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.

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.

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

Note : This will connect my Google Drive files to Google collab. Hence my files wont be deleted after this session expirtaion. Becomes easy to share and navigate.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

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

```
#loading the dataset
df = pd.read_csv('/content/drive/MyDrive/Community_Crime_Statistics_20240522.csv')
df.head()
```

	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

```
#shape of the dataset
df.shape
```

```
(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.

```
#checking for missing values
df.isnull().sum()
```

	0
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.

```
#checking for the datatypes
df.dtypes
```

	0
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.

```
#Descriptive statistics
df.describe()
```

	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

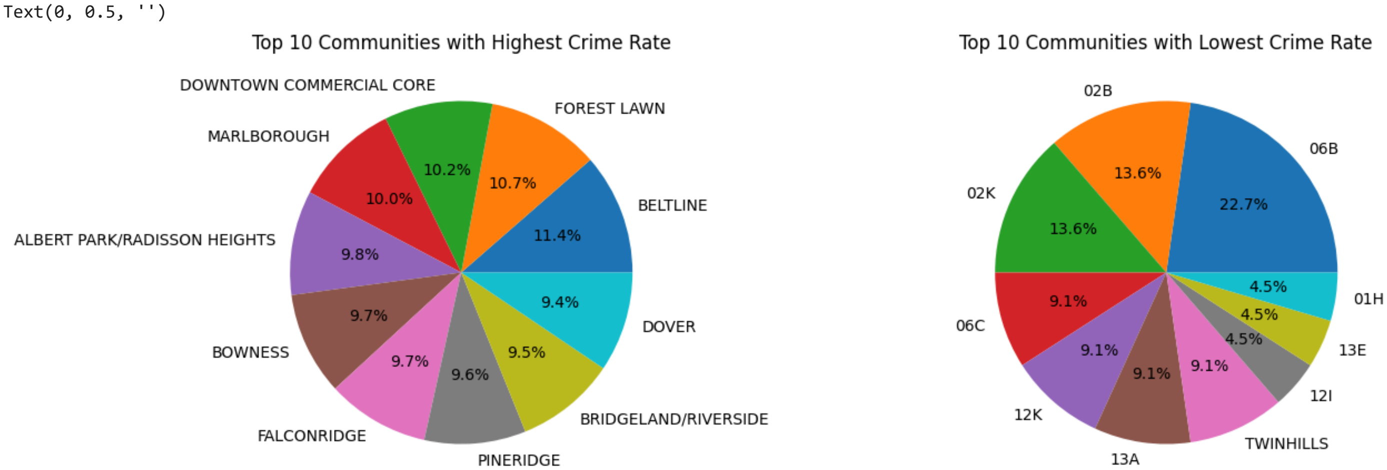
Exploratory Data Analysis

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

```
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('')
```

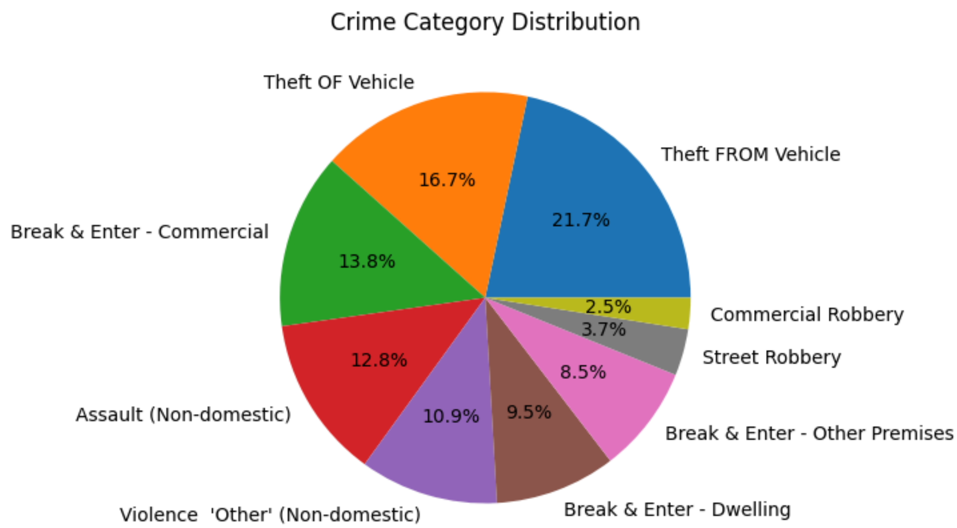
```
Text(0, 0.5, '')
```



Crime Category Distribution

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

