```
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session
```

Smart Farming System and Crop Health Monitoring

```
import pandas as pd
import numpy as np

# Load datasets
soil_df =
pd.read_csv('/kaggle/input/farming/Soil_Sensing_LoRa_Node_Farmer_2_Cor
n.csv')
weather_df =
pd.read_csv('/kaggle/input/farming/Weather_Station_1.csv')

# ------------------------------ Data Cleaning
------------------------------

# Convert time columns to consistent datetime format (without
timezone)
soil_df['time'] = pd.to_datetime(soil_df['time']).dt.tz_localize(None)
weather_df['observation_time'] =
pd.to_datetime(weather_df['observation_time']).dt.tz_localize(None)
```

```
# Handle missing values using forward fill (updated method)
soil_df.ffill(inplace=True)
weather_df.ffill(inplace=True)

# ----------------------------- Merge Datasets
-----------------------------

# Merge based on nearest timestamps with a 30-minute tolerance
merged_df = pd.merge_asof(
    soil_df.sort_values('time'),
    weather_df.sort_values('observation_time'),
    left_on='time',
    right_on='observation_time',
    direction='nearest',
    tolerance=pd.Timedelta('30min')
)

# Drop rows with NaNs after merging
merged_df.dropna(inplace=True)

print("□ Merge successful. Data is ready for EDA.")
```

```
□ Merge successful. Data is ready for EDA.
```

```
# Display basic information about the dataset
print("Dataset Information:")
merged_df.info()

# Display summary statistics for numerical columns
print("\nSummary Statistics:")
display(merged_df.describe())

# Display the first five rows of the dataset
print("\nSample Data:")
display(merged_df.head())
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
Index: 2398 entries, 16 to 2413
Data columns (total 32 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   time                          2398 non-null   datetime64[ns]
 1   batt_vol                      2398 non-null   float64
 2   temperature_x                 2398 non-null   float64
 3   humidity_x                    2398 non-null   float64
 4   soil_sensor1_temp             2398 non-null   float64
 5   soil_sensor2_temp             2398 non-null   float64
 6   soil_sensor1_vwc              2398 non-null   float64
 7   soil_sensor2_vwc              2398 non-null   float64
 8   soil_sensor1_conductivity     2398 non-null   float64
 9   soil_sensor2_conductivity    2398 non-null   float64
 10  observation_time             2398 non-null   datetime64[ns]
 11  humidity_y                   2398 non-null   float64
 12  pressure                     2398 non-null   float64
 13  rain                         2398 non-null   float64
 14  rain_inches_last_hour        2398 non-null   float64
 15  soil_moist_1                 2398 non-null   float64
 16  soil_moist_2                 2398 non-null   float64
 17  soil_moist_3                 2398 non-null   float64
 18  soil_moist_4                 2398 non-null   float64
 19  soil_temp_1                  2398 non-null   float64
 20  soil_temp_2                  2398 non-null   float64
 21  soil_temp_3                  2398 non-null   float64
 22  soil_temp_4                  2398 non-null   float64
 23  solar_radiation              2398 non-null   float64
 24  solar_radiation_high         2398 non-null   float64
 25  temperature_y                2398 non-null   float64
 26  temperature_high             2398 non-null   float64
 27  temperature_low              2398 non-null   float64
 28  wind_direction_degrees       2398 non-null   float64
 29  wind_gust_direction_degrees  2398 non-null   float64
 30  wind_gust_speed_mph          2398 non-null   float64
 31  wind_speed_mph               2398 non-null   float64
dtypes: datetime64[ns](2), float64(30)
memory usage: 618.2 KB

Summary Statistics:

                                time     batt_vol  temperature_x
humidity_x  \
count                           2398  2398.000000    2398.000000
2398.000000
mean   2021-06-30 17:57:53.401584640     7.681004      68.057018
83.247615
min              2021-04-26 03:49:57     0.402363    -557.608000
2.140000
25%    2021-05-10 03:51:16.249999872     5.895580      57.348500
64.420000
50%       2021-05-22 20:08:27.500000     5.922404      67.127000
74.605000
75%       2021-08-23 05:09:44.500000     6.094846      80.793500
83.270000
max              2021-09-20 19:14:21   122.465971     579.434000
606.490000
std                              NaN     9.793480      86.494632
60.833632

       soil_sensor1_temp  soil_sensor2_temp  soil_sensor1_vwc  \
count        2398.000000        2398.000000       2398.000000
mean          425.058148         469.790550          0.331324
```

```
min            32.000000          32.000000          -0.696000
25%            57.560000          58.460000           0.309000
50%            68.360000          68.540000           0.334000
75%            71.780000          73.355000           0.342000
max         11647.220000       11798.780000           1.831000
std          1492.836986        1519.585052           0.210239

       soil_sensor2_vwc  soil_sensor1_conductivity
soil_sensor2_conductivity  \
count       2398.000000                2398.000000
2398.000000
mean           0.146607                   2.802931
1.687299
min           -0.696000                   0.000000
0.000000
25%            0.240000                   0.237000
0.209000
50%            0.284000                   0.258000
0.250000
75%            0.309000                   0.278000
0.280000
max            1.843000                  65.422000
64.202000
std            0.424960                   9.043069
6.932954

       ...  soil_temp_4  solar_radiation  solar_radiation_high
temperature_y  \
count  ...  2398.000000      2398.000000           2398.000000
2398.000000
mean   ...    63.399917       226.962052            265.864053
65.912427
min    ...    49.000000         0.000000              0.000000
34.000000
25%    ...    55.000000         0.000000              0.000000
58.000000
50%    ...    62.000000        49.000000             65.000000
68.000000
75%    ...    73.000000       416.000000            520.000000
75.000000
max    ...    77.000000      1097.000000           1322.000000
92.000000
std    ...     9.340486       296.844174            340.075365
12.484911

       temperature_high  temperature_low  wind_direction_degrees  \
count       2398.000000      2398.000000             2398.000000
mean          66.243953        65.583820              153.465388
min           34.000000        34.000000                0.000000
25%           58.000000        58.000000               90.000000
```

```
50%            68.000000        67.000000                157.500000
75%            75.000000        75.000000                202.500000
max            92.000000        92.000000                337.500000
std            12.532116        12.453077                 91.631290

       wind_gust_direction_degrees  wind_gust_speed_mph
wind_speed_mph
count                  2398.000000          2398.000000
2398.000000
mean                    157.265430            11.225605
6.792327
min                       0.000000             0.000000
0.000000
25%                      90.000000             6.000000
3.000000
50%                     157.500000            10.000000
5.000000
75%                     225.000000            15.000000
9.000000
max                     337.500000            39.000000
27.000000
std                      92.102406             7.150534
4.946210

[8 rows x 32 columns]


Sample Data:

                  time  batt_vol  temperature_x  humidity_x  \
16 2021-04-26 03:49:57  5.976053         35.528       71.50
17 2021-04-26 04:19:15  5.981801         35.114       71.24
18 2021-04-26 04:48:33  5.981801         35.258       71.24
19 2021-04-26 05:17:50  5.983717         63.230       71.44
20 2021-04-26 05:47:08  5.983717         35.240       71.71

    soil_sensor1_temp  soil_sensor2_temp  soil_sensor1_vwc
soil_sensor2_vwc  \
16              51.08              32.00             0.333
-0.696
17              51.08              32.00             0.334
-0.696
18              50.90              32.00             0.333
-0.696
19              51.62              72.32             0.337
-0.693
20              50.54              32.00             0.333
-0.696

    soil_sensor1_conductivity  soil_sensor2_conductivity  ...
```

```
soil_temp_4  \
16                        0.250                          0.000  ...
49.0
17                        0.252                          0.000  ...
49.0
18                        0.249                          0.000  ...
49.0
19                       33.017                          0.048  ...
49.0
20                        0.249                          0.000  ...
49.0

    solar_radiation  solar_radiation_high  temperature_y
temperature_high  \
16              0.0                   0.0           42.0
42.0
17              0.0                   0.0           42.0
42.0
18              0.0                   0.0           42.0
42.0
19              0.0                   0.0           42.0
42.0
20              0.0                   0.0           41.0
42.0

    temperature_low  wind_direction_degrees
wind_gust_direction_degrees  \
16             42.0                    90.0
90.0
17             42.0                    90.0
90.0
18             42.0                    90.0
90.0
19             42.0                    90.0
90.0
20             41.0                    90.0
90.0

    wind_gust_speed_mph  wind_speed_mph
16                 10.0             6.0
17                 10.0             7.0
18                 10.0             7.0
19                  9.0             6.0
20                  7.0             4.0

[5 rows x 32 columns]
```

