IoT_Smart_Parking_RNN

February 25, 2025

1 *Final Project - IOT Smart Parking*

Install and Import Dependencies

[ ]:
```
# Install necessary libraries
!pip install pandas numpy scikit-learn

# Import required libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages
(2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages
(1.26.4)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-
packages (1.6.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.1)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas) (2025.1)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

Load Dataset

[ ]:
```
# Load the dataset
df = pd.read_csv('IIoT_Smart_Parking_Management.csv')

# Ensure 'Timestamp' is in datetime format
```

```python
df['Timestamp'] = pd.to_datetime(df['Timestamp'])

print("Dataset Loaded and Timestamp converted.")
df.head()
```

```
Dataset Loaded and Timestamp converted.
```

[ ]:

```
                      Timestamp  Parking_Spot_ID  Sensor_Reading_Proximity  \
0 2021-01-01 00:00:00.000000000               20                  1.023651
1 2021-01-02 06:39:16.756756756               49                  3.903349
2 2021-01-03 13:18:33.513513513               38                 10.315709
3 2021-01-04 19:57:50.270270270               31                  6.588039
4 2021-01-06 02:37:07.027027027                8                  8.213969

   Sensor_Reading_Pressure  Vehicle_Type_Weight  Vehicle_Type_Height  \
0                 1.541461          1831.770127             4.392528
1                 1.621719          1330.815754             4.595638
2                 6.292374          1255.134827             4.313721
3                 1.659870          1523.442919             3.567329
4                 3.278467          1758.490837             5.145836

    User_Type  Weather_Temperature  Weather_Precipitation  \
0     Visitor            18.092553                      1
1  Registered            13.397533                      0
2  Registered            21.687410                      0
3     Visitor            18.683461                      0
4     Visitor            19.214876                      0

  Nearby_Traffic_Level  …  Occupancy_Status  Vehicle_Type  \
0                  Low  …          Occupied           Car
1                  Low  …          Occupied           Car
2                 High  …            Vacant           Car
3               Medium  …            Vacant    Motorcycle
4                 High  …          Occupied           Car

   Parking_Violation  Sensor_Reading_Ultrasonic  Parking_Duration  \
0                  0                 102.951052                 4
1                  0                  87.559131                 3
2                  1                 100.061854                 5
3                  1                 110.594598                 2
4                  0                  84.786963                 2

   Environmental_Noise_Level Dynamic_Pricing_Factor Spot_Size  \
0                  55.620740                    0.8  Standard
1                  56.682386                    1.2   Compact
2                  59.239322                    0.8  Standard
3                  44.545155                    0.8  Standard
```

```
4                  48.012604                    0.8   Standard

  Proximity_To_Exit User_Parking_History
0          6.610474             6.660310
1          8.678719             6.766187
2         13.795262            -0.910052
3          1.678721            10.415888
4         20.012252             4.355544

[5 rows x 28 columns]
```

Extract Time-Based Features

[ ]:
```python
# Extract features from the timestamp
df['Hour'] = df['Timestamp'].dt.hour
df['DayOfWeek'] = df['Timestamp'].dt.dayofweek
df['Month'] = df['Timestamp'].dt.month
df['IsWeekend'] = (df['DayOfWeek'] >= 5).astype(int)

print("Time-based features extracted.")
df[['Hour', 'DayOfWeek', 'Month', 'IsWeekend']].head()
```

```
Time-based features extracted.
```

[ ]:

	Hour	DayOfWeek	Month	IsWeekend
0	0	4	1	0
1	6	5	1	1
2	13	6	1	1
3	19	0	1	0
4	2	2	1	0

Convert Target Variable (Occupancy Status)

[ ]:
```python
# Map 'Occupied' to 1 and 'Vacant' to 0
df['Occupancy_Status_Numeric'] = df['Occupancy_Status'].map({'Occupied': 1,␣
↪'Vacant': 0})

print("Converted 'Occupancy_Status' to numeric.")
df[['Occupancy_Status', 'Occupancy_Status_Numeric']].head()
```

```
Converted 'Occupancy_Status' to numeric.
```

[ ]:

	Occupancy_Status	Occupancy_Status_Numeric
0	Occupied	1
1	Occupied	1
2	Vacant	0
3	Vacant	0
4	Occupied	1

Generate Rolling Averages & Lag Features