```
Text(0, 0.5, '')
```

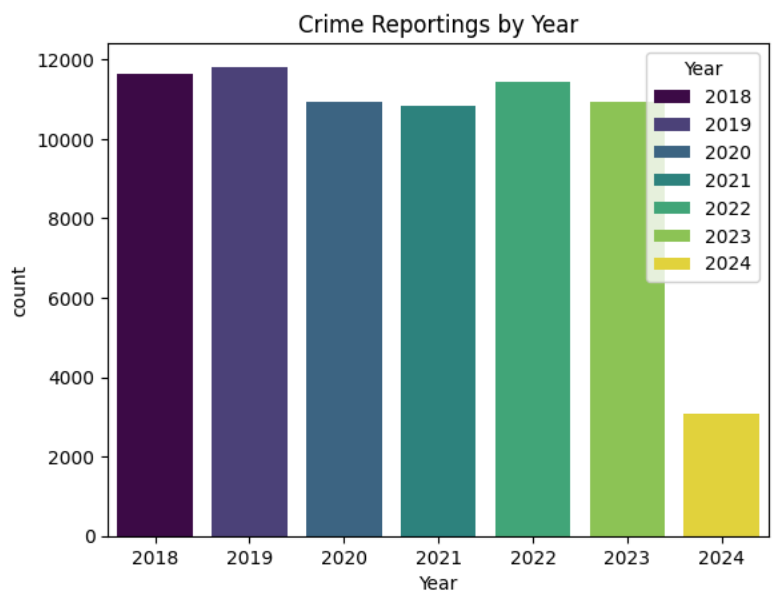


This graph shows the distribution of crimes in each category by the number of crimes. The top crime category is Theft from Vehicle with 21.7% of the total crimes, followed by Theft of Vehicle with 16.7% and Break and Enter - Commercial with 13.8%. The least crime category inc;udes commerical or street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

Crime Reportings Over the Years

```
sns.countplot(x = 'Year', data = df, hue = 'Year', palette='viridis').set_title('Crime Reportings by Year')
```

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

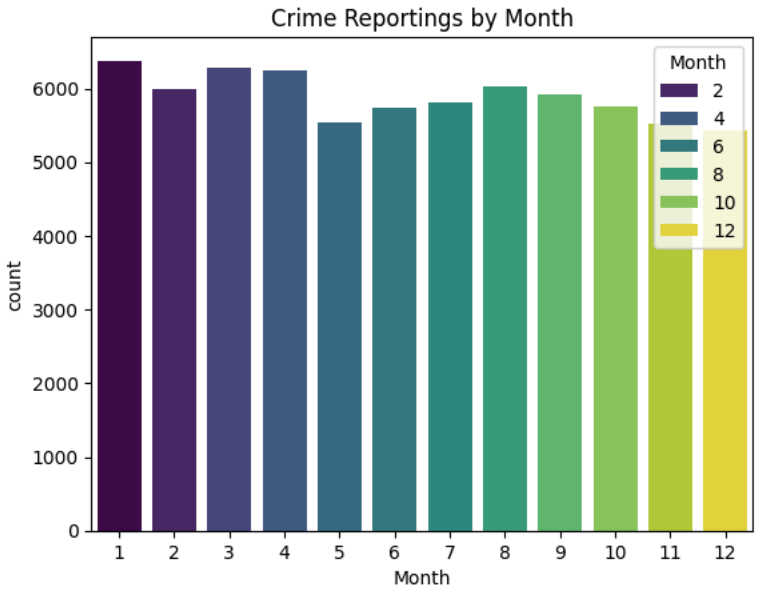


This bar graph shows the distribution of number of crimes reported in the year. The year 2019 had the highest reportings of crimes followed by 2022 and 2018. The crime reportings in 2024 are less due to limited data till April 2024.

Crime Reportings by Month