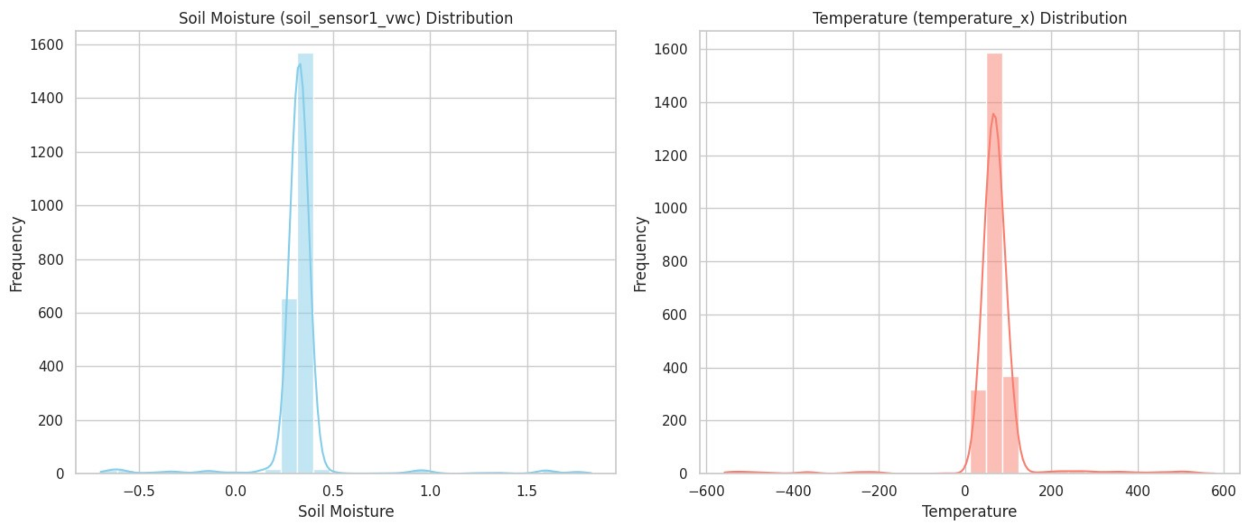
```
# Check for missing values in the dataset
missing_values = merged_df.isnull().sum().sort_values(ascending=False)
```

```python
print("Missing Values Per Column:")
display(missing_values[missing_values > 0])
```

```
Missing Values Per Column:

Series([], dtype: int64)
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Set plot style
sns.set(style="whitegrid")

# Plot distributions of target variables
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Soil moisture distribution
sns.histplot(merged_df['soil_sensor1_vwc'], bins=30, kde=True,
ax=axes[0], color='skyblue')
axes[0].set_title('Soil Moisture (soil_sensor1_vwc) Distribution')
axes[0].set_xlabel('Soil Moisture')
axes[0].set_ylabel('Frequency')

# Temperature distribution
sns.histplot(merged_df['temperature_x'], bins=30, kde=True,
ax=axes[1], color='salmon')
axes[1].set_title('Temperature (temperature_x) Distribution')
axes[1].set_xlabel('Temperature')
axes[1].set_ylabel('Frequency')

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

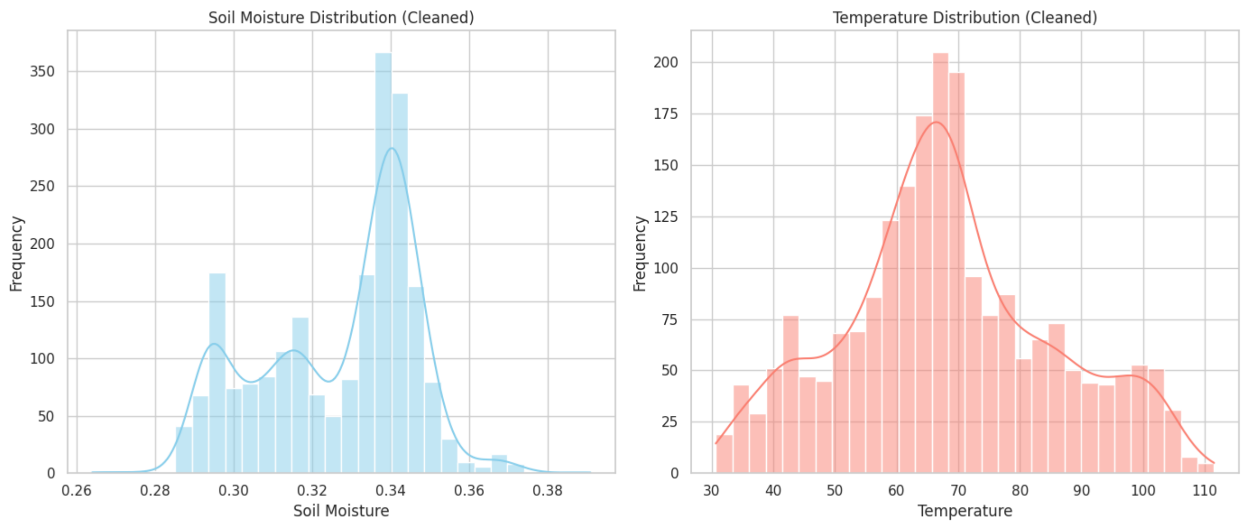
```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
def remove_outliers_iqr(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    cleaned_df = df[(df[column] >= lower_bound) & (df[column] <=
upper_bound)]
    return cleaned_df

# Remove outliers from both target variables
cleaned_df = remove_outliers_iqr(merged_df, 'soil_sensor1_vwc')
cleaned_df = remove_outliers_iqr(cleaned_df, 'temperature_x')

# Plot distributions after outlier removal
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

sns.histplot(cleaned_df['soil_sensor1_vwc'], bins=30, kde=True,
ax=axes[0], color='skyblue')
axes[0].set_title('Soil Moisture Distribution (Cleaned)')
axes[0].set_xlabel('Soil Moisture')
axes[0].set_ylabel('Frequency')

sns.histplot(cleaned_df['temperature_x'], bins=30, kde=True,
ax=axes[1], color='salmon')
axes[1].set_title('Temperature Distribution (Cleaned)')
axes[1].set_xlabel('Temperature')
axes[1].set_ylabel('Frequency')

