BASIC

```
import numpy as np
import pandas as pd
```

```
! pip install -q kaggle kagglehub
```

```
import kagglehub

# Download latest version
path = kagglehub.dataset_download("claytonmiller/open-smart-home-iotieqenergy-data")

print("Path to dataset files:", path)
```

```
Path to dataset files: /root/.cache/kagglehub/datasets/claytonmiller/open-smart-home-iotieqenergy-data/versions/1
```

```
!ls $path/Measurements
```

```
Bathroom_Brightness.csv                 Room2_Humidity.csv
Bathroom_Humidity.csv                   Room2_OutdoorTemperature.csv
Bathroom_SetpointHistory.csv            Room2_SetpointHistory.csv
Bathroom_Temperature.csv                Room2_Temperature.csv
Bathroom_ThermostatTemperature.csv      Room2_ThermostatTemperature.csv
Bathroom_Virtual_OutdoorTemperature.csv Room3_Brightness.csv
Kitchen_Brightness.csv                  Room3_Humidity.csv
Kitchen_Humidity.csv                    Room3_left_ThermostatTemperature.csv
Kitchen_SetpointHistory.csv             Room3_right_ThermostatTemperature.csv
Kitchen_Temperature.csv                 Room3_SetpointHistory.csv
Kitchen_ThermostatTemperature.csv       Room3_Temperature.csv
Kitchen_Virtual_OutdoorTemperature.csv  Room3_Virtual_OutdoorTemperature.csv
Room1_Brightness.csv                    Toilet_Brightness.csv
Room1_Humidity.csv                      Toilet_Humidity.csv
Room1_SetpointHistory.csv               Toilet_SetpointHistory.csv
Room1_Temperature.csv                   Toilet_Temperature.csv
Room1_ThermostatTemperature.csv         Toilet_ThermostatTemperature.csv
Room1_Virtual_OutdoorTemperature.csv    Toilet_Virtual_OutdoorTemperature.csv
Room2_Brightness.csv
```

```
df1 = pd.read_csv(path+'/Measurements/Room1_Brightness.csv',delimiter='\t',names=['DateTime','Luminance in lux'])
df2 = pd.read_csv(path+'/Measurements/Room1_Humidity.csv',delimiter='\t',names=['DateTime','relative Humidity in %'])
df3 = pd.read_csv(path+'/Measurements/Room1_SetpointHistory.csv',delimiter='\t',names=['DateTime','setpoint for the room in degree Celsius'])
df4 = pd.read_csv(path+'/Measurements/Room1_Temperature.csv',delimiter='\t',names=['DateTime','indoor air temperature in degree celsius'])
df5 = pd.read_csv(path+'/Measurements/Room1_ThermostatTemperature.csv',delimiter='\t',names=['DateTime','Thermostat mounted to the radiator temperature in degree celsius'])
df1['DateTime'] = pd.to_datetime(df1['DateTime'], unit='s')
df2['DateTime'] = pd.to_datetime(df2['DateTime'], unit='s')
df3['DateTime'] = pd.to_datetime(df3['DateTime'], unit='s')
df4['DateTime'] = pd.to_datetime(df4['DateTime'], unit='s')
df5['DateTime'] = pd.to_datetime(df5['DateTime'], unit='s')
df1.head()
```

	DateTime	Luminance in lux
0	2017-03-09 06:22:50	1.83
1	2017-03-09 06:32:55	0.00
2	2017-03-09 06:43:00	0.92
3	2017-03-09 06:53:04	2.75
4	2017-03-09 07:03:10	5.49

Next steps: Generate code with df1 View recommended plots New interactive sheet

```
df1.to_csv("/content/Brightness.csv")
df2.to_csv("/content/Humidity.csv")
df3.to_csv("/content/SetpointHistory.csv")
df4.to_csv("/content/Temperature.csv")
df5.to_csv("/content/ThermostatTemperature.csv")
```

```
df4.head()
```

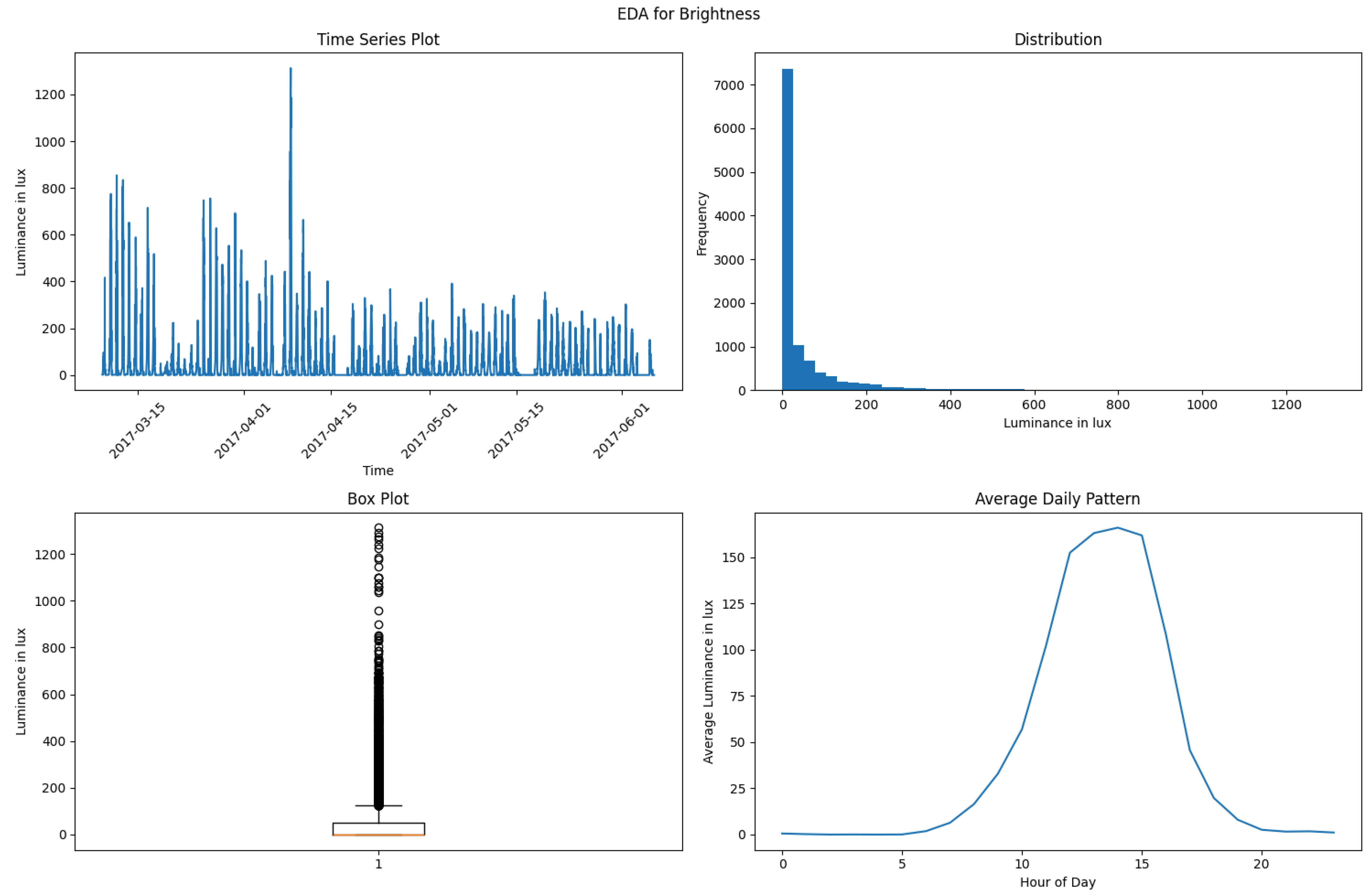
	DateTime	indoor air temperature in degree celsius
0	2017-03-09 00:51:30	19.53
1	2017-03-09 03:32:04	19.37
2	2017-03-09 05:12:26	19.53
3	2017-03-09 05:22:30	20.00
4	2017-03-09 05:32:33	20.31