```
sns.countplot(x = 'Month', data = df, hue = 'Month', palette='viridis').set_title('Crime Reportings by Month')
```

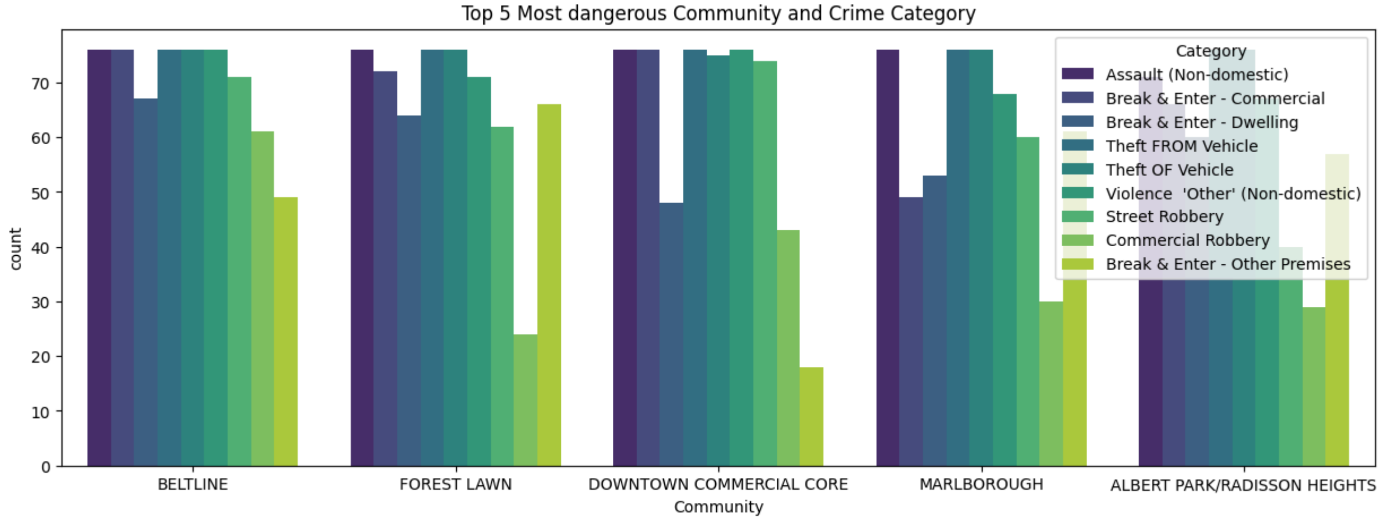
```
Text(0.5, 1.0, 'Crime Reportings by Month')
```

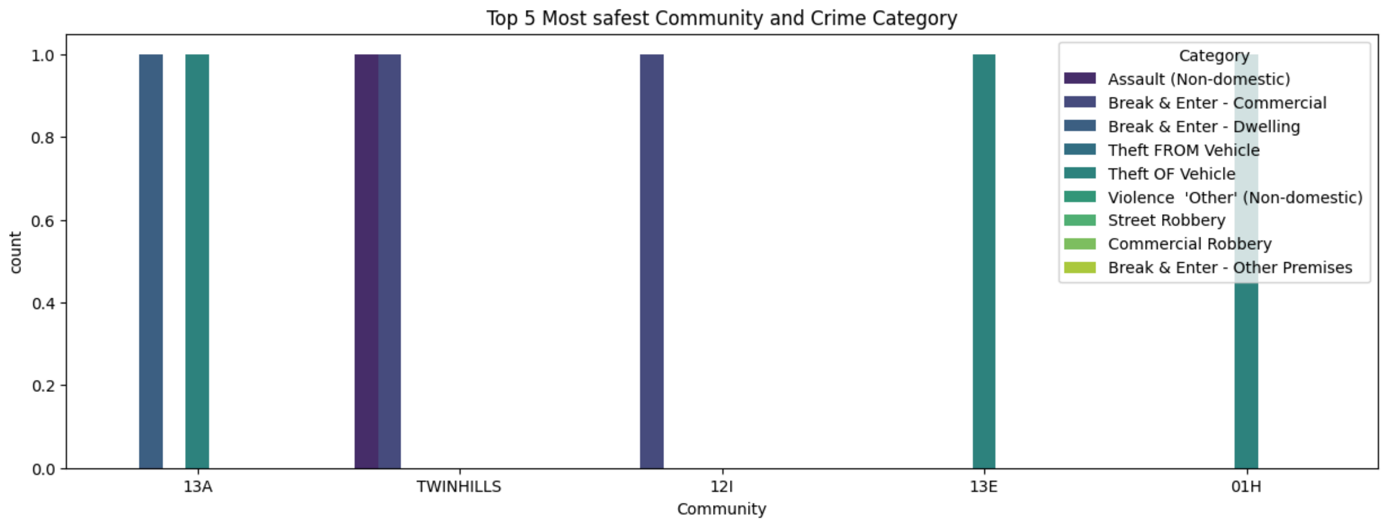


Community and Category Analysis