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

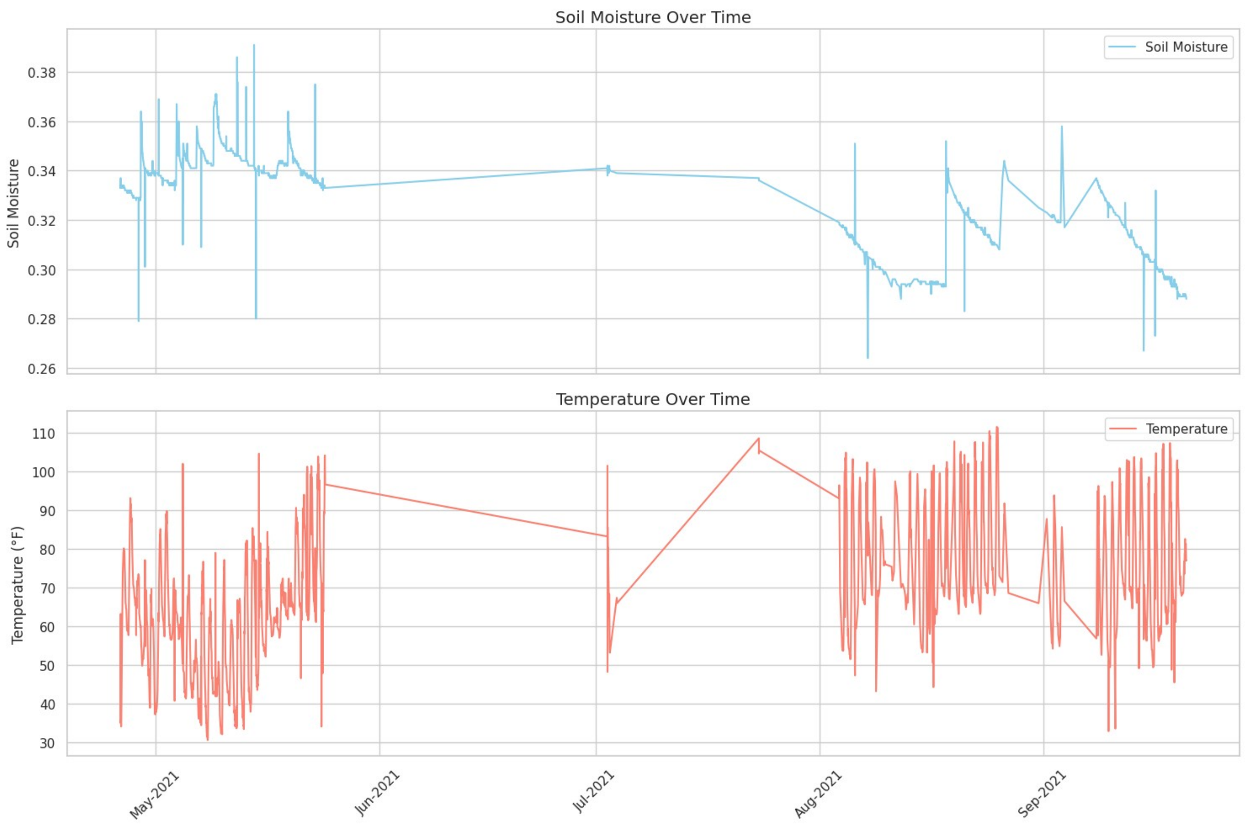
```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
```

```
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```python
import matplotlib.dates as mdates

# Set 'time' as index for plotting
cleaned_df = cleaned_df.sort_values('time').set_index('time')

# Plot time series for soil moisture and temperature
fig, axes = plt.subplots(2, 1, figsize=(15, 10), sharex=True)

# Soil Moisture Trend
axes[0].plot(cleaned_df.index, cleaned_df['soil_sensor1_vwc'],
color='skyblue', label='Soil Moisture')
axes[0].set_title('Soil Moisture Over Time', fontsize=14)
axes[0].set_ylabel('Soil Moisture')
axes[0].legend()

# Temperature Trend
axes[1].plot(cleaned_df.index, cleaned_df['temperature_x'],
color='salmon', label='Temperature')
axes[1].set_title('Temperature Over Time', fontsize=14)
axes[1].set_ylabel('Temperature (°F)')
axes[1].legend()

# Formatting x-axis
axes[1].xaxis.set_major_locator(mdates.MonthLocator())
```

```
axes[1].xaxis.set_major_formatter(mdates.DateFormatter('%b-%Y'))
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Observations from Time Series Trends:

Soil Moisture:

Gradual decline over time with noticeable drops. Possible irrigation or weather-induced changes. Temperature:

Clear seasonal pattern with fluctuations. Sharp changes indicate external influences (e.g., rainfall, cloud cover).

```
# Create lag features (1, 3, and 6 time steps)
lags = [1, 3, 6]
for lag in lags:
    cleaned_df[f'soil_moisture_lag_{lag}'] = 
cleaned_df['soil_sensor1_vwc'].shift(lag)
    cleaned_df[f'temperature_lag_{lag}'] = 
cleaned_df['temperature_x'].shift(lag)

# Create rolling mean features (3, 6, and 12 time steps)
windows = [3, 6, 12]
```

```
for window in windows:
    cleaned_df[f'soil_moisture_roll_mean_{window}'] =
cleaned_df['soil_sensor1_vwc'].rolling(window=window).mean()
    cleaned_df[f'temperature_roll_mean_{window}'] =
cleaned_df['temperature_x'].rolling(window=window).mean()

# Drop rows with NaN from feature creation
cleaned_df = cleaned_df.dropna()

# Check new features
cleaned_df.head()
```

```
                     batt_vol  temperature_x  humidity_x
soil_sensor1_temp  \
time

2021-04-26 09:41:29  5.960725         56.660       66.18
49.46
2021-04-26 10:40:04  5.941564         64.202       57.19
49.28
2021-04-26 11:09:22  5.941564         68.000       53.25
49.10
2021-04-26 11:38:39  5.935816         71.114       50.03
49.10
2021-04-26 12:07:57  5.935816         73.778       47.38
49.10

                     soil_sensor2_temp  soil_sensor1_vwc
soil_sensor2_vwc  \
time

2021-04-26 09:41:29               32.0             0.333             -
0.696
2021-04-26 10:40:04               32.0             0.333             -
0.696
2021-04-26 11:09:22               32.0             0.334             -
0.696
2021-04-26 11:38:39               32.0             0.334             -
0.696
2021-04-26 12:07:57               32.0             0.334             -
0.696

                     soil_sensor1_conductivity
soil_sensor2_conductivity  \
time

2021-04-26 09:41:29                      0.249
0.0
2021-04-26 10:40:04                      0.253
0.0
```