Next steps: Generate code with df4 View recommended plots New interactive sheet

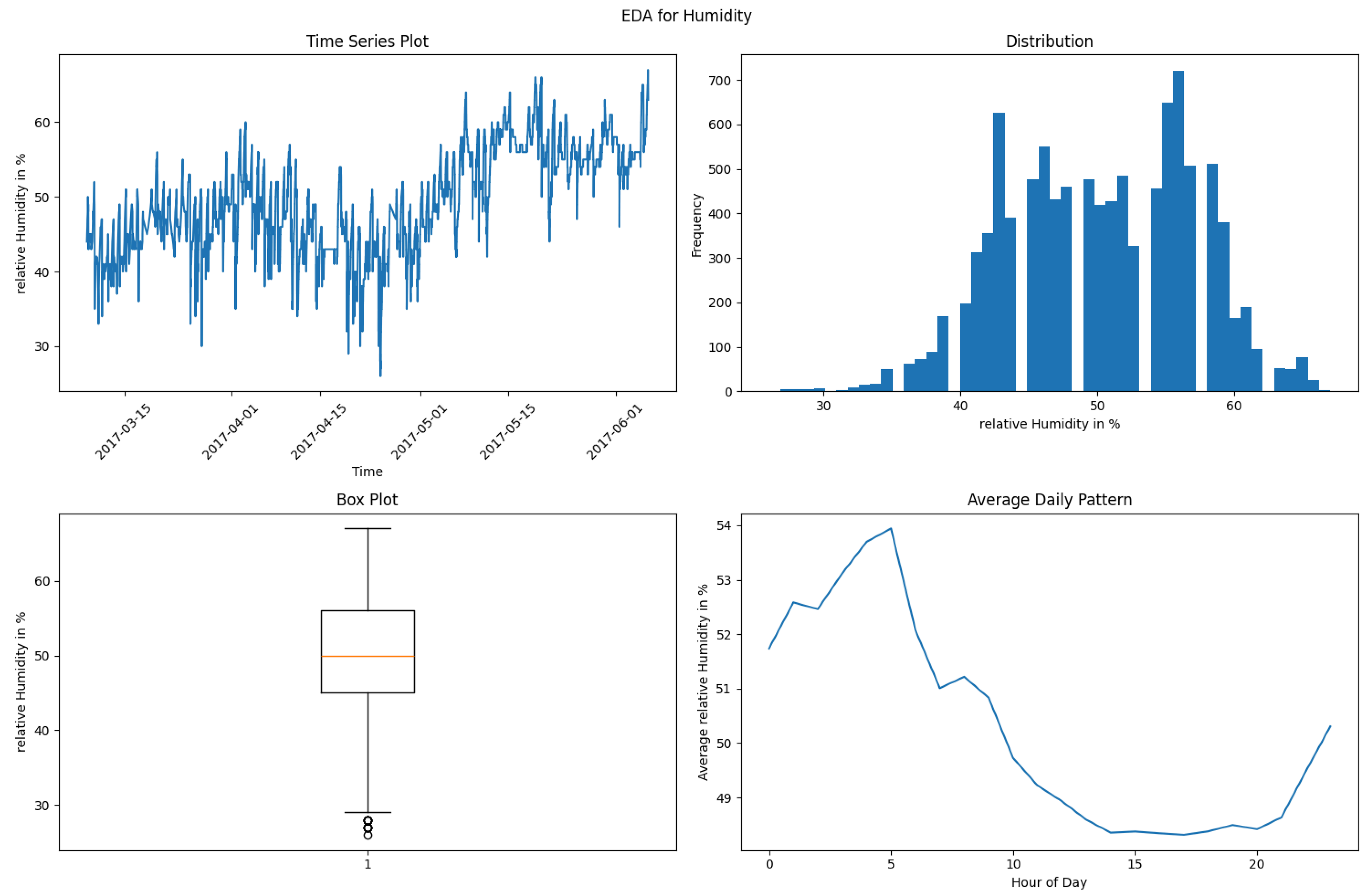
Start coding or generate with AI.

```
import pandas as pd
import matplotlib.pyplot as plt

def perform_eda(df, sensor_type):
    """Performs Exploratory Data Analysis on a given DataFrame.

    Args:
        df (pd.DataFrame): The DataFrame containing sensor data.
        sensor_type (str): A descriptive name for the sensor type.
    """

    print(f"\nAnalyzing {sensor_type}:")
    print("-" * (len(sensor_type) + 10))

    # Assuming the second column contains the sensor readings
    value_col = df.columns[1]

    stats = {
        'mean': df[value_col].mean(),
        'std': df[value_col].std(),
        'min': df[value_col].min(),
        'max': df[value_col].max(),
        'missing_values': df[value_col].isnull().sum(),
        'total_readings': len(df)
    }

    # Print statistics
    for stat, value in stats.items():
        print(f"{stat}: {value:.2f}")

    # Create visualizations
    fig, axes = plt.subplots(2, 2, figsize=(15, 10))
    fig.suptitle(f'EDA for {sensor_type}')

    # Time series plot
    axes[0, 0].plot(df['DateTime'], df[value_col])  # Using 'DateTime' column
    axes[0, 0].set_title('Time Series Plot')
    axes[0, 0].set_xlabel('Time')
    axes[0, 0].set_ylabel(value_col)
    axes[0, 0].tick_params(axis='x', rotation=45)

    # Histogram
    axes[0, 1].hist(df[value_col], bins=50)
    axes[0, 1].set_title('Distribution')
    axes[0, 1].set_xlabel(value_col)
    axes[0, 1].set_ylabel('Frequency')

    # Box plot
    axes[1, 0].boxplot(df[value_col])
    axes[1, 0].set_title('Box Plot')
    axes[1, 0].set_ylabel(value_col)

    # Daily pattern
    df['hour'] = pd.to_datetime(df['DateTime']).dt.hour  # Extract hour from 'DateTime'
    hourly_avg = df.groupby('hour')[value_col].mean()
    axes[1, 1].plot(hourly_avg.index, hourly_avg.values)
    axes[1, 1].set_title('Average Daily Pattern')
    axes[1, 1].set_xlabel('Hour of Day')
    axes[1, 1].set_ylabel(f'Average {value_col}')

    plt.tight_layout()
    plt.show()

# Example usage:
perform_eda(df1, "Brightness")
perform_eda(df2, "Humidity")
perform_eda(df3, "Setpoint History")
perform_eda(df4, "Temperature")
perform_eda(df5, "Thermostat Temperature")
```

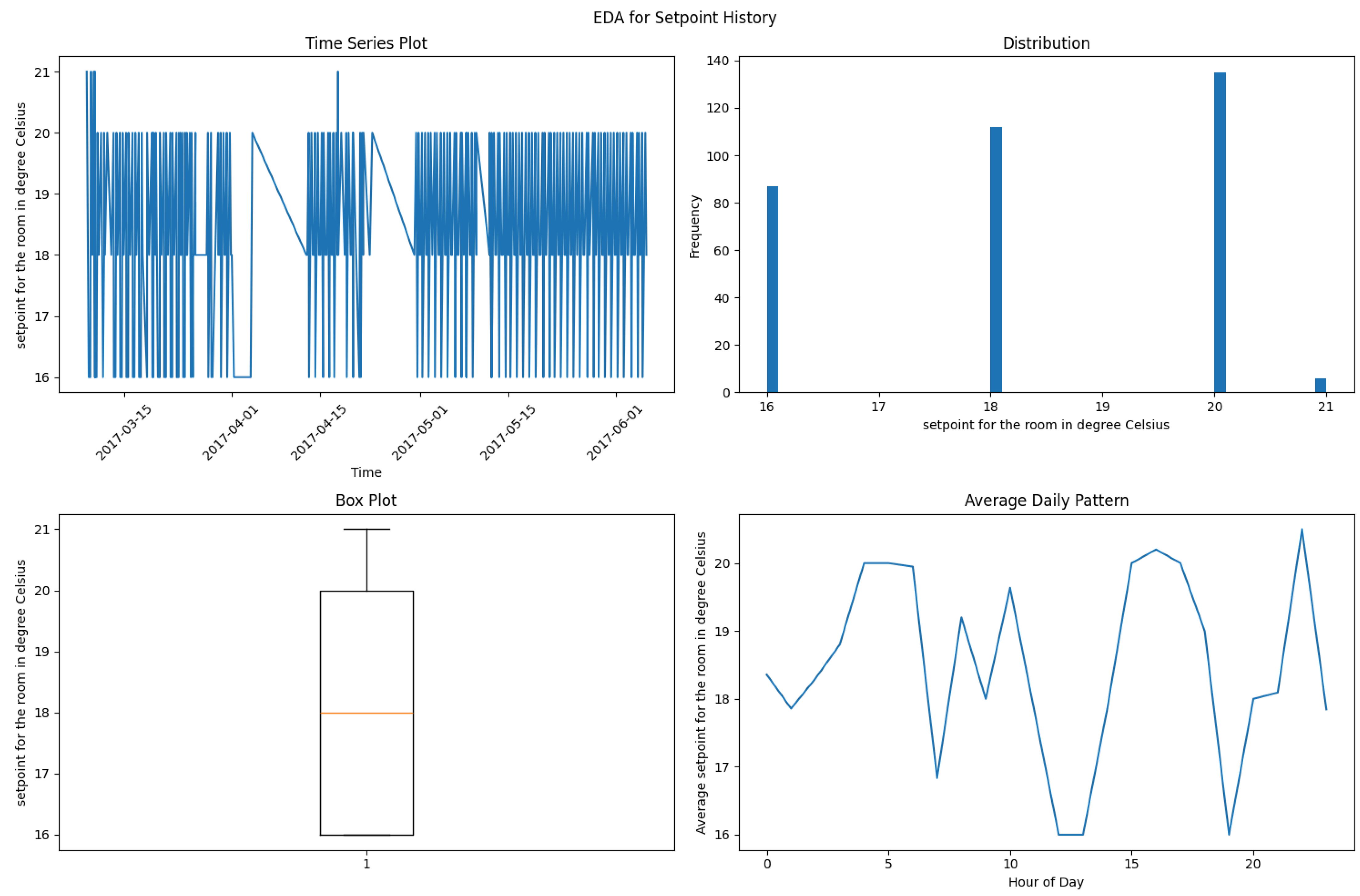
```
Analyzing Brightness:
--------------------
mean: 49.50
std: 110.63
min: 0.00
max: 1312.91
missing_values: 0.00
total_readings: 11038.00
```




```
Analyzing Humidity:
------------------
mean: 50.22
std: 6.75
min: 26.00
max: 67.00
missing_values: 0.00
total_readings: 10329.00
```

