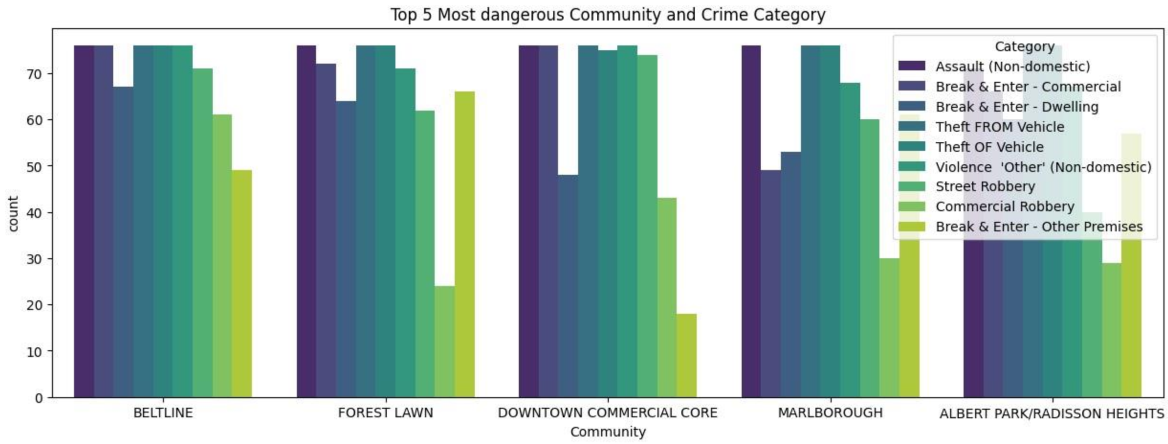


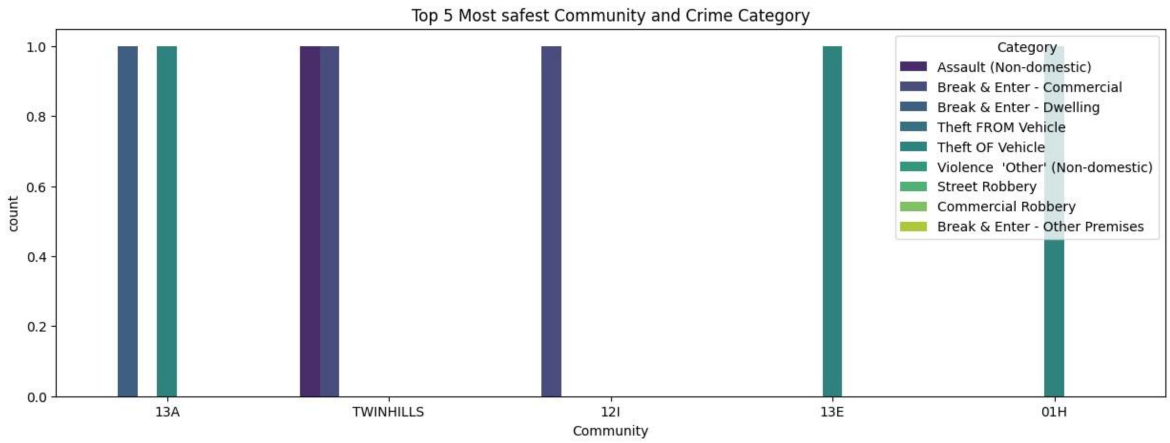
Community and Category Analysis

In [ ]:

```
plt.figure(figsize=(15, 5)) sns.countplot(x = 'Community', data = df, hue =
o 'Category', palette='viridis', sns.move_legend(plt.gca(), "upper right")
plt.figure(figsize=(15, 5)) sns.countplot(x = 'Community', data = df, hue =
'Category', palette='viridis',
o
```

Out[ ]: Text(0.5, 1.0, 'Top 5 Most safest Community and Crime Category')