```
2021-04-26 11:09:22                      0.251
0.0
2021-04-26 11:38:39                      0.253
0.0
2021-04-26 12:07:57                      0.252
0.0

                       observation_time  ...  soil_moisture_lag_3  \
time                                     ...
2021-04-26 09:41:29 2021-04-26 09:45:00  ...                0.334
2021-04-26 10:40:04 2021-04-26 10:45:00  ...                0.334
2021-04-26 11:09:22 2021-04-26 11:15:00  ...                0.333
2021-04-26 11:38:39 2021-04-26 11:45:00  ...                0.333
2021-04-26 12:07:57 2021-04-26 12:15:00  ...                0.333

                     temperature_lag_3  soil_moisture_lag_6  \
time
2021-04-26 09:41:29             39.362                0.333
2021-04-26 10:40:04             43.322                0.333
2021-04-26 11:09:22             52.520                0.333
2021-04-26 11:38:39             56.660                0.334
2021-04-26 12:07:57             64.202                0.334

                     temperature_lag_6  soil_moisture_roll_mean_3  \
time
2021-04-26 09:41:29             34.574                   0.333333
2021-04-26 10:40:04             34.142                   0.333000
2021-04-26 11:09:22             34.376                   0.333333
2021-04-26 11:38:39             39.362                   0.333667
2021-04-26 12:07:57             43.322                   0.334000

                     temperature_roll_mean_3
soil_moisture_roll_mean_6  \
time

2021-04-26 09:41:29                   50.834
0.333333
2021-04-26 10:40:04                   57.794
0.333333
2021-04-26 11:09:22                   62.954
0.333500
2021-04-26 11:38:39                   67.772
0.333500
2021-04-26 12:07:57                   70.964
0.333500

                     temperature_roll_mean_6
soil_moisture_roll_mean_12  \
time
```

```
2021-04-26 09:41:29                      43.397
0.333583
2021-04-26 10:40:04                      48.407
0.333583
2021-04-26 11:09:22                      54.011
0.333583
2021-04-26 11:38:39                      59.303
0.333667
2021-04-26 12:07:57                      64.379
0.333417

                     temperature_roll_mean_12
time
2021-04-26 09:41:29                      41.6105
2021-04-26 10:40:04                      44.0000
2021-04-26 11:09:22                      46.7405
2021-04-26 11:38:39                      49.7285
2021-04-26 12:07:57                      50.6075

[5 rows x 43 columns]
```

```python
from sklearn.model_selection import train_test_split

# Target variables
target_soil_moisture = 'soil_sensor1_vwc'
target_temperature = 'temperature_x'

# Features (excluding targets and datetime columns)
features = [col for col in cleaned_df.columns if col not in [
    target_soil_moisture, target_temperature, 'observation_time'
] and not col.startswith('soil_sensor') and not
col.startswith('temperature')]

# Prepare data for soil moisture prediction
X_soil = cleaned_df[features]
y_soil = cleaned_df[target_soil_moisture]

# Prepare data for temperature prediction
X_temp = cleaned_df[features]
y_temp = cleaned_df[target_temperature]

# Train-test split (80-20 split)
X_train_soil, X_test_soil, y_train_soil, y_test_soil =
train_test_split(X_soil, y_soil, test_size=0.2, random_state=42)
X_train_temp, X_test_temp, y_train_temp, y_test_temp =
train_test_split(X_temp, y_temp, test_size=0.2, random_state=42)

# Confirm shapes
print(f"Soil Moisture - Train: {X_train_soil.shape}, Test:
{X_test_soil.shape}")
```

```
print(f"Temperature - Train: {X_train_temp.shape}, Test:
{X_test_temp.shape}")
```

```
Soil Moisture - Train: (1717, 26), Test: (430, 26)
Temperature - Train: (1717, 26), Test: (430, 26)
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error

# Initialize the Random Forest Regressor with hyperparameters
rf_soil = RandomForestRegressor(
    n_estimators=200,
    max_depth=10,
    min_samples_split=4,
    min_samples_leaf=2,
    random_state=42,
    n_jobs=-1
)

# Train the model
rf_soil.fit(X_train_soil, y_train_soil)

# Make predictions
y_pred_soil = rf_soil.predict(X_test_soil)

# Evaluate performance
r2_soil = r2_score(y_test_soil, y_pred_soil)
mae_soil = mean_absolute_error(y_test_soil, y_pred_soil)
rmse_soil = mean_squared_error(y_test_soil, y_pred_soil,
squared=False)

print(f"Random Forest - Soil Moisture Prediction:")
print(f"R²: {r2_soil:.4f}, MAE: {mae_soil:.4f}, RMSE:
{rmse_soil:.4f}")
```

```
Random Forest - Soil Moisture Prediction:
R²: 0.9579, MAE: 0.0011, RMSE: 0.0040
```

```
# Initialize the Random Forest Regressor with similar hyperparameters
rf_temp = RandomForestRegressor(
    n_estimators=200,
    max_depth=10,
    min_samples_split=4,
    min_samples_leaf=2,
    random_state=42,
    n_jobs=-1
)

# Train the model
rf_temp.fit(X_train_temp, y_train_temp)
```

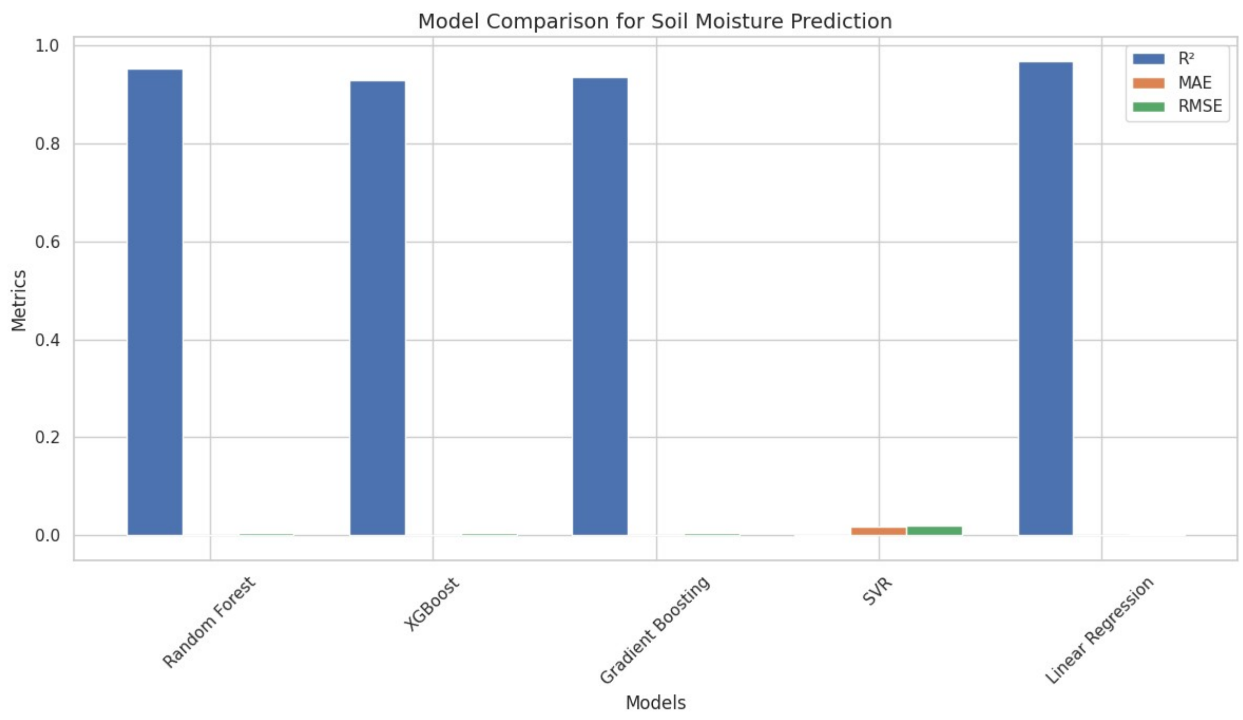
```
# Make predictions
y_pred_temp = rf_temp.predict(X_test_temp)