```
plt.figure(figsize=(15, 5))
sns.countplot(x = 'Community', data = df, hue = 'Category', palette='viridis', order = df['Community'].value_counts().head(5).index).set_tit
sns.move_legend(plt.gca(), "upper right")
plt.figure(figsize=(15, 5))
sns.countplot(x = 'Community', data = df, hue = 'Category', palette='viridis', order = df['Community'].value_counts().tail(5).index).set_tit
```

```
Text(0.5, 1.0, 'Top 5 Most safest Community and Crime Category')
```



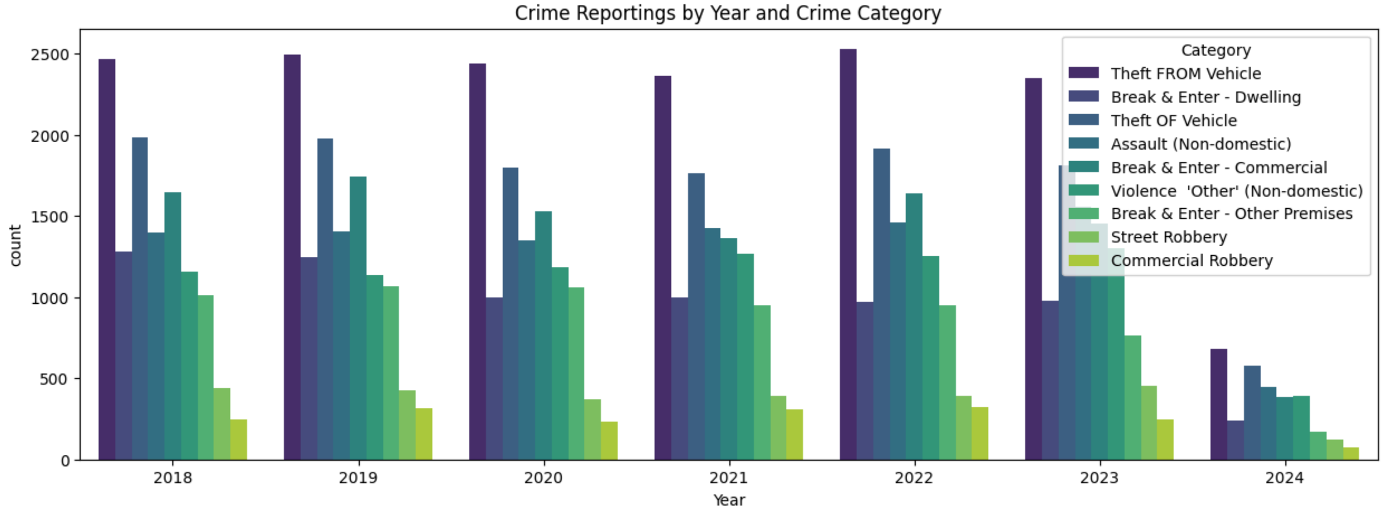


These two graphs shows the analysis of communities with the crime category. This help us to visualize the pattern of crime in each community. We can see that certain cateogries are more common in certain communities than others. In the top 5 dangerous communities, Forest Lawn has the highest of Break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

Year and Category Analysis

