

In [3]: **import** pandas **as** pd

```
df = pd.read_csv('IIoT_Smart_Parking_Management.csv')

df['Timestamp'] = pd.to_datetime(df['Timestamp'])
df.isnull().sum()
df['Year'] = df['Timestamp'].dt.year
df['Month'] = df['Timestamp'].dt.month
df['Date'] = df['Timestamp'].dt.day
df['Day_of_Week'] = df['Timestamp'].dt.day_name()
df['Hour'] = df['Timestamp'].dt.hour
#df.to_csv('IIoT_Smart_Parking_Management_clean.csv')
print("Null values")
df.isnull().sum()
```

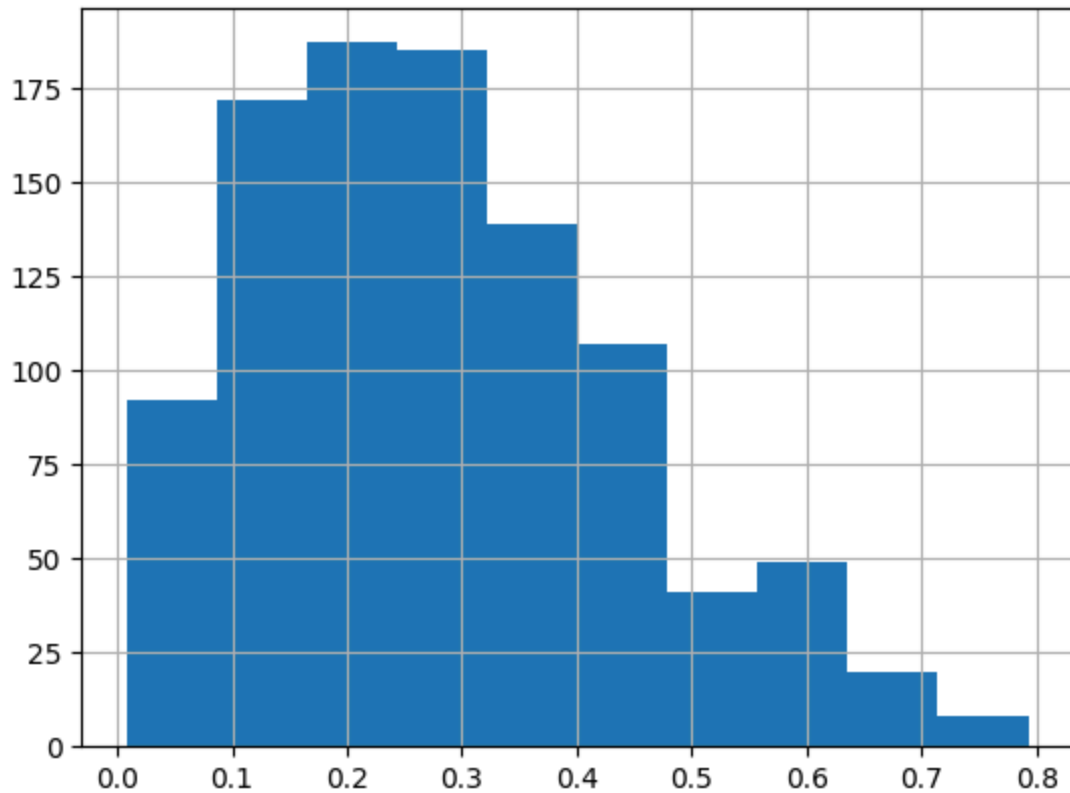
Null values

```
Out[3]: Timestamp      0
Parking_Spot_ID      0
Sensor_Reading_Proximity  0
Sensor_Reading_Pressure  0
Vehicle_Type_Weight  0
Vehicle_Type_Height  0
User_Type      0
Weather_Temperature  0
Weather_Precipitation  0
Nearby_Traffic_Level  0
Entry_Time      0
Exit_Time      0
Electric_Vehicle  0
Reserved_Status  0
Occupancy_Rate  0
Payment_Amount  0
Parking_Lot_Section  0
Payment_Status  0
Occupancy_Status  0
Vehicle_Type  0
Parking_Violation  0
Sensor_Reading_Ultrasonic  0
Parking_Duration  0
Environmental_Noise_Level  0
Dynamic_Pricing_Factor  0
Spot_Size  0
Proximity_To_Exit  0
User_Parking_History  0
Year  0
Month  0
Date  0
Day_of_Week  0
Hour  0
dtype: int64
```