# Evaluate performance
r2_temp = r2_score(y_test_temp, y_pred_temp)
mae_temp = mean_absolute_error(y_test_temp, y_pred_temp)
rmse_temp = mean_squared_error(y_test_temp, y_pred_temp,
squared=False)

print(f"Random Forest - Temperature Prediction:")
print(f"R²: {r2_temp:.4f}, MAE: {mae_temp:.4f}, RMSE:
{rmse_temp:.4f}")
```

```
Random Forest - Temperature Prediction:
R²: 0.8962, MAE: 3.3712, RMSE: 5.4506
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

#  Replace these variables with your actual data variables
X_train = X_train_soil  # Training features
X_test = X_test_soil    # Testing features
y_train = y_train_soil  # Training target
y_test = y_test_soil    # Testing target

# Models for comparison
models = {
    'Random Forest': RandomForestRegressor(n_estimators=200,
max_depth=10, random_state=42),
    'XGBoost': XGBRegressor(n_estimators=200, max_depth=6,
learning_rate=0.05, random_state=42),
    'Gradient Boosting': GradientBoostingRegressor(n_estimators=200,
max_depth=6, learning_rate=0.05, random_state=42),
    'SVR': SVR(C=10, kernel='rbf'),
    'Linear Regression': LinearRegression()
}

results = []

# Train and evaluate models
for name, model in models.items():
```

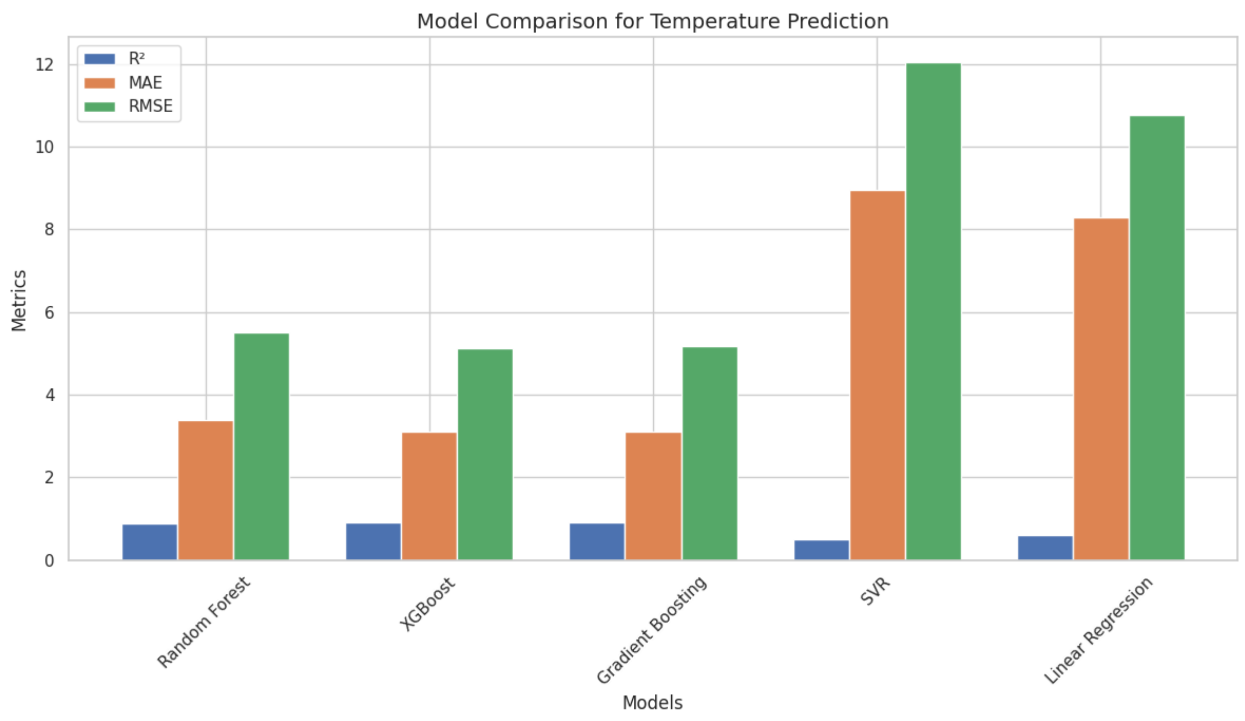
```python
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    results.append({'Model': name, 'R²': r2, 'MAE': mae, 'RMSE':
rmse})
    print(f"{name}: R²={r2:.4f}, MAE={mae:.4f}, RMSE={rmse:.4f}")

# Results DataFrame
results_df = pd.DataFrame(results)

# Plot comparison
fig, ax = plt.subplots(figsize=(12, 7))
x = np.arange(len(results_df['Model']))
width = 0.25

ax.bar(x - width, results_df['R²'], width, label='R²')
ax.bar(x, results_df['MAE'], width, label='MAE')
ax.bar(x + width, results_df['RMSE'], width, label='RMSE')

ax.set_xlabel('Models', fontsize=12)
ax.set_ylabel('Metrics', fontsize=12)
ax.set_title('Model Comparison for Soil Moisture Prediction',
fontsize=14)
ax.set_xticks(x)
ax.set_xticklabels(results_df['Model'], rotation=45)
ax.legend()
plt.tight_layout()
plt.show()
```