```
[ ]: # Rolling average for past occupancy status
df['RollingAvg_Occupancy'] = df['Occupancy_Status_Numeric'].rolling(window=5,␣
 ↪min_periods=1).mean()

# Create lag features for past occupancy states
df['Prev_Occupancy'] = df['Occupancy_Status_Numeric'].shift(1)
df['Prev2_Occupancy'] = df['Occupancy_Status_Numeric'].shift(2)

# Fill NaN values caused by shifting
df.fillna(0, inplace=True)

print("Rolling averages and lag features generated.")
df[['RollingAvg_Occupancy', 'Prev_Occupancy', 'Prev2_Occupancy']].head()
```

```
Rolling averages and lag features generated.
```

[ ]:

	RollingAvg_Occupancy	Prev_Occupancy	Prev2_Occupancy
0	1.000000	0.0	0.0
1	1.000000	1.0	0.0
2	0.666667	1.0	1.0
3	0.500000	0.0	1.0
4	0.600000	0.0	0.0

Simulate Weather Data

```
[ ]: # Simulated weather data (replace with real data if available)
df['Rainfall'] = np.random.choice([0, 1], size=len(df))  # 0 = No Rain, 1 = Rain
df['Temperature'] = np.random.randint(15, 35, size=len(df))  # Simulated␣
 ↪temperature values

print("Simulated weather data added.")
df[['Rainfall', 'Temperature']].head()
```

```
Simulated weather data added.
```

[ ]:

	Rainfall	Temperature
0	1	34
1	1	24
2	0	31
3	0	20
4	0	32

Compute Aggregated Features

```
[ ]: # Calculate average occupancy per hour and per day of the week
df['Hourly_Occupancy'] = df.groupby('Hour')['Occupancy_Status_Numeric'].
 ↪transform('mean')
df['Daily_Occupancy'] = df.groupby('DayOfWeek')['Occupancy_Status_Numeric'].
 ↪transform('mean')
```

```python
print("Aggregated occupancy features computed.")
df[['Hourly_Occupancy', 'Daily_Occupancy']].head()
```

```
Aggregated occupancy features computed.
```

```
[ ]:   Hourly_Occupancy  Daily_Occupancy
0          0.604651         0.534722
1          0.642857         0.573427
2          0.585366         0.573427
3          0.428571         0.524476
4          0.658537         0.559441
```

One-Hot Encoding for Categorical Features

```python
[ ]: # One-hot encode 'DayOfWeek'
encoder = OneHotEncoder(sparse_output=False)
encoded_features = encoder.fit_transform(df[['DayOfWeek']])

# Add encoded columns to the DataFrame
df_encoded = pd.DataFrame(encoded_features, columns=encoder.
 ↪get_feature_names_out())
df = pd.concat([df, df_encoded], axis=1)

# Drop the original 'DayOfWeek' column
df.drop(columns=['DayOfWeek'], inplace=True)

print("One-hot encoding completed.")
df.head()
```

```
One-hot encoding completed.
```

```
[ ]:                      Timestamp  Parking_Spot_ID  Sensor_Reading_Proximity  \
0 2021-01-01 00:00:00.000000000               20                  1.023651
1 2021-01-02 06:39:16.756756756               49                  3.903349
2 2021-01-03 13:18:33.513513513               38                 10.315709
3 2021-01-04 19:57:50.270270270               31                  6.588039
4 2021-01-06 02:37:07.027027027                8                  8.213969

   Sensor_Reading_Pressure  Vehicle_Type_Weight  Vehicle_Type_Height  \
0                 1.541461          1831.770127             4.392528
1                 1.621719          1330.815754             4.595638
2                 6.292374          1255.134827             4.313721
3                 1.659870          1523.442919             3.567329
4                 3.278467          1758.490837             5.145836

    User_Type  Weather_Temperature  Weather_Precipitation  \
0     Visitor            18.092553                      1
1  Registered            13.397533                      0
```

```
2  Registered           21.687410                      0
3     Visitor           18.683461                      0
4     Visitor           19.214876                      0