EDA

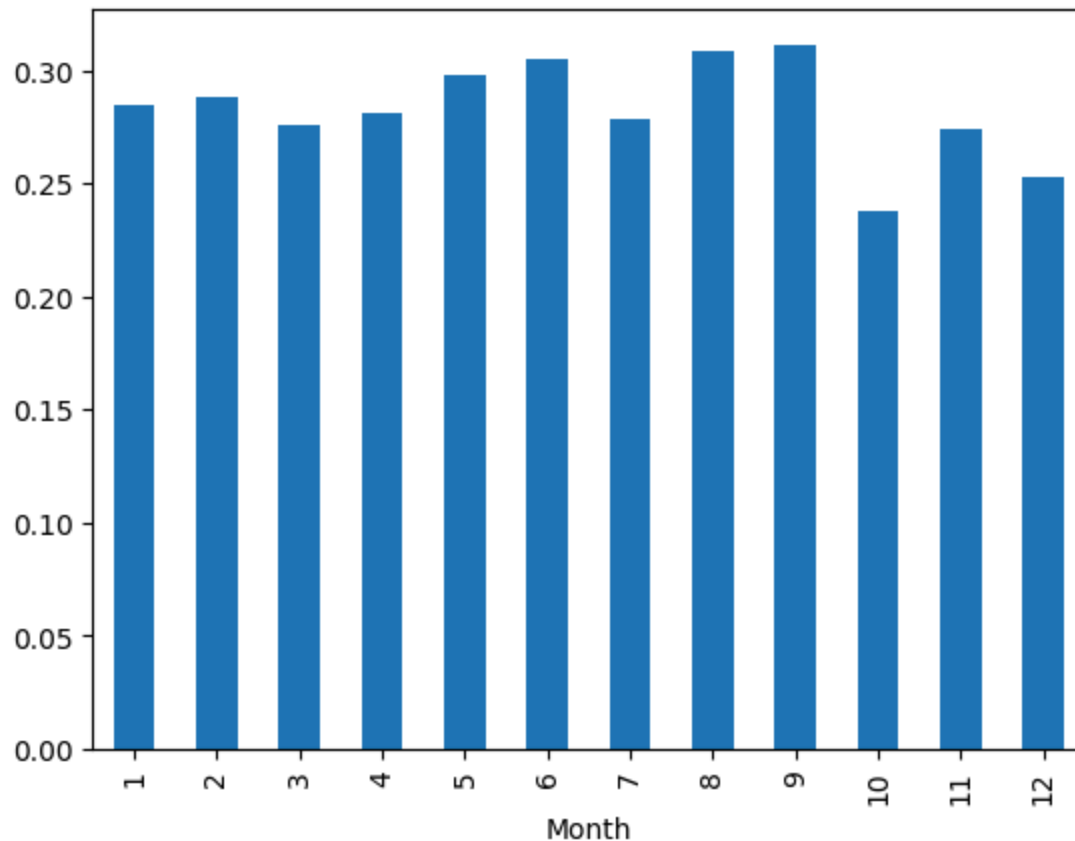
```
In [13]: df['Occupancy_Rate'].describe()  
df['Occupancy_Rate'].hist()
```

Out[13]: <Axes: >



```
In [16]: monthly_mean = df.groupby('Month')['Occupancy_Rate'].mean()  
monthly_mean.plot(kind='bar')
```