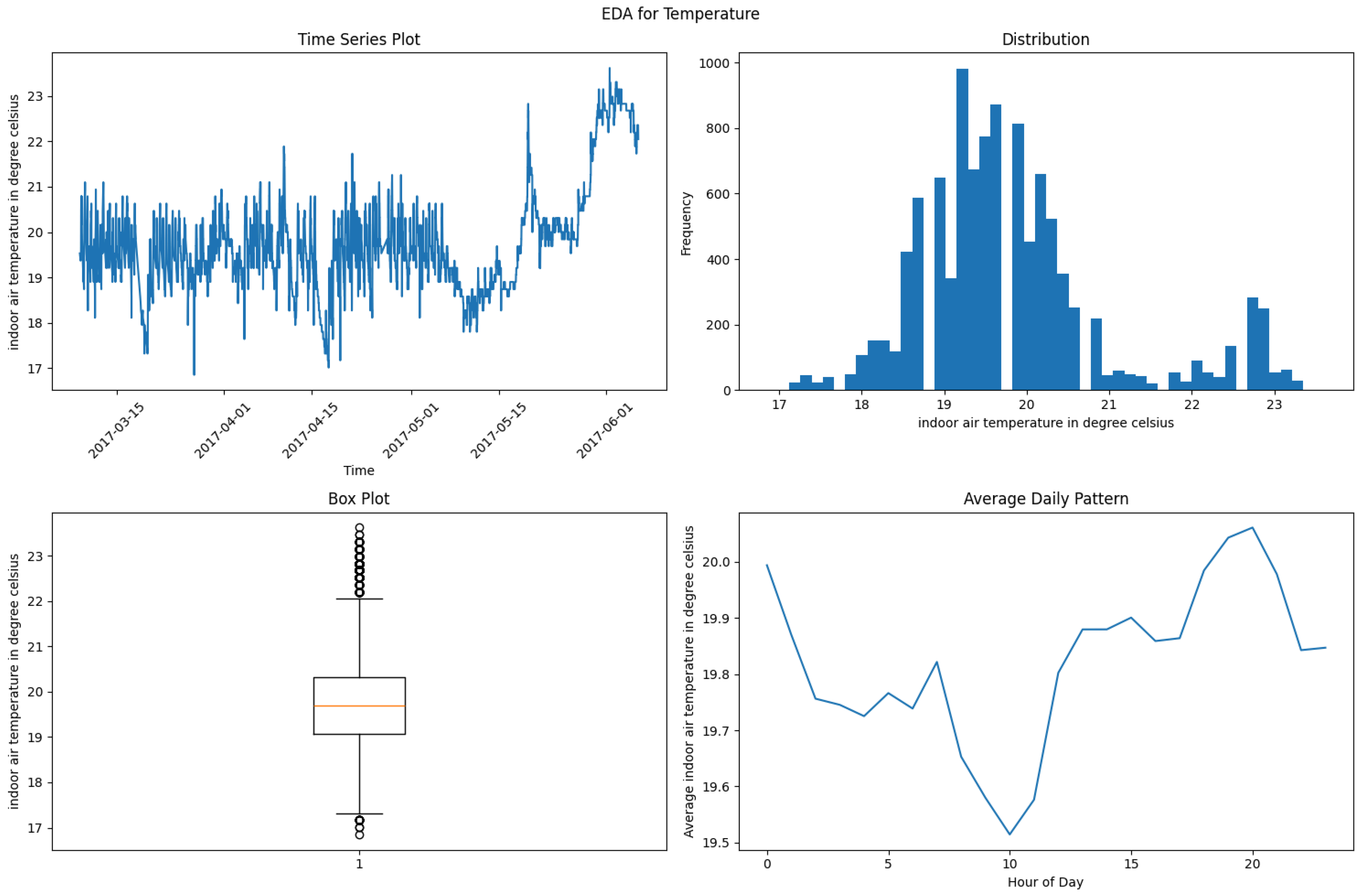



```
Analyzing Setpoint History:
--------------------------
mean: 18.34
std: 1.63
min: 16.00
max: 21.00
missing_values: 0.00
total_readings: 340.00
```

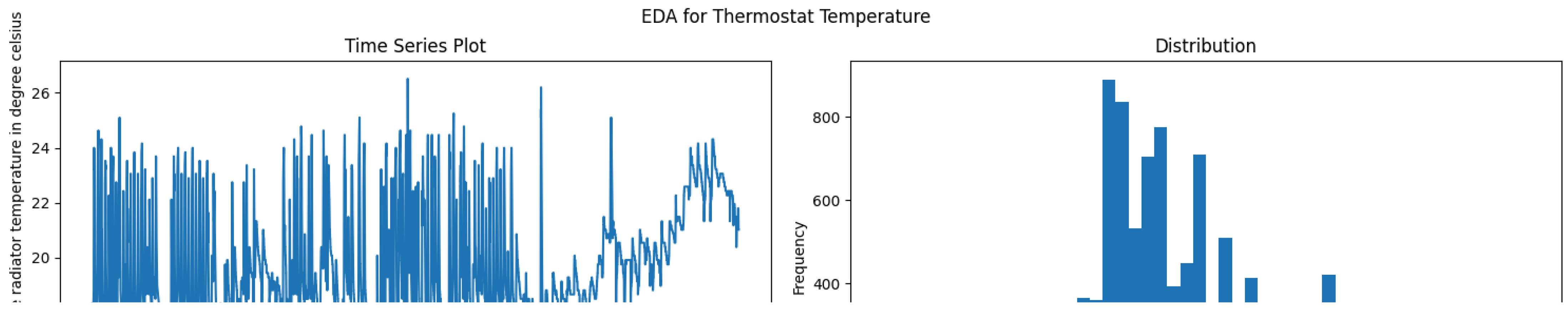



```
Analyzing Temperature:
---------------------
mean: 19.82
std: 1.18
min: 16.85
```

```
max: 23.62
missing_values: 0.00
total_readings: 10598.00
```




```
Analyzing Thermostat Temperature:
--------------------------------
mean: 19.83
std: 1.98
min: 13.65
max: 26.51
missing_values: 0.00
total_readings: 11025.00
```