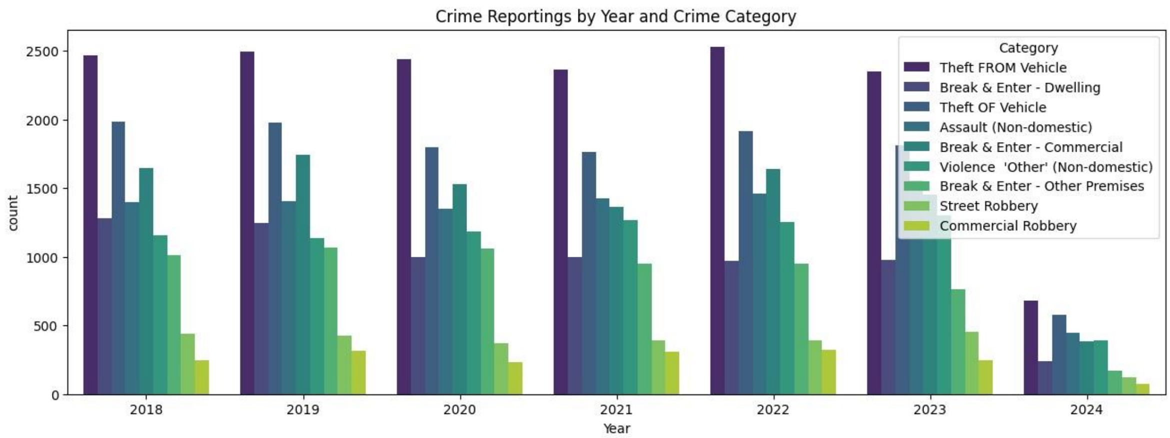


These two graphs shows the analysis of communities with the crime category. This help us to visualize the pattern of crime in each community. We can see that certain cateogries are more common in certain communities than others. In the top 5 dangerous communities, Forest Lawn has the highest of Break & Enter - other premises, Malbrough has the lowest Commerical Robbery. These are the few examples of the analysis.

Year and Category Analysis

In [ ]:
```
plt.figure(figsize=(15, 5)) sns.countplot(x = 'Year', data = df, hue = 'Category',
 palette='viridis').set_ti
```

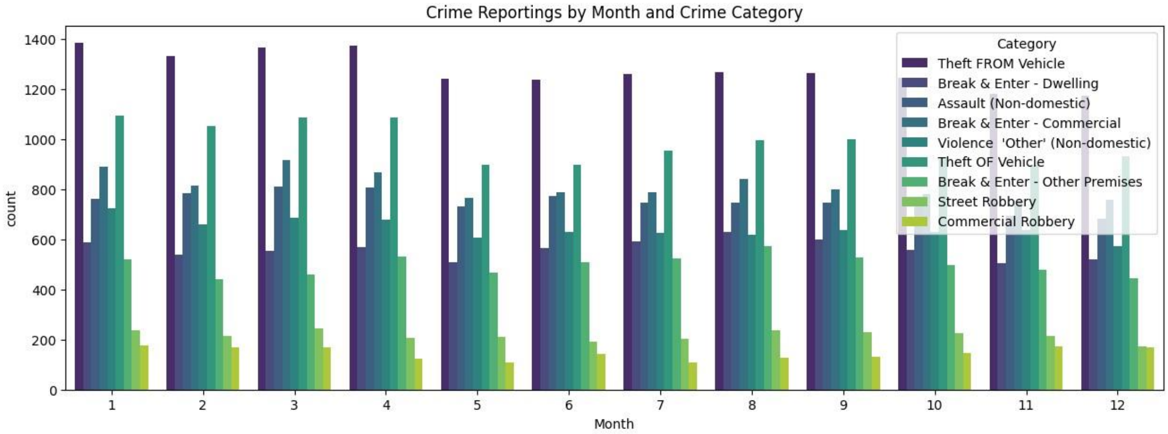
Out[ ]: Text(0.5, 1.0, 'Crime Reportings by Year and Crime Category')



Month and Category Analysis

In [ ]:
```
plt.figure(figsize=(15, 5))
t sns.countplot(x = 'Month', data = df, hue = 'Category', palette='viridis').set_
```