Out[16]: <Axes: xlabel='Month'>



```
In [19]: import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(20, 15))

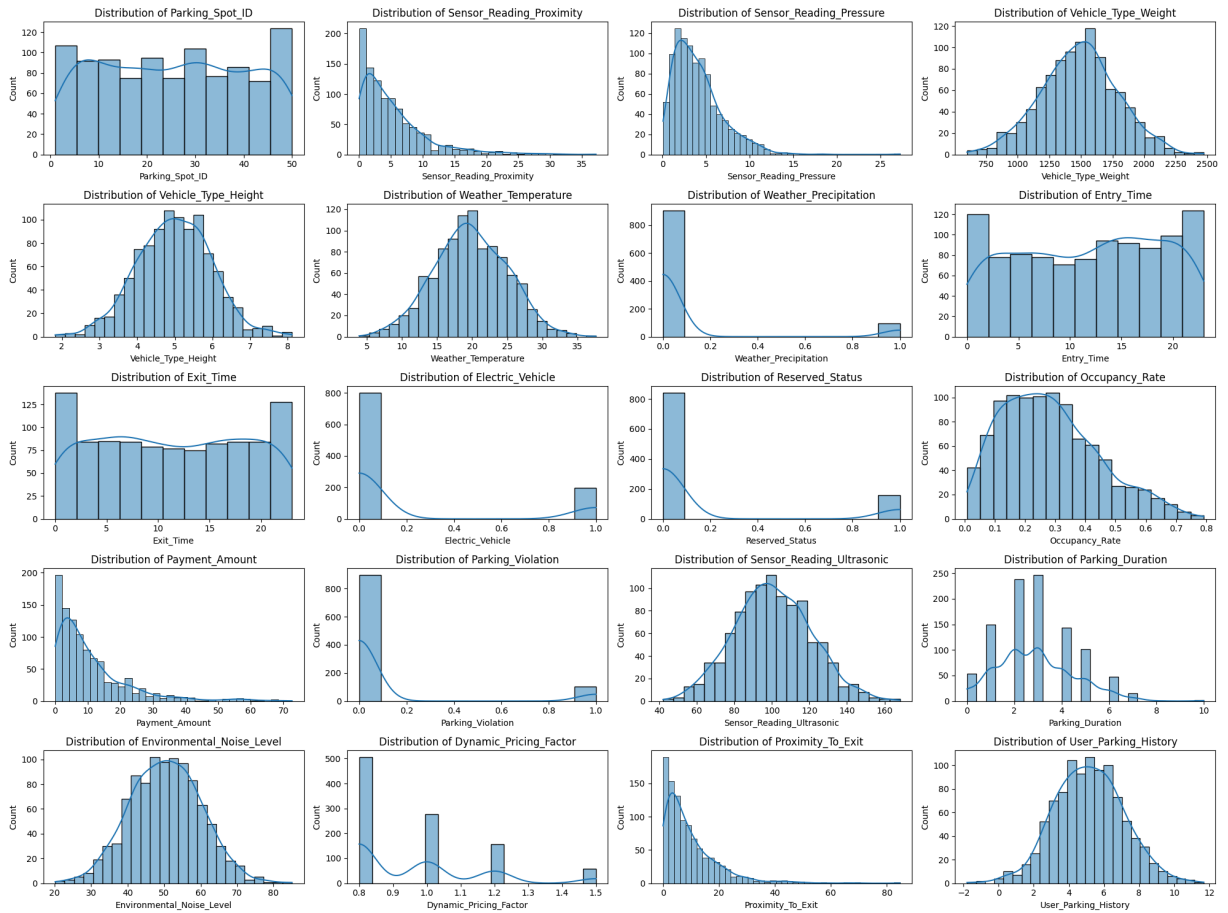
num_cols = df.select_dtypes(include=['float64', 'int64']).columns

for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')

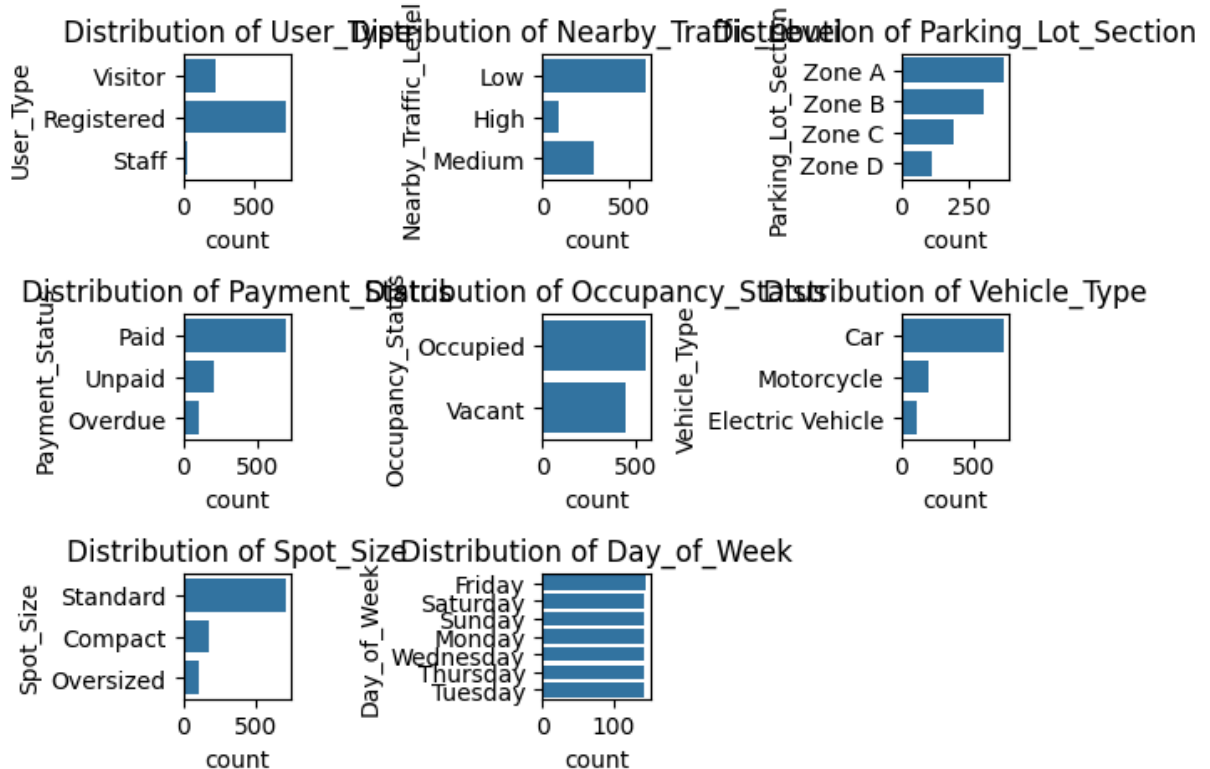
plt.tight_layout()
plt.show()

ctg_cols = df.select_dtypes(include=['object']).columns
print(ctg_cols)
for i, col in enumerate(ctg_cols):
    plt.subplot(3, 3, i+1)
    sns.countplot(y=df[col])
    plt.title(f'Distribution of {col}')

plt.tight_layout()
plt.show()
```



```
Index(['User_Type', 'Nearby_Traffic_Level', 'Parking_Lot_Section',
      'Payment_Status', 'Occupancy_Status', 'Vehicle_Type', 'Spot_Size',
      'Day_of_Week'],
      dtype='object')
```