  Nearby_Traffic_Level  …  Temperature  Hourly_Occupancy  Daily_Occupancy  \
0                  Low  …           34          0.604651         0.534722
1                  Low  …           24          0.642857         0.573427
2                 High  …           31          0.585366         0.573427
3               Medium  …           20          0.428571         0.524476
4                 High  …           32          0.658537         0.559441

   DayOfWeek_0  DayOfWeek_1  DayOfWeek_2 DayOfWeek_3 DayOfWeek_4 DayOfWeek_5  \
0          0.0          0.0          0.0         0.0         1.0         0.0
1          0.0          0.0          0.0         0.0         0.0         1.0
2          0.0          0.0          0.0         0.0         0.0         0.0
3          1.0          0.0          0.0         0.0         0.0         0.0
4          0.0          0.0          1.0         0.0         0.0         0.0

  DayOfWeek_6
0         0.0
1         0.0
2         1.0
3         0.0
4         0.0

[5 rows x 46 columns]
```

Normalize Numerical Features

[ ]:
```python
# List of numerical features to normalize
numeric_columns = ['RollingAvg_Occupancy', 'Prev_Occupancy', 'Prev2_Occupancy',␣
 ↪'Hourly_Occupancy', 'Daily_Occupancy', 'Temperature']

# Apply Min-Max scaling
scaler = MinMaxScaler()
df[numeric_columns] = scaler.fit_transform(df[numeric_columns])

print("Normalization completed.")
df[numeric_columns].head()
```

```
Normalization completed.
```

[ ]:
```
   RollingAvg_Occupancy  Prev_Occupancy  Prev2_Occupancy  Hourly_Occupancy  \
0              1.000000             0.0              0.0          0.722719
1              1.000000             1.0              0.0          0.846154
2              0.666667             1.0              1.0          0.660413
3              0.500000             0.0              1.0          0.153846
4              0.600000             0.0              0.0          0.896811
```

```
   Daily_Occupancy  Temperature
0         0.440586     1.000000
1         0.745921     0.473684
2         0.745921     0.842105
3         0.359751     0.263158
4         0.635587     0.894737
```

Save Processed Dataset

[ ]:
```
# Save the processed dataset as CSV
df.to_csv('Processed_Parking_Data.csv', index=False)

print("Feature engineering completed and saved as 'Processed_Parking_Data.csv'.
↪")
```

```
Feature engineering completed and saved as 'Processed_Parking_Data.csv'.
```

Feature Engineering Summary

Feature engineering transforms raw data into useful features to improve model performance.

Key Techniques Used

- Time-Based Features : Extracted Hour, DayOfWeek, Month, IsWeekend to capture occupancy patterns.
- Target Variable Transformation : Converted Occupancy_Status ("Occupied" → 1, "Vacant" → 0) for ML compatibility.
- Rolling Averages : RollingAvg_Occupancy (window=5) to smooth fluctuations in occupancy trends.
- Lag Features : Prev_Occupancy & Prev2_Occupancy to capture sequential dependencies.
- Weather Features : Simulated Rainfall & Temperature to analyze weather impact on parking.
- Aggregated Features : Hourly_Occupancy & Daily_Occupancy to capture time-based trends.
- One-Hot Encoding : Encoded DayOfWeek as binary variables for ML compatibility.
- Feature Scaling : Applied MinMaxScaler to normalize numeric features (0 to 1 range).

Using the Processed Parking Dataset after Feature Engineering

[ ]:
```
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense, Dropout
from sklearn.preprocessing import MinMaxScaler, LabelEncoder # Import␣
↪LabelEncoder here
from sklearn.model_selection import train_test_split
```

```python
from sklearn.metrics import accuracy_score


# Load dataset
df = pd.read_csv('Processed_Parking_Data.csv')

# Inspect the data
print(df.head())

# Preprocessing
# Considering 'occupied_spots' is the target variable and other columns are␣
↪features
# The original code used 'occupancy', which was not in the DataFrame
target_column = 'Occupancy_Status'
features = [col for col in df.columns if col != target_column and col !=␣
↪'Timestamp' and df[col].dtype != object]

X = df[features].values
y = df[target_column].values

# Normalize features
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# Encode target variable to numeric using LabelEncoder
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)