Out[ ]: Text(0.5, 1.0, 'Crime Reportings by Month and Crime Category')



From the above, graphs, charts, and visualization I have studied the patterns, trends and relationships in the data. This will help me to build a better model for prediction.

```
from sklearn.preprocessing import LabelEncoder

#Label Encoding Object
le = LabelEncoder()

#Object type columns
object_type_columns = df.select_dtypes(include='object').columns

#Label Encoding for col in
object_type_columns:
    df[col] = le.fit_transform(df[col]) df.head()
```

Data Preprocessing Part 2

In [ ]:

Out[ ]:

	Community	Category	Crime Count	Year	Month
0	0	0	1	2022	11
1	0	1	1	2019	6
2	0	1	1	2019	8
3	0	1	2	2020	3

4	0	1	2	2020	7

```
# Prepare sequences for LSTM def
create_sequences(data, seq_length):
    xs = []     ys = []     for i in
range(len(data) - seq_length):
        x = data.iloc[i:(i + seq_length)].to_numpy()
y = data.iloc[i + seq_length]['Crime Count']
xs.append(x)
```

```
        ys.append(y)
  return np.array(xs),    np.array(ys)
```

```
seq_length = 3 X, y =
create_sequences(              f, seq_length)
```

Building a Neural Network Model

In [ ]:

In [ ]:

Train Test Split

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, r
```

Building and Training the LSTM Model

In [ ]:
```
from tensorflow.keras.models import Sequential from
tensorflow.keras.layers import LSTM, Dense, Dropout from
tensorflow.keras.optimizers import Adam
```

In [ ]:

```
# Build the LSTM model model = Sequential() model.add(LSTM(50, activation='relu',
input_shape=(seq_length, X_train.shape[2] model.add(Dropout(0.2))
model.add(Dense(1))