Create synthetic data

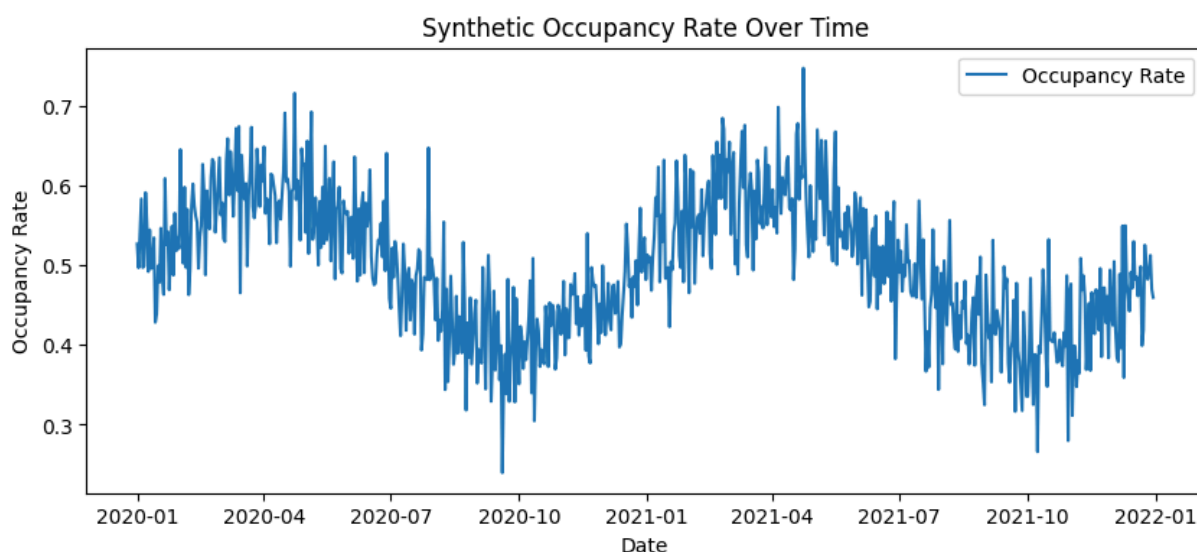
```
In [31]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

np.random.seed(42)

date_range = pd.date_range(start='2020-01-01', periods=730, freq='D')

occupancy_rate = 0.5 + 0.1 * np.sin(2 * np.pi * date_range.dayofyear / 365)
occupancy_rate = np.clip(occupancy_rate, 0, 1) # Ensure values are between 0 and 1
#print(occupancy_rate)
df = pd.DataFrame({'ds': date_range, 'Occupancy_Rate': occupancy_rate})

# Plot the synthetic occupancy data
plt.figure(figsize=(10, 4))
plt.plot(df['ds'], df['Occupancy_Rate'], label='Occupancy Rate')
plt.xlabel('Date')
plt.ylabel('Occupancy Rate')
plt.title('Synthetic Occupancy Rate Over Time')
plt.legend()
plt.show()
```



Model building

```
In [35]: scaler = MinMaxScaler(feature_range=(0, 1))
df['Occupancy_Rate'] = scaler.fit_transform(df[['Occupancy_Rate']])

def create_sequences(data, window_size):
    X, y = [], []
```

```

    for i in range(len(data) - window_size):
        X.append(data[i : i + window_size])
        y.append(data[i + window_size])
    return np.array(X), np.array(y)

window_size = 30
data = df['Occupancy_Rate'].values
X, y = create_sequences(data, window_size)
print("X shape:", X.shape, "y shape:", y.shape)

X = np.reshape(X, (X.shape[0], X.shape[1], 1))
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

model = Sequential()
model.add(LSTM(50, input_shape=(window_size, 1))) # 50 LSTM units
model.add(Dense(1)) # Single output (next day's occupancy rate)

model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()

history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_s

plt.figure(figsize=(8, 4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title("Training Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()

predictions = model.predict(X_test)

predictions_inv = scaler.inverse_transform(predictions)
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

plt.figure(figsize=(10, 4))
plt.plot(y_test_inv, label='Actual Occupancy')
plt.plot(predictions_inv, label='Predicted Occupancy')
plt.xlabel('Time Steps (Test Samples)')
plt.ylabel('Occupancy Rate')
plt.title("Actual vs. Predicted Occupancy Rate")
plt.legend()
plt.show()

```

X shape: (700, 30) y shape: (700,)

/opt/anaconda3/lib/python3.12/site-packages/keras/src/layers/rnn/rnn.py:204:
 UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
 super().__init__(**kwargs)

Model: "sequential"

Layer (type)	Output Shape	Par
lstm (LSTM)	(None, 50)	10
dense (Dense)	(None, 1)	

Total params: 10,451 (40.82 KB)

Trainable params: 10,451 (40.82 KB)

Non-trainable params: 0 (0.00 B)