# Reshape input for RNN (samples, timesteps, features)
timesteps = 1  # Can be adjusted based on sequence dependency
X_reshaped = X_scaled.reshape((X_scaled.shape[0], timesteps, X_scaled.shape[1]))

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_reshaped, y_encoded,␣
↪test_size=0.2, random_state=42)

# Build RNN Model
model = Sequential([
    SimpleRNN(50, activation='relu', return_sequences=True,␣
↪input_shape=(timesteps, X.shape[1])),
    Dropout(0.2),
    SimpleRNN(50, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='sigmoid')
])

# Compile the model
```

```
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Train the model
history = model.fit(X_train, y_train, epochs=20, batch_size=16,␣
 ↪validation_data=(X_test, y_test))

# Evaluate the model
y_pred = (model.predict(X_test) > 0.5).astype(int)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')


# Save the trained model
model.save('trained_rnn_model.h5')
np.save('X_test.npy', X_test)
np.save('y_test.npy', y_test)
```

```
                      Timestamp  Parking_Spot_ID  Sensor_Reading_Proximity  \
0 2021-01-01 00:00:00.000000000               20                  1.023651
1 2021-01-02 06:39:16.756756756               49                  3.903349
2 2021-01-03 13:18:33.513513513               38                 10.315709
3 2021-01-04 19:57:50.270270270               31                  6.588039
4 2021-01-06 02:37:07.027027027                8                  8.213969

   Sensor_Reading_Pressure  Vehicle_Type_Weight  Vehicle_Type_Height  \
0                 1.541461          1831.770127             4.392528
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2                 6.292374          1255.134827             4.313721
3                 1.659870          1523.442919             3.567329
4                 3.278467          1758.490837             5.145836

    User_Type  Weather_Temperature  Weather_Precipitation  \
0     Visitor            18.092553                      1
1  Registered            13.397533                      0
2  Registered            21.687410                      0
3     Visitor            18.683461                      0
4     Visitor            19.214876                      0

  Nearby_Traffic_Level  …  Temperature  Hourly_Occupancy  Daily_Occupancy  \
0                  Low  …     1.000000          0.722719         0.440586
1                  Low  …     0.473684          0.846154         0.745921
2                 High  …     0.842105          0.660413         0.745921
3               Medium  …     0.263158          0.153846         0.359751
4                 High  …     0.894737          0.896811         0.635587

   DayOfWeek_0  DayOfWeek_1  DayOfWeek_2 DayOfWeek_3 DayOfWeek_4 DayOfWeek_5  \
```

```
0           0.0         0.0         0.0         0.0         1.0         0.0
1           0.0         0.0         0.0         0.0         0.0         1.0
2           0.0         0.0         0.0         0.0         0.0         0.0
3           1.0         0.0         0.0         0.0         0.0         0.0
4           0.0         0.0         1.0         0.0         0.0         0.0

  DayOfWeek_6
0         0.0
1         0.0
2         1.0
3         0.0
4         0.0

[5 rows x 46 columns]
Epoch 1/20

/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200:
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)

50/50            5s 16ms/step -
accuracy: 0.5092 - loss: 0.6867 - val_accuracy: 0.8400 - val_loss: 0.5388
Epoch 2/20
50/50            1s 6ms/step -
accuracy: 0.8577 - loss: 0.4895 - val_accuracy: 1.0000 - val_loss: 0.2539
Epoch 3/20
50/50            0s 6ms/step -
accuracy: 0.9621 - loss: 0.2192 - val_accuracy: 1.0000 - val_loss: 0.0707
Epoch 4/20
50/50            0s 6ms/step -
accuracy: 0.9876 - loss: 0.1025 - val_accuracy: 1.0000 - val_loss: 0.0206
Epoch 5/20
50/50            1s 5ms/step -
accuracy: 0.9870 - loss: 0.0483 - val_accuracy: 1.0000 - val_loss: 0.0086
Epoch 6/20
50/50            0s 5ms/step -
accuracy: 0.9992 - loss: 0.0263 - val_accuracy: 1.0000 - val_loss: 0.0045
Epoch 7/20
50/50            0s 5ms/step -
accuracy: 0.9990 - loss: 0.0158 - val_accuracy: 1.0000 - val_loss: 0.0026
Epoch 8/20
50/50            0s 6ms/step -
accuracy: 1.0000 - loss: 0.0100 - val_accuracy: 1.0000 - val_loss: 0.0015
Epoch 9/20
50/50            1s 5ms/step -
accuracy: 1.0000 - loss: 0.0049 - val_accuracy: 1.0000 - val_loss: 9.7657e-04
Epoch 10/20
```