# Compile the model
optimizer = Adam(learning_rate=0.001) model.compile(optimizer=optimizer,
loss='mse')

# Train the model
history = model.fit(X_train, y_train, epochs=100, validation_data=(X_val, y_val
```

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```
3092/3092 [==============================] - 9s 3ms/step - loss: 368.3250 - val_l
oss: 12.2236 Epoch 2/100
3092/3092 [==============================] - 9s 3ms/step - loss: 13.1753 - val_lo
ss: 9.2046 Epoch 3/100
3092/3092 [==============================] - 7s 2ms/step - loss: 10.1402 - val_lo
ss: 5.4251 Epoch 4/100
3092/3092 [==============================] - 7s 2ms/step - loss: 6.6290 - val_los
s: 4.8992 Epoch 5/100
```

```
3092/3092 [==============================] - 7s 2ms/step - loss: 6.6735 - val_los
s: 4.9798 Epoch 6/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.6858 - val_los
s: 5.1378 Epoch 7/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.8741 - val_los
s: 5.0281 Epoch 8/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.6256 - val_los
s: 4.8595 Epoch 9/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.8799 - val_los
s: 5.1668
Epoch 10/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.6717 - val_los
s: 4.9109
Epoch 11/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.7738 - val_los
s: 5.1230
Epoch 12/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.8282 - val_los
s: 5.1127
Epoch 13/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.7929 - val_los
s: 4.7676
Epoch 14/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6273 - val_los
s: 4.8039
Epoch 15/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.8839 - val_los
s: 4.8101
Epoch 16/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.6465 - val_los
s: 4.7539
Epoch 17/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.5960 - val_los
s: 5.1675
Epoch 18/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4866 - val_los
s: 6.1844
Epoch 19/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5935 - val_los
s: 4.6616
Epoch 20/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.9473 - val_los
s: 5.1832
Epoch 21/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5673 - val_los
s: 4.7347
Epoch 22/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5726 - val_los
s: 5.0483
Epoch 23/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.4310 - val_los
s: 4.7352
Epoch 24/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5576 - val_los
s: 4.7369
Epoch 25/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.6070 - val_los
s: 4.7857
Epoch 26/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.4853 - val_los
s: 4.9823
Epoch 27/100
```

```
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4301 - val_los
s: 4.6676
Epoch 28/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.7564 - val_los
s: 6.6096
Epoch 29/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.6978 - val_los
s: 5.3235
Epoch 30/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.6758 - val_los
s: 5.1226
Epoch 31/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.5496 - val_los
s: 4.8413
Epoch 32/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.3276 - val_los
s: 4.9500
Epoch 33/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5483 - val_los
s: 4.9332
Epoch 34/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.5993 - val_los
s: 4.9068
Epoch 35/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5452 - val_los
s: 4.7737
Epoch 36/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.7006 - val_los
s: 4.7271
Epoch 37/100
3092/3092 [==============================] - 8s 2ms/step - loss: 5.4117 - val_los
s: 4.9678
Epoch 38/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4684 - val_los
s: 5.2002
Epoch 39/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.6481 - val_los
s: 5.6867
Epoch 40/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.5738 - val_los
s: 4.7146
Epoch 41/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4375 - val_los
s: 4.7131
Epoch 42/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4098 - val_los
s: 4.8912
Epoch 43/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4567 - val_los
s: 4.8491
Epoch 44/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5003 - val_los
s: 4.9664
Epoch 45/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5602 - val_los
s: 4.6880
Epoch 46/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.4180 - val_los
s: 5.6115
Epoch 47/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4679 - val_los
s: 4.8983
```

```
Epoch 48/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.8144 - val_los
s: 4.8802
Epoch 49/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.5283 - val_los
s: 4.6533
Epoch 50/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4935 - val_los
s: 4.7072
Epoch 51/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5349 - val_los
s: 5.1914
Epoch 52/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4986 - val_los
s: 4.6977
Epoch 53/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5809 - val_los
s: 5.3368
Epoch 54/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5513 - val_los
s: 4.6322
Epoch 55/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.6919 - val_los
s: 4.6831
Epoch 56/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.3303 - val_los
s: 4.8628
Epoch 57/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5249 - val_los
s: 4.8582
Epoch 58/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.6541 - val_los
s: 4.9105
Epoch 59/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6767 - val_los
s: 4.8064
Epoch 60/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5925 - val_los
s: 4.8082
Epoch 61/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.5196 - val_los
s: 4.6729
Epoch 62/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5900 - val_los
s: 4.7126
Epoch 63/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.3842 - val_los
s: 5.2713
Epoch 64/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.8055 - val_los
s: 5.0269
Epoch 65/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5551 - val_los
s: 5.0761
Epoch 66/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6513 - val_los
s: 4.9608
Epoch 67/100
3092/3092 [==============================] - 7s 2ms/step - loss: 5.4326 - val_los
s: 4.9216
Epoch 68/100
```