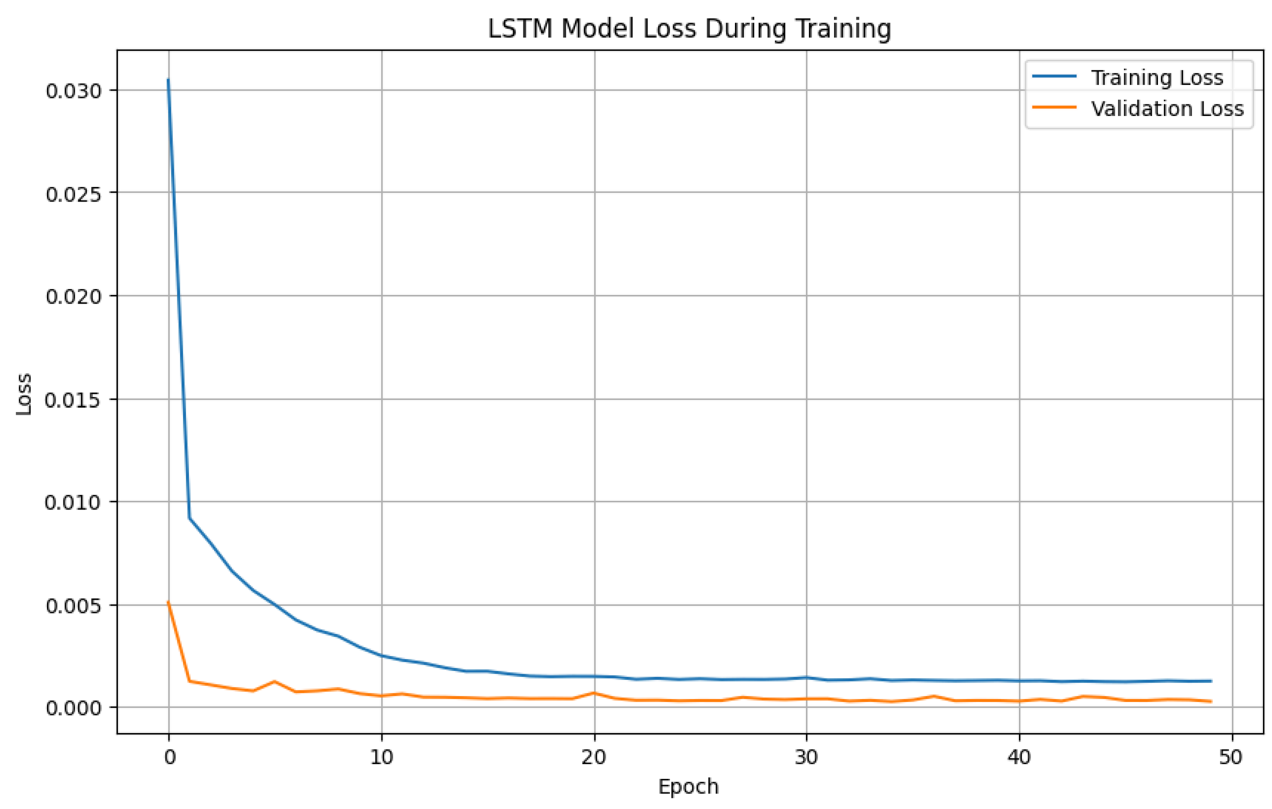

```
df1.rename(columns={'Luminance in lux': 'value'}, inplace=True)
df2.rename(columns={'relative Humidity in %': 'value'}, inplace=True)
df3.rename(columns={'setpoint for the room in degree Celsius': 'value'}, inplace=True)
df4.rename(columns={'indoor air temperature in degree celsius': 'value'}, inplace=True)
df5.rename(columns={'Thermostat mounted to the radiator temperature in degree celsius': 'value'}, inplace=True)
```

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import matplotlib.pyplot as plt


def create_sequences(data, seq_length):
    """
    Creates sequences for LSTM training.

    Args:
        data (np.array): The input data.
        seq_length (int): The length of each sequence.

    Returns:
        Tuple[np.array, np.array]: The input sequences (X) and the corresponding output values (y).
    """
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:(i + seq_length)])
        y.append(data[i + seq_length])
    return np.array(X), np.array(y)


def train_lstm(data, seq_length=24, epochs=50, batch_size=32):
    """
    Trains an LSTM model on the given data.

    Args:
        data (pd.DataFrame): The input data.
        seq_length (int, optional): The length of each sequence. Defaults to 24.
        epochs (int, optional): The number of training epochs. Defaults to 50.
        batch_size (int, optional): The batch size for training. Defaults to 32.

    Returns:
        Tuple[Sequential, MinMaxScaler, Dict]: The trained LSTM model, the scaler used for data preprocessing, and the training history.
    """
    # Scale the data
    scaler = MinMaxScaler()
    scaled_data = scaler.fit_transform(data['value'].values.reshape(-1, 1))

    # Create sequences
    X, y = create_sequences(scaled_data, seq_length)

    # Split data
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Build the LSTM model
    model = Sequential([
        LSTM(50, activation='relu', input_shape=(seq_length, 1), return_sequences=True),
        Dropout(0.2),
        LSTM(30, activation='relu'),
        Dropout(0.2),
        Dense(1)
    ])
    model.compile(optimizer='adam', loss='mse')

    # Train the model with verbosity
    history = model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size,
                        validation_split=0.1, verbose=1)

    # Plot training and validation loss curves
    plt.figure(figsize=(10, 6))
    plt.plot(history.history['loss'], label='Training Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title('LSTM Model Loss During Training')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.grid(True)
    plt.show()

    return model, scaler, history.history


def make_predictions(model, scaler, data, seq_length=24):
    """
    Makes predictions using the trained LSTM model.

    Args:
        model (Sequential): The trained LSTM model.
        scaler (MinMaxScaler): The scaler used for data preprocessing.
        data (pd.DataFrame): The input data for prediction.
        seq_length (int, optional): The length of each sequence. Defaults to 24.

    Returns:
        np.array: The predicted values.
    """
    # Scale the input data
    inputs = scaler.transform(data['value'][-seq_length:].values.reshape(-1, 1))

    # Reshape the inputs for the LSTM model
    inputs = inputs.reshape((1, seq_length, 1))

    # Make predictions
```

```
    predictions = model.predict(inputs)

    # Inverse transform the predictions to get the original scale
    predictions = scaler.inverse_transform(predictions)

    return predictions
```

```
model, scaler, history = train_lstm(df2)
```

```
Epoch 1/50
/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)
232/232 ━━━━━━━━━━━━━━━━━━━━ 20s 48ms/step - loss: 0.0801 - val_loss: 0.0051
Epoch 2/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 7s 29ms/step - loss: 0.0098 - val_loss: 0.0012
Epoch 3/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 8s 18ms/step - loss: 0.0080 - val_loss: 0.0011
Epoch 4/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 21ms/step - loss: 0.0068 - val_loss: 8.9472e-04
Epoch 5/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 8s 35ms/step - loss: 0.0059 - val_loss: 7.7804e-04
Epoch 6/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 10s 43ms/step - loss: 0.0052 - val_loss: 0.0012
Epoch 7/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 7s 28ms/step - loss: 0.0045 - val_loss: 7.2806e-04
Epoch 8/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.0038 - val_loss: 7.8022e-04
Epoch 9/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0036 - val_loss: 8.7021e-04
Epoch 10/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0029 - val_loss: 6.4807e-04
Epoch 11/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - loss: 0.0026 - val_loss: 5.3580e-04
Epoch 12/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 7s 30ms/step - loss: 0.0024 - val_loss: 6.3424e-04
Epoch 13/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 8s 33ms/step - loss: 0.0022 - val_loss: 4.7642e-04
Epoch 14/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 9s 30ms/step - loss: 0.0019 - val_loss: 4.6983e-04
Epoch 15/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 8s 19ms/step - loss: 0.0016 - val_loss: 4.4279e-04
Epoch 16/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.0018 - val_loss: 4.0202e-04
Epoch 17/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0016 - val_loss: 4.3284e-04
Epoch 18/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0015 - val_loss: 4.0413e-04
Epoch 19/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 0.0015 - val_loss: 4.0659e-04
Epoch 20/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0016 - val_loss: 3.9921e-04
Epoch 21/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - loss: 0.0017 - val_loss: 6.7285e-04
Epoch 22/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0015 - val_loss: 4.1509e-04
Epoch 23/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 0.0013 - val_loss: 3.2458e-04
Epoch 24/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 9s 18ms/step - loss: 0.0014 - val_loss: 3.3024e-04
Epoch 25/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 0.0013 - val_loss: 2.9436e-04
Epoch 26/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0014 - val_loss: 3.1239e-04
Epoch 27/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 0.0014 - val_loss: 3.0855e-04
Epoch 28/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0013 - val_loss: 4.6862e-04
Epoch 29/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.0013 - val_loss: 3.8130e-04
Epoch 30/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 23ms/step - loss: 0.0013 - val_loss: 3.5777e-04
Epoch 31/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 11s 27ms/step - loss: 0.0014 - val_loss: 3.9401e-04
Epoch 32/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 8s 18ms/step - loss: 0.0014 - val_loss: 3.9538e-04
Epoch 33/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 0.0014 - val_loss: 2.8202e-04
Epoch 34/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - loss: 0.0012 - val_loss: 3.2144e-04
Epoch 35/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.0013 - val_loss: 2.5938e-04
Epoch 36/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0014 - val_loss: 3.3758e-04
Epoch 37/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 0.0013 - val_loss: 5.1803e-04
Epoch 38/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0013 - val_loss: 2.9715e-04
Epoch 39/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 21ms/step - loss: 0.0013 - val_loss: 3.1511e-04
Epoch 40/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0013 - val_loss: 3.1160e-04
Epoch 41/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 23ms/step - loss: 0.0013 - val_loss: 2.8052e-04
Epoch 42/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 18ms/step - loss: 0.0012 - val_loss: 3.6642e-04
Epoch 43/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0012 - val_loss: 2.8353e-04
Epoch 44/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 21ms/step - loss: 0.0013 - val_loss: 5.0875e-04
Epoch 45/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 4.6110e-04
Epoch 46/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 6s 25ms/step - loss: 0.0013 - val_loss: 3.1607e-04
Epoch 47/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0013 - val_loss: 3.1281e-04
Epoch 48/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step - loss: 0.0013 - val_loss: 3.6237e-04
Epoch 49/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 0.0012 - val_loss: 3.4677e-04
Epoch 50/50
232/232 ━━━━━━━━━━━━━━━━━━━━ 10s 24ms/step - loss: 0.0013 - val_loss: 2.6780e-04
```