```
50/50            0s 5ms/step -
accuracy: 0.9998 - loss: 0.0073 - val_accuracy: 1.0000 - val_loss: 6.7511e-04
Epoch 11/20
50/50            0s 5ms/step -
accuracy: 0.9964 - loss: 0.0082 - val_accuracy: 1.0000 - val_loss: 6.2078e-04
Epoch 12/20
50/50            0s 6ms/step -
accuracy: 1.0000 - loss: 0.0041 - val_accuracy: 1.0000 - val_loss: 3.5780e-04
Epoch 13/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 0.0031 - val_accuracy: 1.0000 - val_loss: 2.7406e-04
Epoch 14/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 0.0017 - val_accuracy: 1.0000 - val_loss: 2.1038e-04
Epoch 15/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 0.0015 - val_accuracy: 1.0000 - val_loss: 1.6846e-04
Epoch 16/20
50/50            0s 6ms/step -
accuracy: 1.0000 - loss: 0.0023 - val_accuracy: 1.0000 - val_loss: 2.2771e-04
Epoch 17/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 0.0014 - val_accuracy: 1.0000 - val_loss: 1.3923e-04
Epoch 18/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 0.0013 - val_accuracy: 1.0000 - val_loss: 9.7770e-05
Epoch 19/20
50/50            0s 5ms/step -
accuracy: 1.0000 - loss: 6.9037e-04 - val_accuracy: 1.0000 - val_loss:
1.0089e-04
Epoch 20/20
50/50            0s 5ms/step -
accuracy: 0.9997 - loss: 0.0014 - val_accuracy: 1.0000 - val_loss: 2.2835e-04

WARNING:tensorflow:5 out of the last 15 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x78d138a0cd60> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function
repeatedly in a loop, (2) passing tensors with different shapes, (3) passing
Python objects instead of tensors. For (1), please define your @tf.function
outside of the loop. For (2), @tf.function has reduce_retracing=True option that
can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.

7/7            1s 63ms/step

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
```

recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.

Accuracy: 100.00%

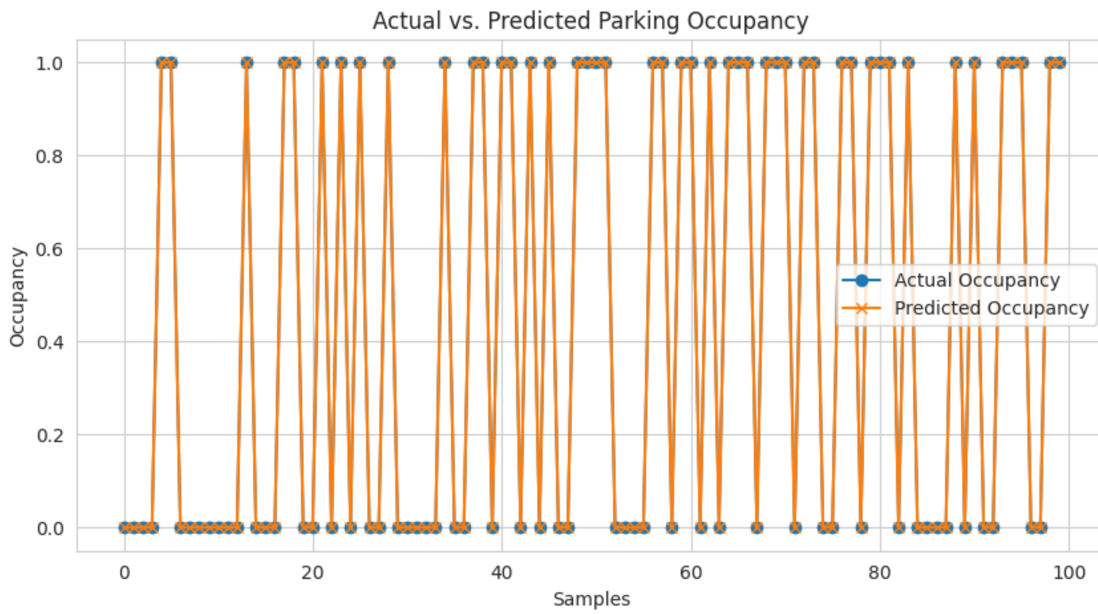
[ ]:
```
import numpy as np
import tensorflow as tf
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns #Import seaborn