```
Random Forest: R²=0.9541, MAE=0.0011, RMSE=0.0042
XGBoost: R²=0.9304, MAE=0.0014, RMSE=0.0051
Gradient Boosting: R²=0.9372, MAE=0.0012, RMSE=0.0049
SVR: R²=-0.0022, MAE=0.0168, RMSE=0.0195
Linear Regression: R²=0.9688, MAE=0.0010, RMSE=0.0034
```



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

#  Replace these variables with your actual temperature dataset
variables
X_train = X_train_temp  # Training features for temperature
X_test = X_test_temp    # Testing features for temperature
y_train = y_train_temp  # Training target (temperature)
y_test = y_test_temp    # Testing target (temperature)

# Models for comparison
models = {
    'Random Forest': RandomForestRegressor(n_estimators=200,
max_depth=10, random_state=42),
    'XGBoost': XGBRegressor(n_estimators=200, max_depth=6,
learning_rate=0.05, random_state=42),
    'Gradient Boosting': GradientBoostingRegressor(n_estimators=200,
max_depth=6, learning_rate=0.05, random_state=42),
    'SVR': SVR(C=10, kernel='rbf'),
    'Linear Regression': LinearRegression()
}

results = []

# Train and evaluate models
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    results.append({'Model': name, 'R²': r2, 'MAE': mae, 'RMSE':
rmse})
    print(f"{name}: R²={r2:.4f}, MAE={mae:.4f}, RMSE={rmse:.4f}")

# Results DataFrame
results_df = pd.DataFrame(results)

# Plot comparison
fig, ax = plt.subplots(figsize=(12, 7))
x = np.arange(len(results_df['Model']))
width = 0.25

ax.bar(x - width, results_df['R²'], width, label='R²')
ax.bar(x, results_df['MAE'], width, label='MAE')
ax.bar(x + width, results_df['RMSE'], width, label='RMSE')

ax.set_xlabel('Models', fontsize=12)
ax.set_ylabel('Metrics', fontsize=12)
ax.set_title('Model Comparison for Temperature Prediction',
fontsize=14)
ax.set_xticks(x)
ax.set_xticklabels(results_df['Model'], rotation=45)
ax.legend()
plt.tight_layout()
plt.show()
```

```
Random Forest: R²=0.8945, MAE=3.3946, RMSE=5.4962
XGBoost: R²=0.9086, MAE=3.1183, RMSE=5.1161
Gradient Boosting: R²=0.9063, MAE=3.1018, RMSE=5.1788
SVR: R²=0.4933, MAE=8.9472, RMSE=12.0446
Linear Regression: R²=0.5948, MAE=8.2830, RMSE=10.7710
```



```
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error

# ----------------------------- Data Preparation
-----------------------------

# Scale features and target
scaler_X = MinMaxScaler()
scaler_y = MinMaxScaler()

X_train_scaled = scaler_X.fit_transform(X_train_soil)
X_test_scaled = scaler_X.transform(X_test_soil)
y_train_scaled = scaler_y.fit_transform(y_train_soil.values.reshape(-
1, 1))
y_test_scaled = scaler_y.transform(y_test_soil.values.reshape(-1, 1))

# Reshape features for LSTM input: (samples, timesteps, features)
X_train_scaled = X_train_scaled.reshape((X_train_scaled.shape[0], 1,
X_train_scaled.shape[1]))
X_test_scaled = X_test_scaled.reshape((X_test_scaled.shape[0], 1,
X_test_scaled.shape[1]))

# ----------------------------- LSTM Model Building
```

```
-----------------------------

model = Sequential()
model.add(LSTM(128, return_sequences=True,
input_shape=(X_train_scaled.shape[1], X_train_scaled.shape[2]),
activation='tanh'))
model.add(Dropout(0.2))
model.add(LSTM(64, activation='tanh'))
model.add(Dense(32, activation='relu'))
model.add(Dense(1))

model.compile(optimizer='adam', loss='mse')

# Early stopping to prevent overfitting
early_stop = EarlyStopping(monitor='val_loss', patience=15,
restore_best_weights=True)

# ------------------------------ Model Training
-----------------------------

history = model.fit(
    X_train_scaled, y_train_scaled,
    epochs=100,  # Increase epochs if needed
    batch_size=32,
    validation_split=0.1,
    callbacks=[early_stop],
    verbose=1
)

# ------------------------------ Evaluation
-----------------------------

# Predict on test set
y_pred_scaled = model.predict(X_test_scaled)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_actual = scaler_y.inverse_transform(y_test_scaled)

# Calculate metrics
r2 = r2_score(y_actual, y_pred)
mae = mean_absolute_error(y_actual, y_pred)
rmse = mean_squared_error(y_actual, y_pred, squared=False)

print(f"\nLSTM Soil Moisture Prediction:")
print(f"R²: {r2:.4f}")
print(f"MAE: {mae:.4f}")
print(f"RMSE: {rmse:.4f}")
```

```
/usr/local/lib/python3.10/dist-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)

Epoch 1/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.1244 - val_loss:
0.0041
Epoch 2/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0034 - val_loss:
0.0015
Epoch 3/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
0.0015
Epoch 4/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0021 - val_loss:
0.0014
Epoch 5/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
0.0013
Epoch 6/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0013
Epoch 7/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
0.0012
Epoch 8/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0013
Epoch 9/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0013
Epoch 10/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 11/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0012
Epoch 12/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0015 - val_loss:
0.0012
Epoch 13/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0012
Epoch 14/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0015 - val_loss:
0.0012
Epoch 15/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0012
Epoch 16/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
```

```
0.0012
Epoch 17/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0011
Epoch 18/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 19/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0011
Epoch 20/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 21/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0012
Epoch 22/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0011
Epoch 23/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0011
Epoch 24/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0011
Epoch 25/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0012
Epoch 26/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0011
Epoch 27/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0011
Epoch 28/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0011
Epoch 29/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0012
Epoch 30/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0010
Epoch 31/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0012
Epoch 32/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0013
```

```
Epoch 33/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0012
Epoch 34/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 35/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0012 - val_loss:
9.6613e-04
Epoch 36/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
9.6707e-04
Epoch 37/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.2884e-04 - val_loss:
0.0011
Epoch 38/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 39/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 40/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.8471e-04 - val_loss:
0.0011
Epoch 41/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0012 - val_loss:
9.0919e-04
Epoch 42/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.8771e-04 - val_loss:
9.5793e-04
Epoch 43/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.3493e-04 - val_loss:
9.5066e-04
Epoch 44/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.5005e-04 - val_loss:
9.3353e-04
Epoch 45/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.0594e-04 - val_loss:
9.3290e-04
Epoch 46/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.0323e-04 - val_loss:
0.0010
Epoch 47/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.9698e-04 - val_loss:
0.0012
Epoch 48/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
9.0885e-04
Epoch 49/100
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.4111e-04 - val_loss:
8.9675e-04
Epoch 50/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.2347e-04 - val_loss:
8.5886e-04
Epoch 51/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.2262e-04 - val_loss:
9.4252e-04
Epoch 52/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.1923e-04 - val_loss:
0.0010
Epoch 53/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.4869e-04 - val_loss:
8.3887e-04
Epoch 54/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.3411e-04 - val_loss:
8.1377e-04
Epoch 55/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.2660e-04 - val_loss:
8.4227e-04
Epoch 56/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.2114e-04 - val_loss:
9.2412e-04
Epoch 57/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.0165e-04 - val_loss:
8.2181e-04
Epoch 58/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.6983e-04 - val_loss:
8.0119e-04
Epoch 59/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.4996e-04 - val_loss:
8.6148e-04
Epoch 60/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.4023e-04 - val_loss:
8.2391e-04
Epoch 61/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 8.0509e-04 - val_loss:
9.5268e-04
Epoch 62/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6.5777e-04 - val_loss:
8.7869e-04
Epoch 63/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 7.5793e-04 - val_loss:
9.0717e-04
Epoch 64/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 7.5255e-04 - val_loss:
7.9705e-04
Epoch 65/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6.5361e-04 - val_loss:
```

```
8.0717e-04
Epoch 66/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 5.7245e-04 - val_loss:
7.9702e-04
Epoch 67/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.6197e-04 - val_loss:
7.9605e-04
Epoch 68/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.3985e-04 - val_loss:
8.5354e-04
Epoch 69/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.8290e-04 - val_loss:
8.1516e-04
Epoch 70/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6.7305e-04 - val_loss:
8.3063e-04
Epoch 71/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.2010e-04 - val_loss:
8.3220e-04
Epoch 72/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.2935e-04 - val_loss:
8.0709e-04
Epoch 73/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.8442e-04 - val_loss:
9.5191e-04
Epoch 74/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.5706e-04 - val_loss:
0.0012
Epoch 75/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.2737e-04 - val_loss:
7.8402e-04
Epoch 76/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.0804e-04 - val_loss:
8.0880e-04
Epoch 77/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.1126e-04 - val_loss:
8.8189e-04
Epoch 78/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.9505e-04 - val_loss:
8.5408e-04
Epoch 79/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.0134e-04 - val_loss:
7.6749e-04
Epoch 80/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.9038e-04 - val_loss:
0.0012
Epoch 81/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.6264e-04 - val_loss:
7.9149e-04
```

```
Epoch 82/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.8645e-04 - val_loss:
8.4414e-04
Epoch 83/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.2872e-04 - val_loss:
9.4964e-04
Epoch 84/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.4185e-04 - val_loss:
9.0546e-04
Epoch 85/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.7181e-04 - val_loss:
8.1869e-04
Epoch 86/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.7574e-04 - val_loss:
8.4343e-04
Epoch 87/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.1999e-04 - val_loss:
8.6342e-04
Epoch 88/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.5257e-04 - val_loss:
8.6155e-04
Epoch 89/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.3856e-04 - val_loss:
0.0011
Epoch 90/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.5667e-04 - val_loss:
7.9449e-04
Epoch 91/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.2982e-04 - val_loss:
7.9337e-04
Epoch 92/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.5737e-04 - val_loss:
9.2164e-04
Epoch 93/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.4128e-04 - val_loss:
9.5718e-04
Epoch 94/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.5177e-04 - val_loss:
8.3452e-04
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step

LSTM Soil Moisture Prediction:
R²: 0.9695
MAE: 0.0013
RMSE: 0.0034
```

```python
import keras_tuner as kt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