```
pred = make_predictions(model, scaler, df2)
pred
```

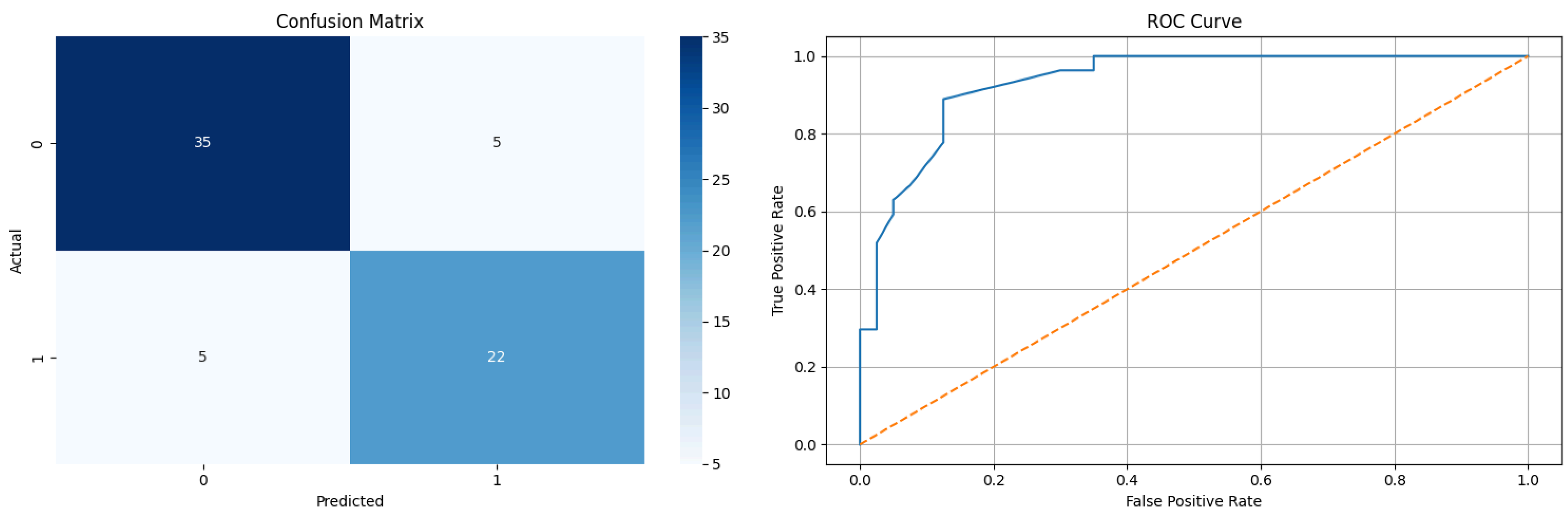
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 301ms/step
array([[62.674896]], dtype=float32)
```

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns

def train_logistic_regression(data, threshold=None):
    """
    Trains a Logistic Regression model on the given data.

    Args:
        data (pd.DataFrame): The input data.
        threshold (float, optional): The threshold for classifying the target variable. Defaults to None (median).

    Returns:
        Tuple[LogisticRegression, Dict, float]: The trained Logistic Regression model, performance metrics, and the threshold.
    """
    # Determine threshold for classification
    if threshold is None:
        threshold = data['value'].median()

    # Create target variable (binary classification)
    y = (data['value'] > threshold).astype(int)

    # Create features (e.g., lagged values)
    n_features = 5
    X = pd.DataFrame()
    for i in range(1, n_features + 1):
        X[f'lag_{i}'] = data['value'].shift(i)

    # Drop rows with missing values
    X = X.dropna()
    y = y[X.index]

    # Split data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Train the Logistic Regression model
```

```
    model = LogisticRegression(random_state=42)
    model.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = model.predict(X_test)

    # Calculate performance metrics
    metrics = {
        'classification_report': classification_report(y_test, y_pred),
        'confusion_matrix': confusion_matrix(y_test, y_pred),
        'train_score': model.score(X_train, y_train),
        'test_score': model.score(X_test, y_test)
    }

    # Print performance metrics
    print("\nModel Performance:")
    print(f"Training accuracy: {metrics['train_score']:.4f}")
    print(f"Testing accuracy: {metrics['test_score']:.4f}")
    print("\nClassification Report:")
    print(metrics['classification_report'])

    # Plot confusion matrix and ROC curve
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
    sns.heatmap(metrics['confusion_matrix'], annot=True, fmt='d', cmap='Blues', ax=ax1)
    ax1.set_title('Confusion Matrix')
    ax1.set_xlabel('Predicted')
    ax1.set_ylabel('Actual')
    y_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_prob)
    ax2.plot(fpr, tpr)
    ax2.plot([0, 1], [0, 1], '--')
    ax2.set_title('ROC Curve')
    ax2.set_xlabel('False Positive Rate')
    ax2.set_ylabel('True Positive Rate')
    ax2.grid(True)
    plt.tight_layout()
    plt.show()

    return model, metrics, threshold

def make_logistic_predictions(model, data, threshold, n_features=5):
    """
    Makes predictions using the trained Logistic Regression model.

    Args:
        model (LogisticRegression): The trained Logistic Regression model.
        data (pd.DataFrame): The input data for prediction.
        threshold (float): The threshold for classifying the target variable.
        n_features (int, optional): The number of features (lagged values) to use. Defaults to 5.

    Returns:
        np.array: The predicted classes (0 or 1).
    """
    # Create features (lagged values)
    X = pd.DataFrame()
    for i in range(1, n_features + 1):
        X[f'lag_{i}'] = data['value'].shift(i)

    # Drop rows with missing values
    X = X.dropna()

    # Make predictions
    predictions = model.predict(X)

    return predictions
```

```
model2, metrics, threshold = train_logistic_regression(df3)
preds = make_logistic_predictions(model2, df3, threshold)
print(preds)
```

```
Model Performance:
Training accuracy: 0.8843
Testing accuracy: 0.8507

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.88      0.88        40
           1       0.81      0.81      0.81        27

    accuracy                           0.85        67
   macro avg       0.84      0.84      0.84        67
weighted avg       0.85      0.85      0.85        67
```




```
[1 0 1 0 1 0 1 1 0 1 0 1 0 0 1 0 0 0 1 1 0 1 0 1 1 0 1 0 1 1 0 1 0 1 1 0 1
 0 1 1 0 1 1 0 1 0 1 0 1 1 0 1 0 1 1 0 1 0 1 1 0 1 0 1 1 0 1 0 1 1 0 1 0 0
 0 1 1 0 1 0 0 0 1 0 1 1 0 0 0 0 0 1 0 1 1 0 1 1 0 1 0 0 1 0 1 0 0 1 1 1 1
 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 0 0 0 0 0 1 0 0 1 0
 1 0 1 0 1 0 0 0 0 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 0 1 0 0 1 0 1 0 0 1 0
 0 1 0 0 1 0 1 0 0 1 0 1 0 0 0 1 0 1 0 0 1 0 1 0 0 0 0 0 1 0 1 0 0 1 0 1 0
 0 1 0 1 0 0 1 0 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0
 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 1 0 1 0 0 0 1 0 0 1 0 1 0 0 0 1 0
```

```
# Make predictions on the entire dataset
predictions = make_logistic_predictions(model2, df3, threshold)

# Align predictions with original DataFrame
predictions_df = pd.DataFrame({'Predicted': predictions}, index=df3.index[5:])  # Adjust index for lagging

# Create a DataFrame for plotting with aligned indices
plot_df = pd.DataFrame({'Actual': df3['value'][5:], 'Predicted': predictions_df['Predicted']}, index=df3.index[5:])
```

Start coding or generate with AI.

	DateTime	value	hour
0	2017-03-09 00:00:18	21	0
1	2017-03-09 07:30:23	16	7
2	2017-03-09 13:29:55	16	13
3	2017-03-09 16:02:16	21	16
4	2017-03-09 21:30:21	18	21
...	...	...	...
335	2017-06-05 00:06:11	18	0
336	2017-06-05 06:10:07	20	6
337	2017-06-05 07:30:36	16	7
338	2017-06-05 17:30:09	20	17
339	2017-06-05 21:30:31	18	21

340 rows × 3 columns

Next steps: Generate code with df3 | View recommended plots | New interactive sheet