Epoch 1/20

16/16  0s 6ms/step - loss: 0.2027 - val_loss: 0.0400

Epoch 2/20

16/16  0s 2ms/step - loss: 0.0223 - val_loss: 0.0107

Epoch 3/20

16/16  0s 3ms/step - loss: 0.0132 - val_loss: 0.0131

Epoch 4/20

16/16  0s 3ms/step - loss: 0.0108 - val_loss: 0.0110

Epoch 5/20

16/16  0s 3ms/step - loss: 0.0111 - val_loss: 0.0111

Epoch 6/20

16/16  0s 3ms/step - loss: 0.0114 - val_loss: 0.0113

Epoch 7/20

16/16  0s 3ms/step - loss: 0.0110 - val_loss: 0.0112

Epoch 8/20

16/16  0s 3ms/step - loss: 0.0106 - val_loss: 0.0108

Epoch 9/20

16/16  0s 3ms/step - loss: 0.0104 - val_loss: 0.0112

Epoch 10/20

16/16  0s 5ms/step - loss: 0.0106 - val_loss: 0.0110

Epoch 11/20

16/16  0s 3ms/step - loss: 0.0103 - val_loss: 0.0103

Epoch 12/20

16/16  0s 3ms/step - loss: 0.0102 - val_loss: 0.0104

Epoch 13/20

16/16  0s 3ms/step - loss: 0.0101 - val_loss: 0.0104

Epoch 14/20

16/16  0s 3ms/step - loss: 0.0100 - val_loss: 0.0106

Epoch 15/20

16/16  0s 3ms/step - loss: 0.0108 - val_loss: 0.0104

Epoch 16/20

16/16  0s 3ms/step - loss: 0.0101 - val_loss: 0.0109

Epoch 17/20

16/16  0s 3ms/step - loss: 0.0099 - val_loss: 0.0108

Epoch 18/20

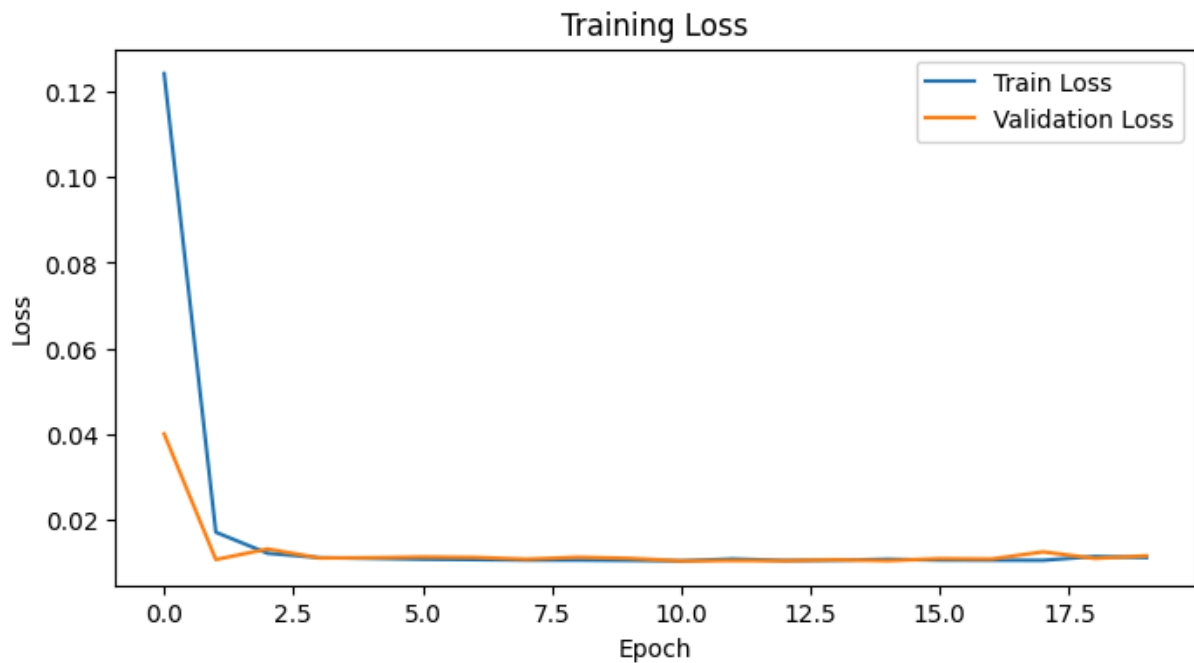
16/16  0s 3ms/step - loss: 0.0105 - val_loss: 0.0124