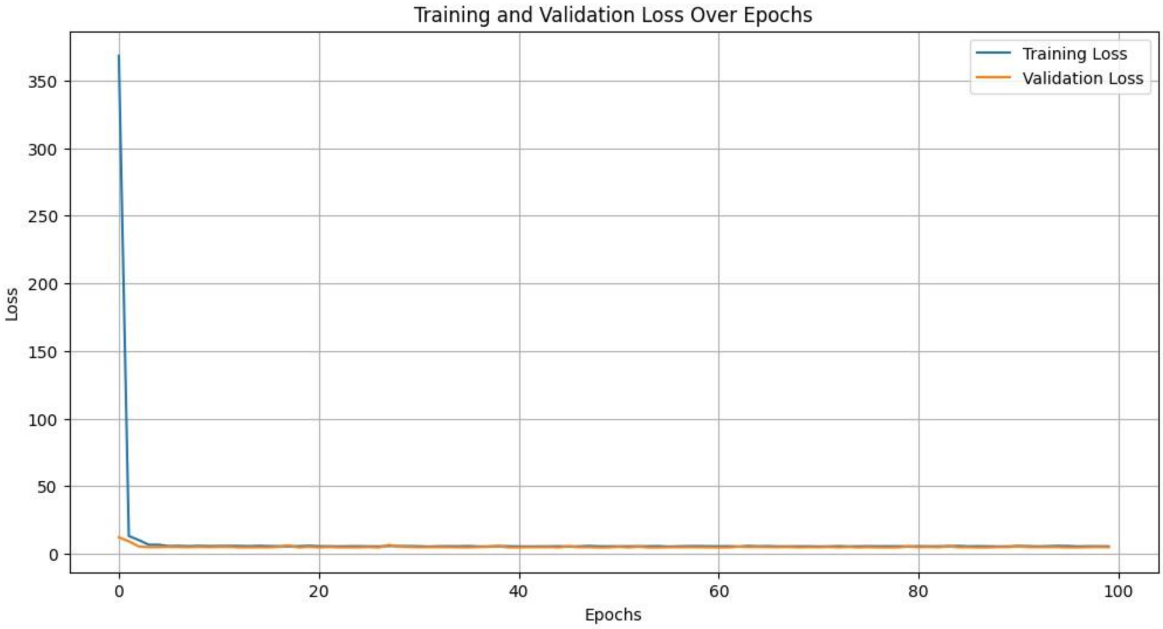
```
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4771 - val_los
s: 5.0531
Epoch 69/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4703 - val_los
s: 4.7350
Epoch 70/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5293 - val_los
s: 4.9257
Epoch 71/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.3698 - val_los
s: 4.8255
Epoch 72/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4702 - val_los
s: 5.0725
Epoch 73/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6325 - val_los
s: 4.7330
Epoch 74/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4535 - val_los
s: 5.1479
Epoch 75/100
3092/3092 [==============================] - 10s 3ms/step - loss: 5.4698 - val_lo
ss: 4.6433 Epoch 76/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6245 - val_los
s: 4.9227
Epoch 77/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5196 - val_los
s: 4.7539
Epoch 78/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5683 - val_los
s: 4.6994
Epoch 79/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5508 - val_los
s: 4.7919
Epoch 80/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5035 - val_los
s: 5.4767
Epoch 81/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5963 - val_los
s: 4.9065
Epoch 82/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5145 - val_los
s: 5.0828
Epoch 83/100
3092/3092 [==============================] - 10s 3ms/step - loss: 5.5162 - val_lo
ss: 4.8715 Epoch 84/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6411 - val_los
s: 5.6281
Epoch 85/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.7950 - val_los
s: 4.8154
Epoch 86/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5023 - val_los
s: 4.8846
Epoch 87/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5841 - val_los
s: 4.6612
Epoch 88/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4837 - val_los
s: 4.7223
Epoch 89/100
```

```
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4101 - val_los
s: 4.9879
Epoch 90/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4269 - val_los
s: 4.9915
Epoch 91/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.7826 - val_los
s: 5.6587
Epoch 92/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.6136 - val_los
s: 4.9782
Epoch 93/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.4317 - val_los
s: 4.9384
Epoch 94/100
3092/3092 [==============================] - 10s 3ms/step - loss: 5.6433 - val_lo
ss: 5.0109 Epoch 95/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.8415 - val_los
s: 4.9563
Epoch 96/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.7377 - val_los
s: 4.7079
Epoch 97/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.4252 - val_los
s: 4.7204
Epoch 98/100
3092/3092 [==============================] - 10s 3ms/step - loss: 5.5803 - val_lo
ss: 4.9075 Epoch 99/100
3092/3092 [==============================] - 9s 3ms/step - loss: 5.5518 - val_los
s: 5.0284
Epoch 100/100
3092/3092 [==============================] - 8s 3ms/step - loss: 5.5170 - val_los
```

```python
plt.figure(figsize=(12, 6)) plt.plot(history.history['loss'],
label='Training Loss') plt.plot(history.history['val_loss'],
label='Validation Loss') plt.title('Training and Validation
Loss Over Epochs') plt.xlabel('Epochs') plt.ylabel('Loss')
plt.legend() plt.grid(True) plt.show()
```

```
s: 4.8733
```