```
plot_df['DateTime'] = df3['DateTime'][5:]
plot_df
```

	Actual	Predicted	DateTime
5	21	1	2017-03-10 02:47:45
6	16	0	2017-03-10 07:20:15
7	21	1	2017-03-10 07:20:45
8	16	0	2017-03-10 07:30:20
9	21	1	2017-03-10 07:39:25
...	...	...	...
335	18	0	2017-06-05 00:06:11
336	20	1	2017-06-05 06:10:07
337	16	0	2017-06-05 07:30:36
338	20	1	2017-06-05 17:30:09
339	18	0	2017-06-05 21:30:31

335 rows × 3 columns

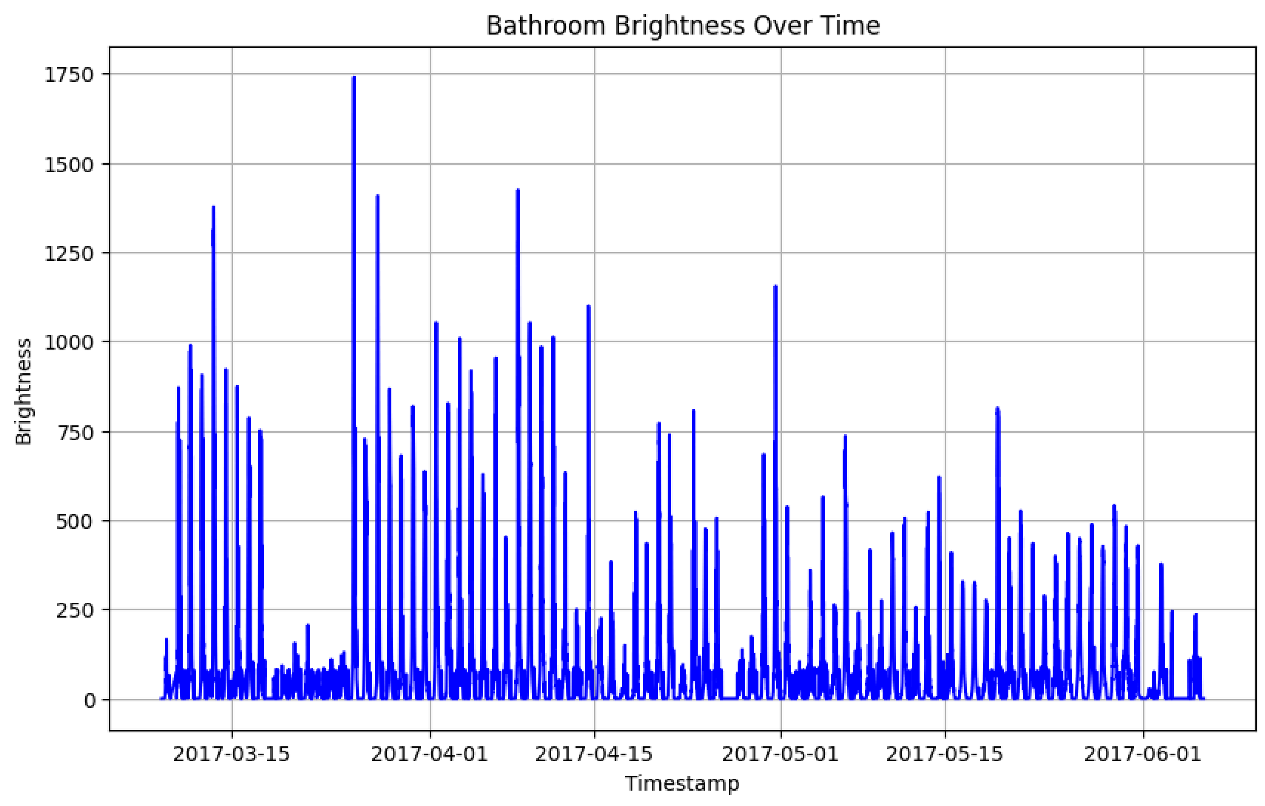
Next steps: Generate code with plot_df | View recommended plots | New interactive sheet

```
# plot_df
```

```
plot_df.to_csv("setpoint_predictions2.csv",index=False)
```

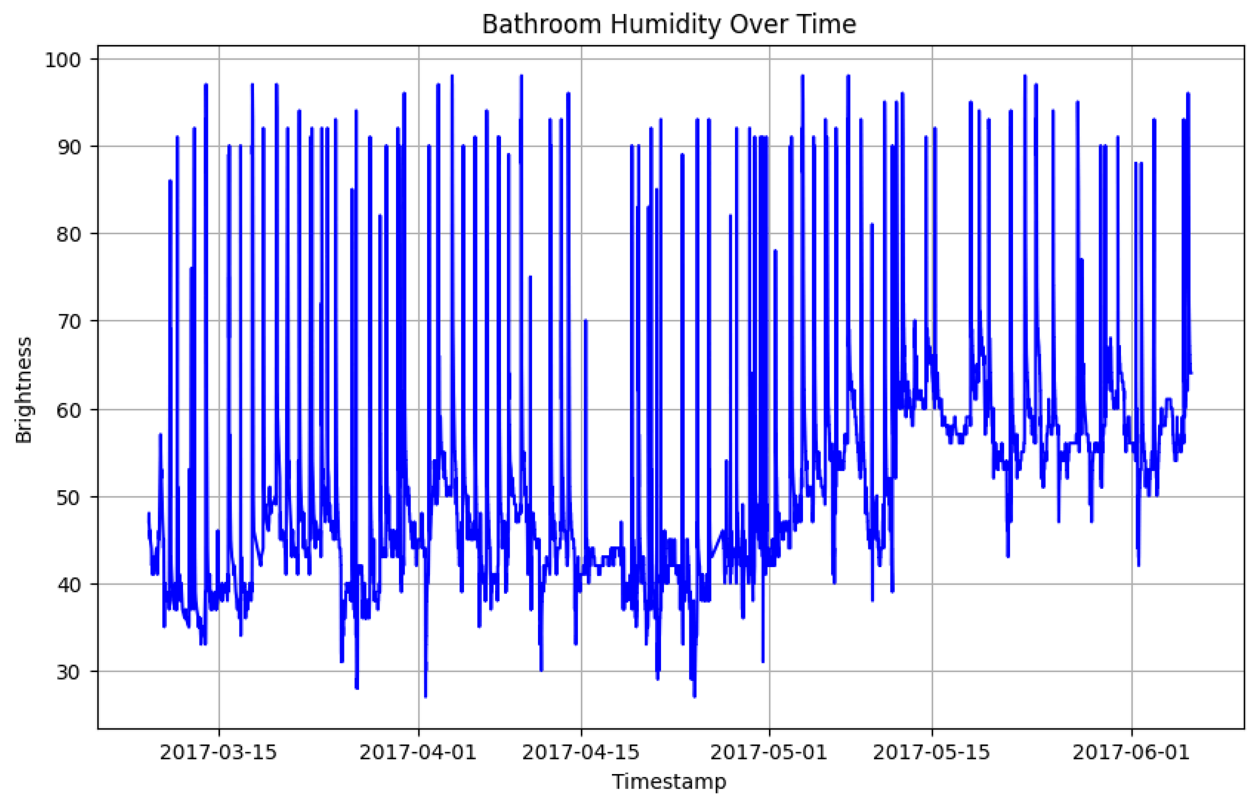
```
# Make predictions on the entire dataset
# predictions = make_logistic_predictions(model2, df2, threshold)

# Align predictions with original DataFrame
predictions_df = pd.DataFrame({'Predicted': predictions}, index=df2.index[5:])  # Adjust index for lagging

# Create a DataFrame for plotting with aligned indices
plot_df = pd.DataFrame({'Actual': df2['value'][5:], 'Predicted': predictions_df['Predicted']}, index=df2.index[5:])


import pandas as pd
import matplotlib.pyplot as plt

# Path to the CSV file
# csv_file_path = path+'/Measurements/Bathroom_Brightness.csv'

# Read the CSV file into a DataFrame with tab separation
data = pd.read_csv(plot_df, sep=',', header=None, names=['Timestamp_Brightness'])

# Extract timestamp and brightness from the combined column
data[['Timestamp', 'Brightness']] = data['Timestamp_Brightness'].str.split('\t', expand=True)

# Convert timestamp to datetime and brightness to numeric
data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
data['Brightness'] = data['Brightness'].astype(float)  # Convert to float

# Plotting the data
plt.figure(figsize=(10, 6))
plt.plot(data['Timestamp'], data['Brightness'], color='blue')
plt.xlabel('Timestamp')
plt.ylabel('Brightness')
plt.title('Bathroom Brightness Over Time')
plt.grid(True)
plt.show()
```