# Load the trained model
model = tf.keras.models.load_model('trained_rnn_model.h5')  # Ensure you save␣
 ↪the model after training

# Load test data (Ensure test data preprocessing matches training)
X_test = np.load('X_test.npy')  # Load preprocessed test features
y_test = np.load('y_test.npy')  # Load actual labels

# Get predictions
y_pred_prob = model.predict(X_test)
y_pred = (y_pred_prob > 0.5).astype(int)

# Evaluate model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

# Print classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=['Not Occupied',␣
 ↪'Occupied']))

# Print confusion matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Plot actual vs predicted values
plt.figure(figsize=(10, 5))
plt.plot(y_test[:100], label='Actual Occupancy', marker='o')
plt.plot(y_pred[:100], label='Predicted Occupancy', marker='x')
plt.xlabel('Samples')
plt.ylabel('Occupancy')
plt.legend()
plt.title('Actual vs. Predicted Parking Occupancy')
plt.show()
```

```python
# Load the trained model
model = tf.keras.models.load_model('trained_rnn_model.h5')

# Load test data (Ensure the same preprocessing as training)
X_test = np.load('X_test.npy')
y_test = np.load('y_test.npy')

# Get predictions
y_pred_prob = model.predict(X_test)
y_pred = (y_pred_prob > 0.5).astype(int)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Display confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Occupied',␣
↪'Occupied'], yticklabels=['Not Occupied', 'Occupied'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

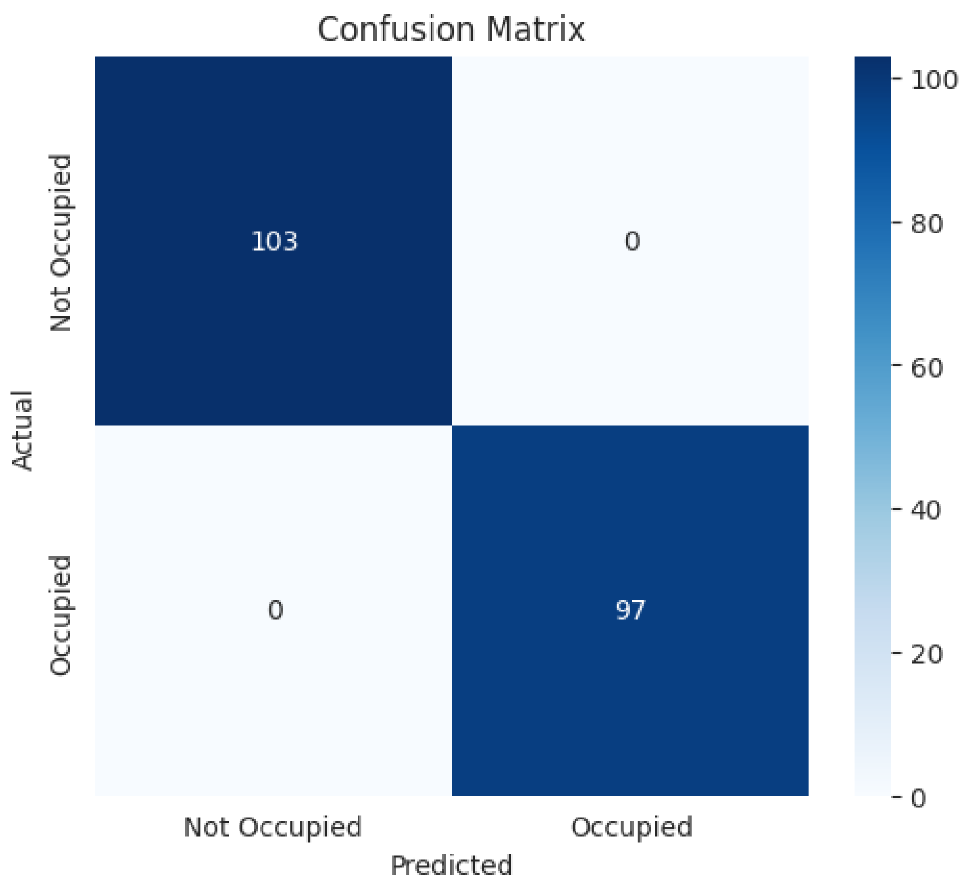
```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
WARNING:tensorflow:5 out of the last 15 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x78d14563e200> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function
repeatedly in a loop, (2) passing tensors with different shapes, (3) passing
Python objects instead of tensors. For (1), please define your @tf.function
outside of the loop. For (2), @tf.function has reduce_retracing=True option that
can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
```

```
7/7               1s 44ms/step
Accuracy: 100.00%

Classification Report:
              precision    recall  f1-score   support

Not Occupied       1.00      1.00      1.00       103
    Occupied       1.00      1.00      1.00        97

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
```

```
weighted avg       1.00      1.00      1.00       200


Confusion Matrix:
[[103   0]
 [  0  97]]
```