In [ ]:



In [ ]:

```
# Evaluate the model
test_loss = model.evaluate(X_test, y_test) print(f'Test
Loss: {test_loss}')

# Predictions
y_pred = model.predict(X_test)


print(f'Predictions: {y_pred.flatten()}') print(f'True
Values: {y_test.flatten()}')
```

```
332/332
     [==============================] - 0s 1ms/step - loss: 4.8978
Test Loss: 4.897756576538086
332/332 [==============================] - 1s 1ms/step Predictions: [3.5760155
2.0850606 2.3349957 ... 3.710539  1.8771566 3.2992563]
True Values: [2 1 1 ... 1 2 2]
```

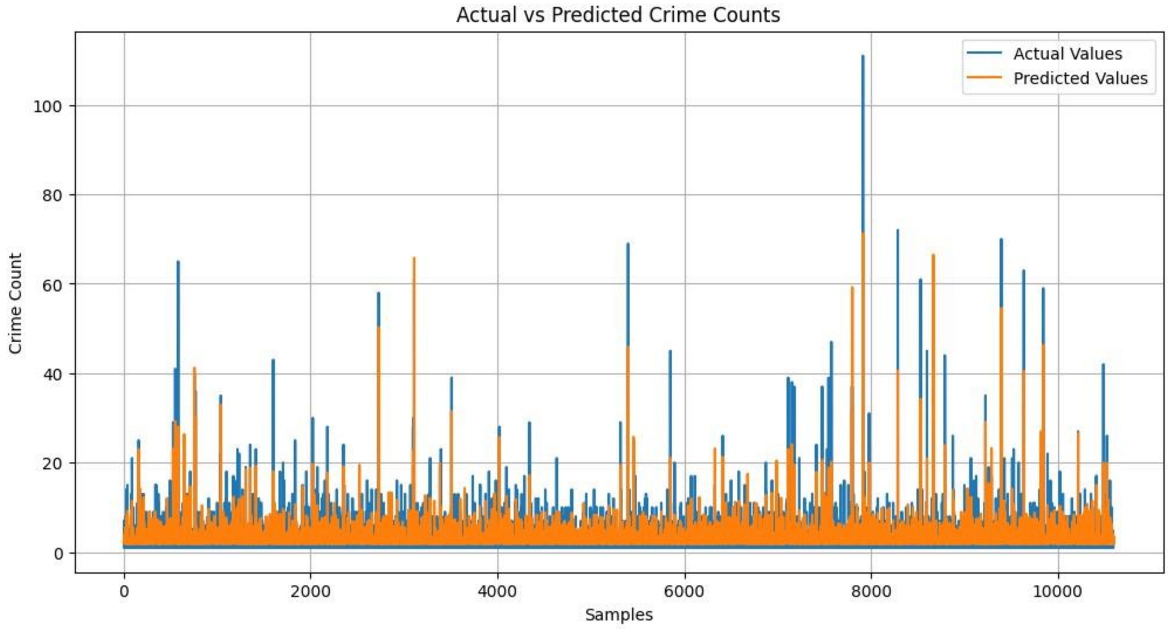
Model Evaluation

Actual vs Predicted Values

In [ ]:

```
# Plotting Actual vs Predicted Values
plt.figure(figsize=(12, 6)) plt.plot(y_test,
label='Actual Values') plt.plot(y_pred,
label='Predicted Values') plt.title('Actual vs
Predicted Crime Counts') plt.xlabel('Samples')
plt.ylabel('Crime Count')


plt.legend()
plt.grid(True)
plt.show()
```



Residual Plot

In [ ]:
```
# Calculating residuals
residuals = y_test.flatten() - y_pred.flatten()

# Plotting residuals plt.figure(figsize=(12, 6))
plt.plot(residuals, label='Residuals')
plt.title('Residuals (Actual - Predicted) Over Samples')
plt.xlabel('Samples') plt.ylabel('Residuals')
plt.legend() plt.grid(True) plt.show()
```