```
plt.figure(figsize=(15, 5))
sns.countplot(x = 'Year', data = df, hue = 'Category', palette='viridis').set_title('Crime Reportings by Year and Crime Category')
```

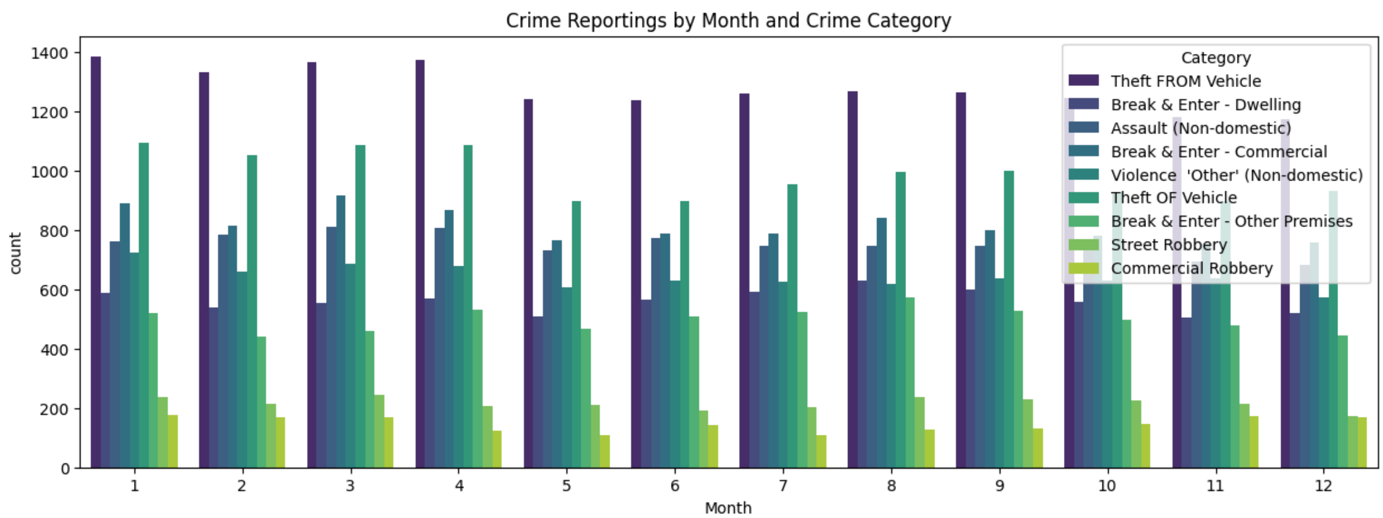
```
Text(0.5, 1.0, 'Crime Reportings by Year and Crime Category')
```



Month and Category Analysis

```
plt.figure(figsize=(15, 5))
sns.countplot(x = 'Month', data = df, hue = 'Category', palette='viridis').set_title('Crime Reportings by Month and Crime Category')
```

```
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.