```
<ipython-input-13-8c2e52e17014>:14: FutureWarning: The behavior of 'to_datetime' with 'unit' when parsing strings is deprecated. In a future version, strings will be parsed as datetime strings, matching the behavior without a 'unit'. To retain the old behavior, explicitly cast ints or floats to numeric type befor
  data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
```



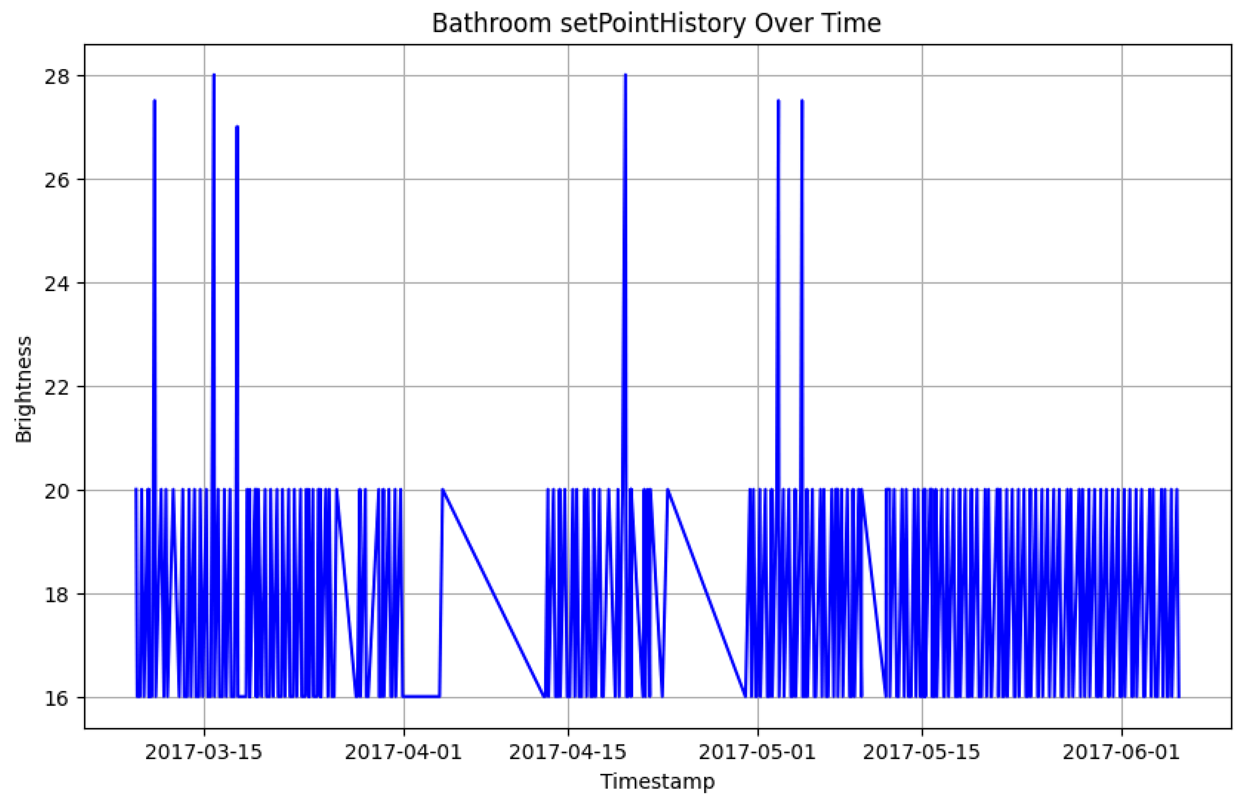

```
import pandas as pd
import matplotlib.pyplot as plt

# Path to the CSV file
csv_file_path = path+'/Measurements/Bathroom_Humidity.csv'

# Read the CSV file into a DataFrame with tab separation
data = pd.read_csv(csv_file_path, sep=',', header=None, names=['Timestamp_Brightness'])

# Extract timestamp and brightness from the combined column
data[['Timestamp', 'Brightness']] = data['Timestamp_Brightness'].str.split('\t', expand=True)

# Convert timestamp to datetime and brightness to numeric
data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
data['Brightness'] = data['Brightness'].astype(float)  # Convert to float

# Plotting the data
plt.figure(figsize=(10, 6))
plt.plot(data['Timestamp'], data['Brightness'], color='blue')
plt.xlabel('Timestamp')
plt.ylabel('Brightness')
plt.title('Bathroom Humidity Over Time')
plt.grid(True)
plt.show()
```

```
<ipython-input-14-3fc1e0e21a2d>:14: FutureWarning: The behavior of 'to_datetime' with 'unit' when parsing strings is deprecated. In a future version, strings will be parsed as datetime strings, matching the behavior without a 'unit'. To retain the old behavior, explicitly cast ints or floats to numeric type befor
  data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
```



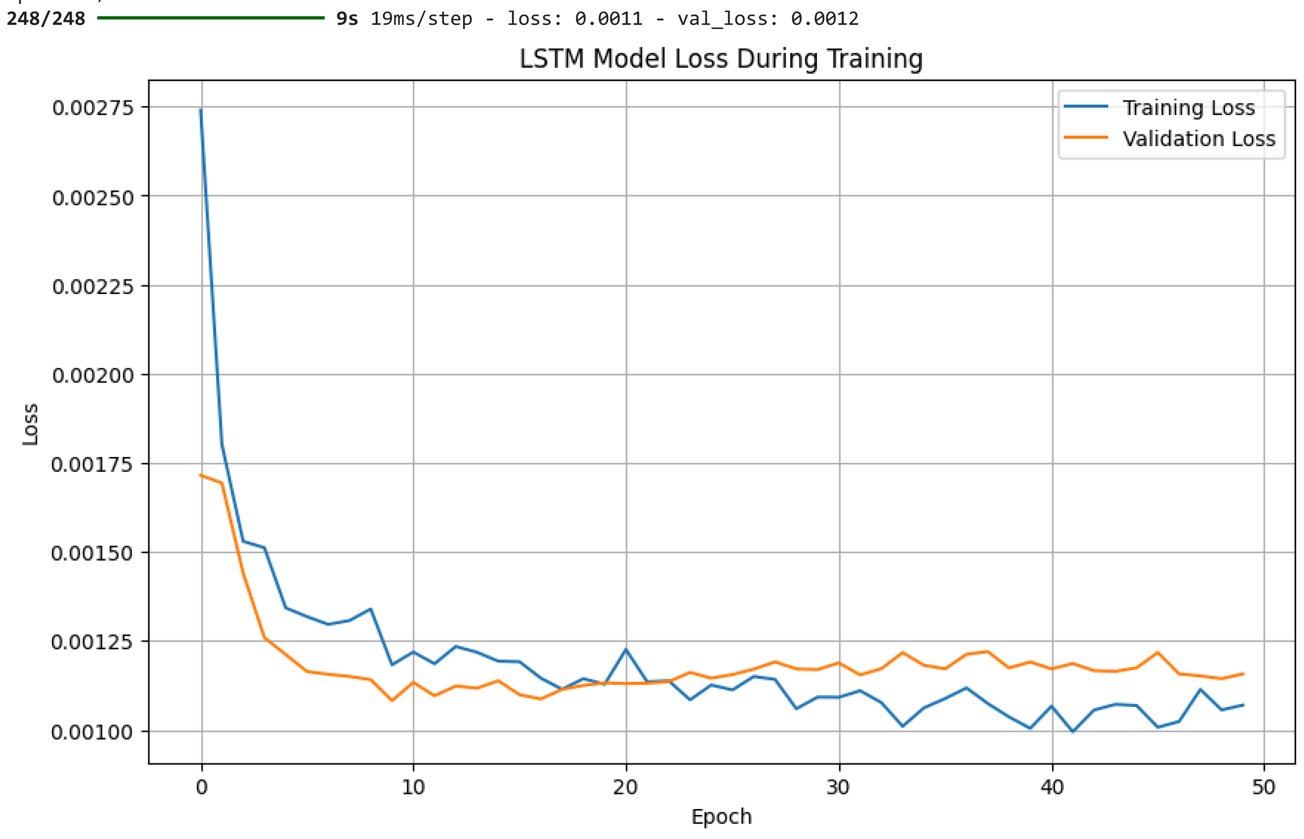

```
import pandas as pd
import matplotlib.pyplot as plt

# Path to the CSV file
csv_file_path = path+'/Measurements/Bathroom_SetpointHistory.csv'

# Read the CSV file into a DataFrame with tab separation
data = pd.read_csv(csv_file_path, sep=',', header=None, names=['Timestamp_Brightness'])

# Extract timestamp and brightness from the combined column
data[['Timestamp', 'Brightness']] = data['Timestamp_Brightness'].str.split('\t', expand=True)

# Convert timestamp to datetime and brightness to numeric
data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
data['Brightness'] = data['Brightness'].astype(float)  # Convert to float