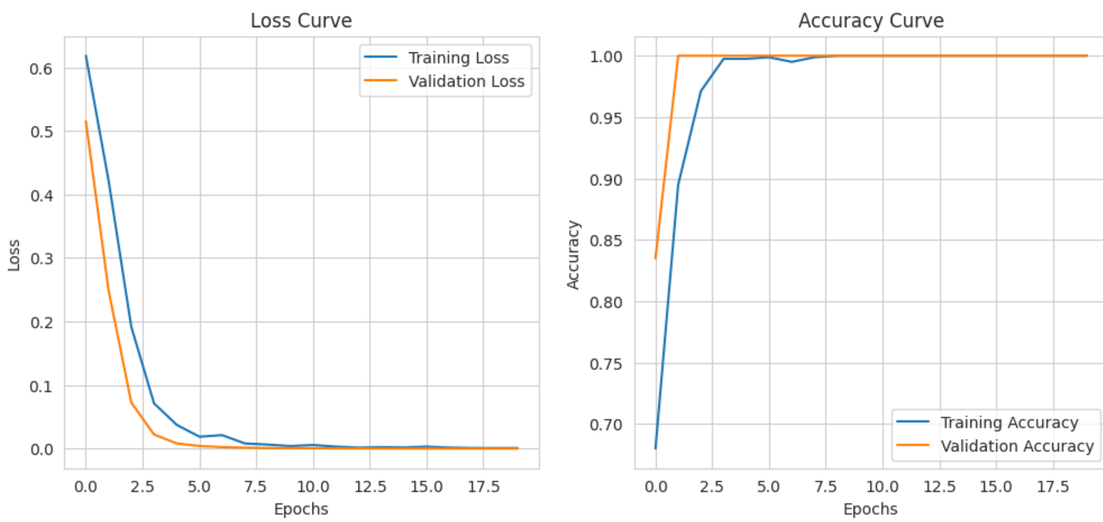

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.