```python
def build_lstm_model(hp):
    model = Sequential()
    model.add(
        LSTM(
            units=hp.Choice('units_1', [32, 64, 96]),
            return_sequences=True,
            input_shape=(X_train_scaled.shape[1],
X_train_scaled.shape[2]),
            activation='tanh'
        )
    )
    model.add(Dropout(rate=hp.Choice('dropout_1', [0.1, 0.2, 0.3])))
    model.add(
        LSTM(
            units=hp.Choice('units_2', [32, 64]),
            activation='tanh'
        )
    )
    model.add(Dense(units=hp.Choice('dense_units', [16, 32, 48]),
activation='relu'))
    model.add(Dense(1))

    model.compile(
        optimizer='adam',
        loss='mse'
    )
    return model

# Setup Bayesian Optimization with fewer trials for efficiency
tuner = kt.BayesianOptimization(
    build_lstm_model,
    objective='val_loss',
    max_trials=5,
    executions_per_trial=1,
    directory='tuning_results',
    project_name='soil_moisture_lstm_optimized'
)

# Perform tuning
tuner.search(
    X_train_scaled, y_train_scaled,
    epochs=30,
    validation_split=0.1,
    callbacks=[EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)],
    verbose=1
)

# Retrieve the best hyperparameters
```

```
best_hp = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:")
for param, value in best_hp.values.items():
    print(f"{param}: {value}")
```

```
Trial 5 Complete [00h 00m 11s]
val_loss: 0.0011297814780846238

Best val_loss So Far: 0.001028774306178093
Total elapsed time: 00h 00m 56s
Best Hyperparameters:
units_1: 64
dropout_1: 0.1
units_2: 32
dense_units: 32
```

Optimized LSTM Architecture: Layer 1: 64 units, 10% dropout Layer 2: 32 units Dense Layer: 32 units Best Validation Loss: 0.0010

```
# Include 'time' column before splitting
X_soil_with_time = cleaned_df[['time'] + [col for col in
cleaned_df.columns if col not in ['soil_sensor1_vwc', 'temperature_x',
'observation_time']]]

# Train-test split with 'time' column
from sklearn.model_selection import train_test_split

X_train_soil_with_time, X_test_soil_with_time, y_train_soil,
y_test_soil = train_test_split(
    X_soil_with_time, cleaned_df['soil_sensor1_vwc'], test_size=0.2,
random_state=42, shuffle=False
)

# Extract 'time' after split
time_test = X_test_soil_with_time['time'].reset_index(drop=True)

# Remove 'time' column from features before LSTM training
X_train_soil = X_train_soil_with_time.drop(columns=['time'])
X_test_soil = X_test_soil_with_time.drop(columns=['time'])

# Build and train the optimized LSTM model
best_model = Sequential()
best_model.add(LSTM(64, return_sequences=True,
input_shape=(X_train_scaled.shape[1], X_train_scaled.shape[2]),
activation='tanh'))
best_model.add(Dropout(0.1))
best_model.add(LSTM(32, activation='tanh'))
best_model.add(Dense(32, activation='relu'))
best_model.add(Dense(1))
```

```python
best_model.compile(optimizer='adam', loss='mse')

# Train the model with early stopping
history = best_model.fit(
    X_train_scaled, y_train_scaled,
    epochs=100,
    validation_split=0.1,
    callbacks=[EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True)],
    verbose=1
)

# Predict on test data
y_pred_scaled = best_model.predict(X_test_scaled)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_actual = scaler_y.inverse_transform(y_test_scaled)

# Evaluate performance
r2 = r2_score(y_actual, y_pred)
mae = mean_absolute_error(y_actual, y_pred)
rmse = mean_squared_error(y_actual, y_pred, squared=False)

print(f"\nOptimized LSTM Soil Moisture Prediction:")
print(f"R²: {r2:.4f}")
print(f"MAE: {mae:.4f}")
print(f"RMSE: {rmse:.4f}")

# Export predictions to CSV
import pandas as pd

time_test = cleaned_df.loc[X_test_soil.index, 'time']

predictions_df = pd.DataFrame({
    'time': time_test,
    'Actual_Soil_Moisture': y_actual.flatten(),
    'Predicted_Soil_Moisture': y_pred.flatten()
})

csv_filename = 'optimized_lstm_soil_moisture_predictions.csv'
predictions_df.to_csv(csv_filename, index=False)
print(f"\nPredictions exported to '{csv_filename}'")
```

```
Epoch 1/100
```

```
/usr/local/lib/python3.10/dist-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)
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - loss: 0.1430 - val_loss:
0.0131
Epoch 2/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0079 - val_loss:
0.0022
Epoch 3/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0023 - val_loss:
0.0016
Epoch 4/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
0.0015
Epoch 5/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0014
Epoch 6/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0013
Epoch 7/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0020 - val_loss:
0.0014
Epoch 8/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0013
Epoch 9/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0015 - val_loss:
0.0013
Epoch 10/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0018 - val_loss:
0.0013
Epoch 11/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0013
Epoch 12/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0021 - val_loss:
0.0013
Epoch 13/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 14/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0017 - val_loss:
0.0013
Epoch 15/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - val_loss:
0.0012
Epoch 16/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0013
Epoch 17/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
```

```
Epoch 18/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 19/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 20/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 21/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0012
Epoch 22/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 23/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0016 - val_loss:
0.0011
Epoch 24/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0015 - val_loss:
0.0011
Epoch 25/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0014 - val_loss:
0.0012
Epoch 26/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0011
Epoch 27/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0012
Epoch 28/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0012
Epoch 29/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0015 - val_loss:
0.0011
Epoch 30/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0011
Epoch 31/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 32/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.6865e-04 - val_loss:
0.0012
Epoch 33/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0012
Epoch 34/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
```

```
0.0011
Epoch 35/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0010
Epoch 36/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
0.0010
Epoch 37/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 38/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.8344e-04 - val_loss:
0.0010
Epoch 39/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.8548e-04 - val_loss:
0.0010
Epoch 40/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.6210e-04 - val_loss:
9.9045e-04
Epoch 41/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.6122e-04 - val_loss:
9.5256e-04
Epoch 42/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
9.4177e-04
Epoch 43/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.9557e-04 - val_loss:
9.7558e-04
Epoch 44/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0012 - val_loss:
0.0010
Epoch 45/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.9283e-04 - val_loss:
9.4284e-04
Epoch 46/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
8.9989e-04
Epoch 47/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.3998e-04 - val_loss:
9.1411e-04
Epoch 48/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.3031e-04 - val_loss:
0.0010
Epoch 49/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.8973e-04 - val_loss:
9.2088e-04
Epoch 50/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
8.9280e-04
Epoch 51/100
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.2893e-04 - val_loss:
9.6542e-04
Epoch 52/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.3750e-04 - val_loss:
0.0011
Epoch 53/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0011 - val_loss:
9.2179e-04
Epoch 54/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
8.5230e-04
Epoch 55/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.6633e-04 - val_loss:
8.9811e-04
Epoch 56/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.4045e-04 - val_loss:
8.2944e-04
Epoch 57/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.5877e-04 - val_loss:
0.0012
Epoch 58/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.7852e-04 - val_loss:
8.0960e-04
Epoch 59/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.7738e-04 - val_loss:
8.7944e-04
Epoch 60/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.3774e-04 - val_loss:
8.4623e-04
Epoch 61/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.7161e-04 - val_loss:
8.0983e-04
Epoch 62/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.7314e-04 - val_loss:
8.1408e-04
Epoch 63/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.7787e-04 - val_loss:
9.5302e-04
Epoch 64/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.9996e-04 - val_loss:
8.4075e-04
Epoch 65/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.1966e-04 - val_loss:
8.1605e-04
Epoch 66/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.9343e-04 - val_loss:
8.3107e-04
Epoch 67/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0010 - val_loss:
8.0109e-04
```

```
Epoch 68/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.6712e-04 - val_loss:
7.9880e-04
Epoch 69/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.6178e-04 - val_loss:
8.2178e-04
Epoch 70/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.3550e-04 - val_loss:
7.9554e-04
Epoch 71/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.4450e-04 - val_loss:
7.8760e-04
Epoch 72/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.1509e-04 - val_loss:
8.1037e-04
Epoch 73/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.4173e-04 - val_loss:
7.7087e-04
Epoch 74/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.7356e-04 - val_loss:
8.1911e-04
Epoch 75/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.8627e-04 - val_loss:
0.0011
Epoch 76/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 7.6399e-04 - val_loss:
7.8335e-04
Epoch 77/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.6180e-04 - val_loss:
8.0175e-04
Epoch 78/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.7542e-04 - val_loss:
8.3024e-04
Epoch 79/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6.1975e-04 - val_loss:
0.0010
Epoch 80/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6.0013e-04 - val_loss:
8.7626e-04
Epoch 81/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 6.5410e-04 - val_loss:
7.9885e-04
Epoch 82/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 7.3326e-04 - val_loss:
7.8032e-04
Epoch 83/100
49/49 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.2310e-04 - val_loss:
9.6384e-04
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```

```
Optimized LSTM Soil Moisture Prediction:
R²: 0.9688
MAE: 0.0015
RMSE: 0.0034

Predictions exported to 'optimized_lstm_soil_moisture_predictions.csv'
```

Predict Temperature

```python
# Include 'time' column before splitting
X_temp_with_time = cleaned_df[['time'] + [col for col in
cleaned_df.columns if col not in ['temperature_x', 'soil_sensor1_vwc',
'observation_time']]]

# Train-test split with 'time' column
from sklearn.model_selection import train_test_split

X_train_temp_with_time, X_test_temp_with_time, y_train_temp,
y_test_temp = train_test_split(
    X_temp_with_time, cleaned_df['temperature_x'], test_size=0.2,
random_state=42, shuffle=False
)

# Extract 'time' from test set
time_test_temp = X_test_temp_with_time['time'].reset_index(drop=True)

# Remove 'time' column from features
X_train_temp = X_train_temp_with_time.drop(columns=['time'])
X_test_temp = X_test_temp_with_time.drop(columns=['time'])

from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error
import pandas as pd

# Train XGBoost model
xgb_temp = XGBRegressor(
    n_estimators=200,
    max_depth=6,
    learning_rate=0.05,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42
)

xgb_temp.fit(X_train_temp, y_train_temp)

# Predict
y_pred_temp = xgb_temp.predict(X_test_temp)
```

```python
# Evaluate
r2_temp = r2_score(y_test_temp, y_pred_temp)
mae_temp = mean_absolute_error(y_test_temp, y_pred_temp)
rmse_temp = mean_squared_error(y_test_temp, y_pred_temp,
squared=False)

print(f"\nXGBoost Temperature Prediction:")
print(f"R²: {r2_temp:.4f}")
print(f"MAE: {mae_temp:.4f}")
print(f"RMSE: {rmse_temp:.4f}")
```

```
XGBoost Temperature Prediction:
R²: 0.8619
MAE: 4.0121
RMSE: 5.8602
```

```python
# Step 1: Extract only the 'time' column as a 1D Series
if 'time' in X_test_temp_with_time.columns:
    time_test_temp = X_test_temp_with_time['time'].iloc[:, 0] if
X_test_temp_with_time['time'].ndim > 1 else
X_test_temp_with_time['time']
else:
    raise KeyError("The 'time' column was not found in
X_test_temp_with_time.")

# Step 2: Flatten actual and predicted arrays
y_actual_temp_flat = np.ravel(y_test_temp)
y_pred_temp_flat = np.ravel(y_pred_temp)

# Step 3: Check lengths for consistency
assert len(time_test_temp) == len(y_actual_temp_flat) ==
len(y_pred_temp_flat), \
    f"Length mismatch: time={len(time_test_temp)},
actual={len(y_actual_temp_flat)}, predicted={len(y_pred_temp_flat)}"

# Step 4: Create DataFrame with predictions
predictions_temp_df = pd.DataFrame({
    'time': time_test_temp.reset_index(drop=True),
    'Actual_Temperature': y_actual_temp_flat,
    'Predicted_Temperature': y_pred_temp_flat
})

# Step 5: Export to CSV
csv_filename = 'xgboost_temperature_predictions.csv'
predictions_temp_df.to_csv(csv_filename, index=False)
print(f"\n Predictions exported to '{csv_filename}' successfully.")
```

```
 Predictions exported to 'xgboost_temperature_predictions.csv'
successfully.
```

```python
import shutil

# Path to the folder you want to download
folder_path = '/kaggle/working/tuning_results'
output_zip_path = '/kaggle/working/tuning_results.zip'

# Zip the folder
shutil.make_archive(base_name=output_zip_path.replace('.zip', ''),
format='zip', root_dir=folder_path)
print(f" Folder zipped successfully at: {output_zip_path}")
```

```
 Folder zipped successfully at: /kaggle/working/tuning_results.zip
```

```python
csv_filename = 'weather_sensor_farmer_data.csv'
cleaned_df.to_csv(csv_filename, index=False)
print(f"\n file exported to '{csv_filename}' successfully.")
```

```

 file exported to 'weather_sensor_farmer_data.csv' successfully.
```