Data Preprocessing Part 2

```
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()
```

	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

Building a Neural Network Model

```
# 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(df, seq_length)
```

Train Test Split

```
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_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)
```

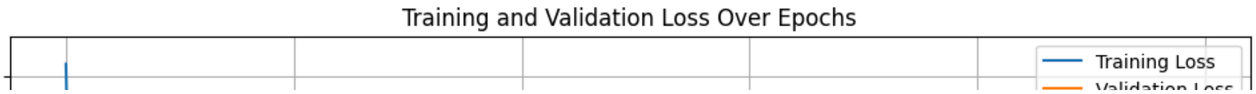
Building and Training the LSTM Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.optimizers import Adam


+# 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), batch_size=16)
```

```
Epoch 1/100
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argume
  super().__init__(**kwargs)
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 18s 5ms/step - loss: 793.7375 - val_loss: 12.1497
Epoch 2/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - loss: 11.0544 - val_loss: 6.0124
Epoch 3/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 7.2999 - val_loss: 6.0322
Epoch 4/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 6.5607 - val_loss: 6.2568
Epoch 5/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - loss: 6.8191 - val_loss: 4.7778
Epoch 6/100
```

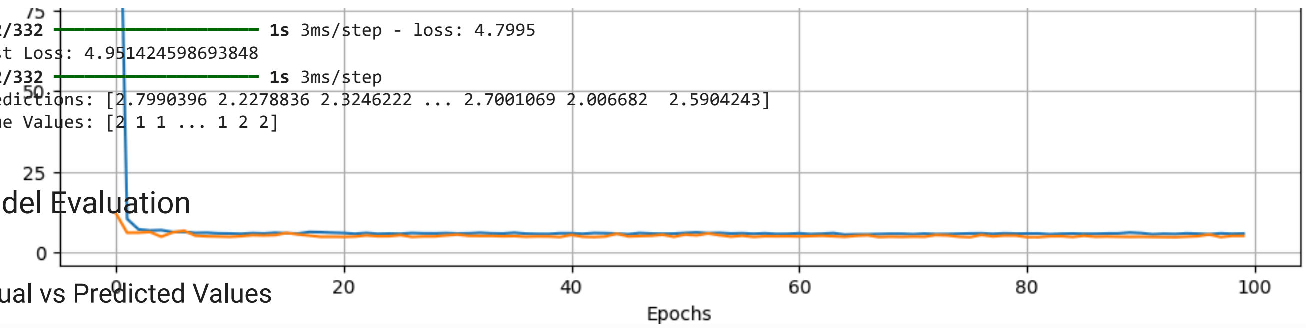
```
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 6.1595 - val_loss: 6.1106
Epoch 7/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 6.0904 - val_loss: 6.6435
Epoch 8/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - loss: 6.4153 - val_loss: 5.0909
Epoch 9/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.9443 - val_loss: 4.9063
Epoch 10/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.6899 - val_loss: 4.8448
Epoch 11/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 11s 4ms/step - loss: 5.7470 - val_loss: 4.7593
Epoch 12/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 5.5974 - val_loss: 4.9502
Epoch 13/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 6.1660 - val_loss: 5.2512
Epoch 14/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.8346 - val_loss: 5.1690
Epoch 15/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.8176 - val_loss: 5.2786
Epoch 16/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 5.9367 - val_loss: 5.9541
Epoch 17/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step - loss: 5.6828 - val_loss: 5.4930
Epoch 18/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 6.1767 - val_loss: 5.1231
Epoch 19/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - loss: 6.1077 - val_loss: 4.7549
Epoch 20/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 5.8838 - val_loss: 4.7743
Epoch 21/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 19s 4ms/step - loss: 5.9621 - val_loss: 4.7376
Epoch 22/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.5560 - val_loss: 4.8310
Epoch 23/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 6.0846 - val_loss: 5.1798
Epoch 24/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.6938 - val_loss: 4.9293
Epoch 25/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 21s 4ms/step - loss: 6.0547 - val_loss: 4.9438
Epoch 26/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - loss: 6.0434 - val_loss: 5.2654
Epoch 27/100
3092/3092 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step - loss: 5.8634 - val_loss: 4.7330
```

```
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()
```




```
# 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 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 4.7995
Test Loss: 4.951424598693848
332/332 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
Predictions: [2.7990396 2.2278836 2.3246222 ... 2.7001069 2.006682  2.5904243]
True Values: [2 1 1 ... 1 2 2]
```



Model Evaluation

Actual vs Predicted Values

```
# 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()
```