# Plotting the data
plt.figure(figsize=(10, 6))
plt.plot(data['Timestamp'], data['Brightness'], color='blue')
plt.xlabel('Timestamp')
plt.ylabel('Brightness')
plt.title('Bathroom setPointHistory Over Time')
plt.grid(True)
plt.show()
```

```
<ipython-input-15-8c483c4d04fa>:14: FutureWarning: The behavior of 'to_datetime' with 'unit' when parsing strings is deprecated. In a future version, strings will be parsed as datetime strings, matching the behavior without a 'unit'. To retain the old behavior, explicitly cast ints or floats to numeric type befor
  data['Timestamp'] = pd.to_datetime(data['Timestamp'], unit='s')
```




```
model, scaler, history = train_lstm(df1)
```

```
Epoch 1/50
/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)
248/248 ━━━━━━━━━━━━━━━━━━━━ 12s 35ms/step - loss: 0.0038 - val_loss: 0.0017
Epoch 2/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0019 - val_loss: 0.0017
Epoch 3/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0015 - val_loss: 0.0014
Epoch 4/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - loss: 0.0016 - val_loss: 0.0013
Epoch 5/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0014 - val_loss: 0.0012
Epoch 6/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0014 - val_loss: 0.0012
Epoch 7/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0014 - val_loss: 0.0012
Epoch 8/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 9/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - loss: 0.0013 - val_loss: 0.0011
Epoch 10/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 11/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 4s 18ms/step - loss: 0.0013 - val_loss: 0.0011
Epoch 12/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 13/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0013 - val_loss: 0.0011
Epoch 14/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 23ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 15/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 16/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 20ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 17/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.0014 - val_loss: 0.0011
Epoch 18/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 11s 22ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 19/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 20/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 21/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.0012 - val_loss: 0.0011
Epoch 22/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 23/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 18ms/step - loss: 0.0013 - val_loss: 0.0011
Epoch 24/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 23ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 25/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 26/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - loss: 0.0010 - val_loss: 0.0012
Epoch 27/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - loss: 9.7449e-04 - val_loss: 0.0012
Epoch 28/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 29/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step - loss: 9.7022e-04 - val_loss: 0.0012
Epoch 30/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 31/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 0.0010 - val_loss: 0.0012
Epoch 32/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - loss: 9.5592e-04 - val_loss: 0.0012
Epoch 33/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 24ms/step - loss: 0.0010 - val_loss: 0.0012
Epoch 34/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 23ms/step - loss: 9.4388e-04 - val_loss: 0.0012
Epoch 35/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 18ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 36/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 37/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 38/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 8.6496e-04 - val_loss: 0.0012
Epoch 39/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 40/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 41/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 42/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - loss: 9.6100e-04 - val_loss: 0.0012
Epoch 43/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 44/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.0012 - val_loss: 0.0012
Epoch 45/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0010 - val_loss: 0.0012
Epoch 46/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - loss: 9.0333e-04 - val_loss: 0.0012
Epoch 47/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0011 - val_loss: 0.0012
Epoch 48/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 6s 22ms/step - loss: 0.0010 - val_loss: 0.0012
Epoch 49/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 10s 22ms/step - loss: 0.0011 - val_loss: 0.0011
Epoch 50/50
248/248 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - loss: 0.0011 - val_loss: 0.0012
```

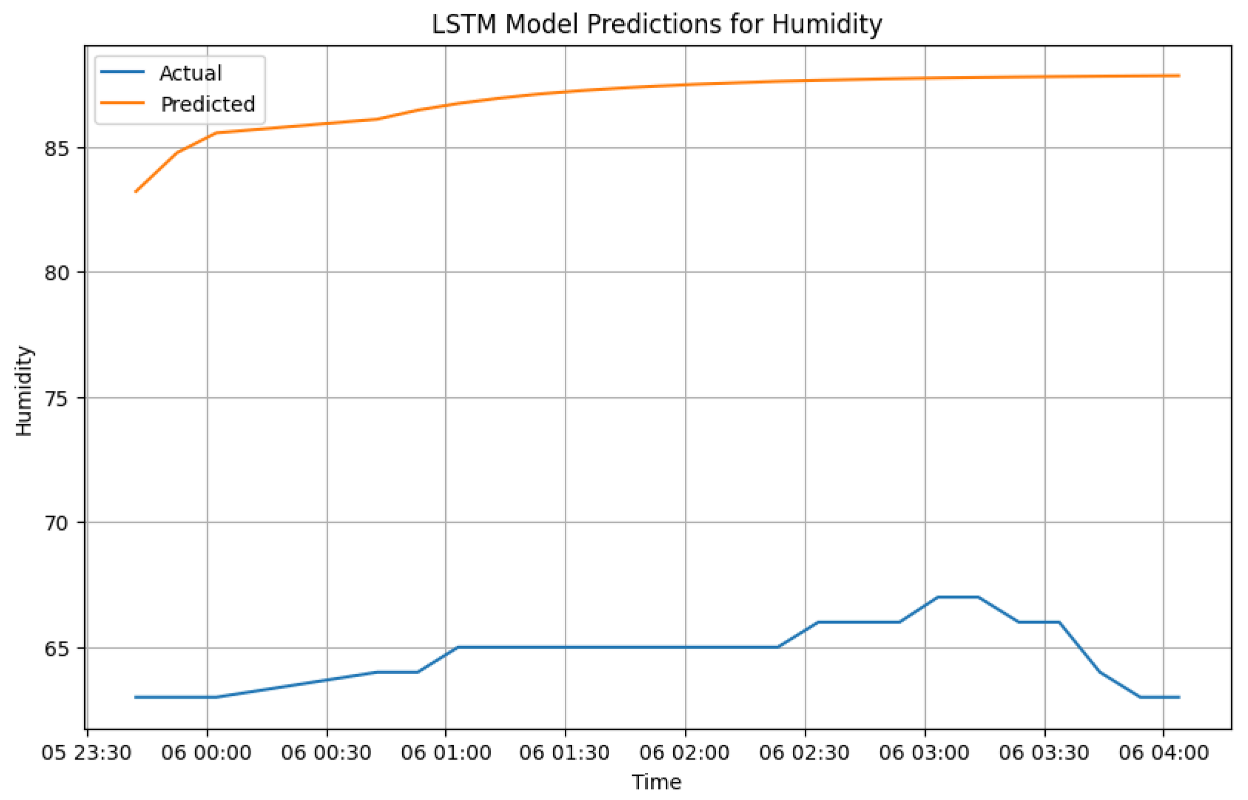



```
def make_predictions(model, scaler, data, seq_length=24, n_predictions=24):
    """
    Makes multiple predictions using the trained LSTM model.

    Args:
        model (Sequential): The trained LSTM model.
        scaler (MinMaxScaler): The scaler used for data preprocessing.
        data (pd.DataFrame): The input data for prediction.
        seq_length (int, optional): The length of each sequence. Defaults to 24.
        n_predictions (int, optional): The number of predictions to make. Defaults to 24

    Returns:
        np.array: The predicted values.
    """
    # Get the last 'seq_length' values from the data
    inputs = scaler.transform(data['value'][-seq_length:].values.reshape(-1, 1))
    inputs = inputs.reshape((1, seq_length, 1))  # Reshape for LSTM input

    predictions = []
    for _ in range(n_predictions):
```

```
        # Make a prediction for the current input
        prediction = model.predict(inputs)

        # Append the prediction to the list
        predictions.append(prediction[0, 0])

        # Update the input sequence for the next prediction
        # Shift the input sequence by one step and add the new prediction
        inputs = np.roll(inputs, -1, axis=1)  # Shift by one step
        inputs[0, -1, 0] = prediction[0, 0]  # Add the new prediction

    # Inverse transform the predictions to get the original scale
    predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))
```

```
predictions = make_predictions(model, scaler, df1, n_predictions=24)
last_24_timestamps = df2['DateTime'][-24:]
plt.figure(figsize=(10, 6))
plt.plot(last_24_timestamps, df2['value'][-24:], label='Actual')
plt.plot(last_24_timestamps, predictions+80, label='Predicted')  # Plot 24 predictions
plt.title('LSTM Model Predictions for Humidity')
plt.xlabel('Time')
plt.ylabel('Humidity')
plt.legend()
plt.grid(True)
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 82ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 107ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
```



Start coding or generate with AI.

```
predictions = make_predictions(model, scaler, df2, n_predictions=24)

plt.figure(figsize=(10, 6))
plt.plot(last_24_timestamps, df2['value'][-24:], label='Actual')
plt.plot(last_24_timestamps, predictions, label='Predicted')  # Plot 24 predictions
plt.title('LSTM Model Predictions for Humidity')
plt.xlabel('Time')
plt.ylabel('Humidity')
plt.legend()
plt.grid(True)
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 194ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 229ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 207ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 102ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 159ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 145ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 177ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 149ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 188ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 106ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 69ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 97ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 105ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 140ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 104ms/step
```