7/7              1s 45ms/step
```

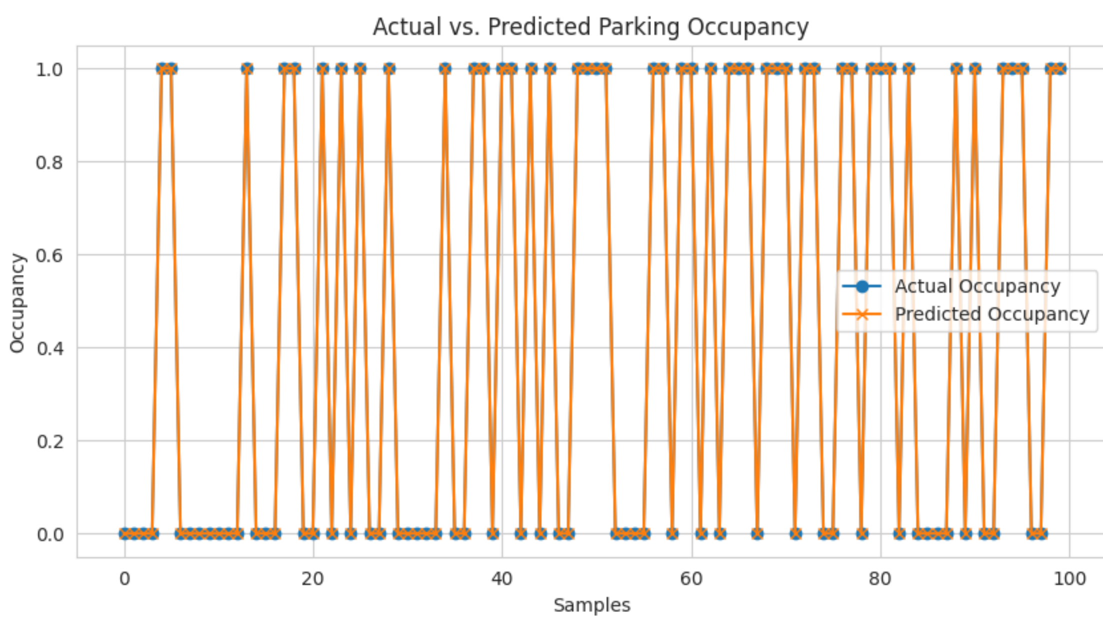


Training History & Actual vs Predicted Values

[ ]:
```
# Plot training history
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Curve')

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Accuracy Curve')
```

```python
plt.show()

# Plot actual vs predicted values
plt.figure(figsize=(10, 5))
plt.plot(y_test[:100], label='Actual Occupancy', marker='o')
plt.plot(y_pred[:100], label='Predicted Occupancy', marker='x')
plt.xlabel('Samples')
plt.ylabel('Occupancy')
plt.legend()
plt.title('Actual vs. Predicted Parking Occupancy')
plt.show()
```





Parameter Count

[ ]:
```python
import tensorflow as tf

# Load the trained model
model = tf.keras.models.load_model('trained_rnn_model.h5')

# Print model summary
model.summary()

# Extract parameter counts
total_params = model.count_params()
trainable_params = np.sum([np.prod(v.shape) for v in model.trainable_variables])
non_trainable_params = total_params - trainable_params

# Display parameter counts
print(f"\nTotal Parameters: {total_params}")
print(f"Trainable Parameters: {trainable_params}")
print(f"Non-Trainable Parameters: {non_trainable_params}")
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
```

```
Model: "sequential_2"


 Layer (type)                       Output Shape                               ␣
↪Param #

 simple_rnn_4 (SimpleRNN)           (None, 1, 50)                                ␣
↪4,450

 dropout_4 (Dropout)                (None, 1, 50)                                  ␣
↪  0

 simple_rnn_5 (SimpleRNN)           (None, 50)                                   ␣
↪5,050

 dropout_5 (Dropout)                (None, 50)                                     ␣
↪  0

 dense_2 (Dense)                    (None, 1)                                      ␣
↪ 51
```

Total params: 9,553 (37.32 KB)

Trainable params: 9,551 (37.31 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 2 (12.00 B)

```
Total Parameters: 9551
Trainable Parameters: 9551
Non-Trainable Parameters: 0
```

Classification Report

[ ]:
```python
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report

# Load the trained model
model = tf.keras.models.load_model('trained_rnn_model.h5')

# Load test data (Ensure the same preprocessing as training)
X_test = np.load('X_test.npy')
y_test = np.load('y_test.npy')

# Get predictions
y_pred_prob = model.predict(X_test)
y_pred = (y_pred_prob > 0.5).astype(int)


# Print classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=['Not Occupied',␣
 ↪'Occupied']))
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be
built. `model.compile_metrics` will be empty until you train or evaluate the
model.
```

```
7/7              1s 48ms/step

Classification Report:
              precision    recall  f1-score   support
```

```
Not Occupied       1.00      1.00      1.00       103
    Occupied       1.00      1.00      1.00        97

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
weighted avg       1.00      1.00      1.00       200
```