Epoch 19/20

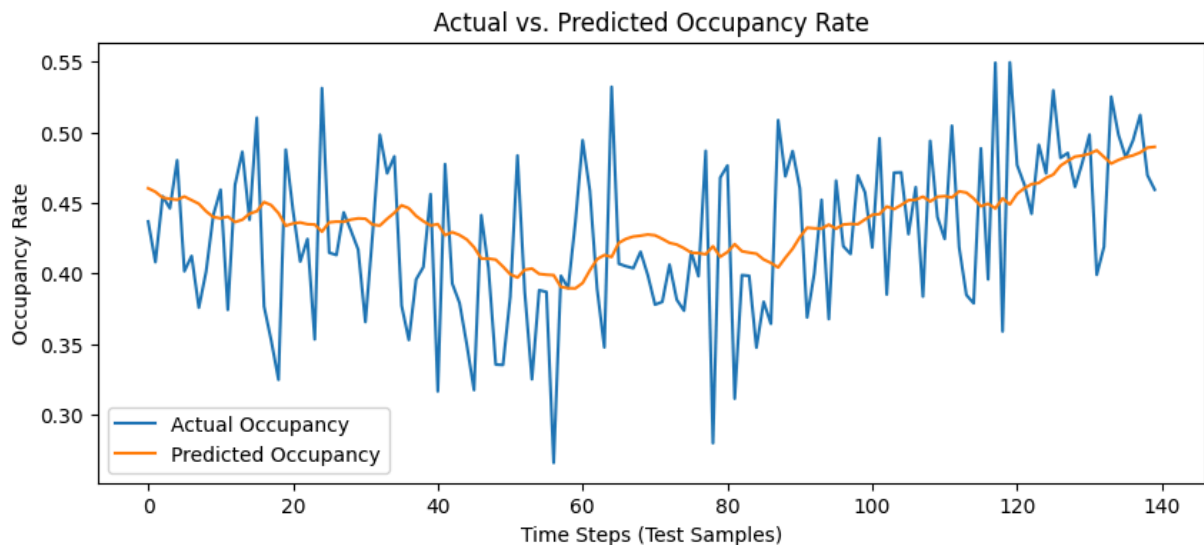
16/16  0s 3ms/step - loss: 0.0104 - val_loss: 0.0109

Epoch 20/20

16/16  0s 3ms/step - loss: 0.0118 - val_loss: 0.0115



5/5 ————— 0s 10ms/step



Model performance

```
In [39]: from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

mae = mean_absolute_error(y_test_inv, predictions_inv)
mse = mean_squared_error(y_test_inv, predictions_inv)
rmse = np.sqrt(mse)
r2 = r2_score(y_test_inv, predictions_inv)

print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R-squared (R2 Score): {r2:.4f}")
```


Mean Absolute Error (MAE): 0.0432
 Mean Squared Error (MSE): 0.0029
 Root Mean Squared Error (RMSE): 0.0539
 R-squared (R^2 Score): 0.0925

Model prediction for next 2 days

```
In [49]: last_sequence = data[-window_size:]
last_sequence = last_sequence.reshape(1, window_size, 1)

future_predictions = []

num_days_to_predict = 2
for i in range(num_days_to_predict):
    next_day_pred_scaled = model.predict(last_sequence) # shape: (1, 1)

    future_predictions.append(next_day_pred_scaled[0, 0])
    next_value = np.array([[[next_day_pred_scaled[0, 0]]]]) # shape (1,1,1)

    last_sequence = np.append(last_sequence[:, 1:, :], next_value, axis=1)

future_predictions = np.array(future_predictions).reshape(-1, 1)
future_predictions_original = scaler.inverse_transform(future_predictions)

print("Predicted occupancy rates for the next 2 days:")
print(future_predictions_original)
```

1/1 ————— 0s 8ms/step
 1/1 ————— 0s 7ms/step
 Predicted occupancy rates for the next 2 days:
 [[0.4888678]
 [0.48966447]]

In []:

In []: