Edge AI Based Smart Irrigation System

Team Members : Maharudra, Nikhil, Surya

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
url=f"https://github.com/Rudra-IISC/Edge-AI-Based-Smart-Irrigation/blob/0805eacf2ef59ce6b1741f17f9fa11bba905acc6/Edge_AI/Output_Data__ET0.csv"
df=pd.read_csv(url)
df.tail()
df.shape
df.head()
```

```
def remove_outliers_iqr(df, features):
    cleaned_df = df.copy()
    for feature in features:
        Q1 = cleaned_df[feature].quantile(0.25)
        Q3 = cleaned_df[feature].quantile(0.75)
        IQR = Q3 - Q1
        lower = Q1 - 1.5 * IQR
        upper = Q3 + 1.5 * IQR
        cleaned_df = cleaned_df[(cleaned_df[feature] >= lower) & (cleaned_df[feature] <= upper)]
        print(f"Removed {len(df) - len(cleaned_df)} outliers from {feature}")
    return cleaned_df
features = ['T2M_MIN', 'T2M_MAX', 'RH2M', 'WS2M', 'ALLSKY_SFC_SW_DWN', 'ET0']
df_cleaned= remove_outliers_iqr(df, features)
df_cleaned.shape
```

```
Removed 122 outliers from T2M_MIN
Removed 124 outliers from T2M_MAX
Removed 125 outliers from RH2M
Removed 243 outliers from WS2M
Removed 298 outliers from ALLSKY_SFC_SW_DWN
Removed 311 outliers from ET0
(5258, 9)
```

```
!pip install -U ydata_profiling

import ydata_profiling
import pandas as pd # Import pandas for reading the CSV

# Load the data into a DataFrame named 'output_data_with_ET0'
output_data_with_ET0 = pd.read_csv(f'https://github.com/Rudra-IISC/Edge-AI-Based-Smart-Irrigation/blob/0805eacf2ef59ce6b1741f17f9fa11bba905acc6/Edge_AI/Output_Data__ET0.csv')

from ydata_profiling.utils.cache import cache_file

report = df_cleaned.profile_report(sort=None, html={"style": {"full_width": True}}, progress_bar=False)
report

profile_report = df_cleaned.profile_report(html={"style": {"full_width": True}})
```

```
profile_report.to_file("example.html")

profile_report = df_cleaned.profile_report(
    explorative=True, html={"style": {"full_width": True}})
profile_report
```

```
Collecting ydata_profiling
  Downloading ydata_profiling-4.16.1-py2.py3-none-any.whl.metadata (22 kB)
Requirement already satisfied: scipy<1.16,>=1.4.1 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (1.15.2)
Requirement already satisfied: pandas!=1.4.0,<3.0,>1.1 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (2.2.2)
Requirement already satisfied: matplotlib<=3.10,>=3.5 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (3.10.0)
Requirement already satisfied: pydantic>=2 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (2.11.3)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (6.0.2)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (3.1.6)
Collecting visions<0.8.2,>=0.7.5 (from visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling)
  Downloading visions-0.8.1-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: numpy<2.2,>=1.16.0 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (2.0.2)
Collecting htmlmin==0.1.12 (from ydata_profiling)
  Downloading htmlmin-0.1.12.tar.gz (19 kB)
  Preparing metadata (setup.py) ... done
Collecting phik<0.13,>=0.11.1 (from ydata_profiling)
  Downloading phik-0.12.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.6 kB)
Requirement already satisfied: requests<3,>=2.24.0 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (2.32.3)
Requirement already satisfied: tqdm<5,>=4.48.2 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (4.67.1)
Requirement already satisfied: seaborn<0.14,>=0.10.1 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (0.13.2)
Collecting multimethod<2,>=1.4 (from ydata_profiling)
  Downloading multimethod-1.12-py3-none-any.whl.metadata (9.6 kB)
Requirement already satisfied: statsmodels<1,>=0.13.2 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (0.14.4)
Requirement already satisfied: typeguard<5,>=3 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (4.4.2)
Collecting imagehash==4.3.1 (from ydata_profiling)
  Downloading ImageHash-4.3.1-py2.py3-none-any.whl.metadata (8.0 kB)
Requirement already satisfied: wordcloud>=1.9.3 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (1.9.4)
Collecting dacite>=1.8 (from ydata_profiling)
  Downloading dacite-1.9.2-py3-none-any.whl.metadata (17 kB)
Requirement already satisfied: numba<=0.61,>=0.56.0 in /usr/local/lib/python3.11/dist-packages (from ydata_profiling) (0.60.0)
Collecting PyWavelets (from imagehash==4.3.1->ydata_profiling)
  Downloading pywavelets-1.8.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (9.0 kB)
Requirement already satisfied: pillow in /usr/local/lib/python3.11/dist-packages (from imagehash==4.3.1->ydata_profiling) (11.2.1)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2<3.2,>=2.11.1->ydata_profiling) (3.0.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib<=3.10,>=3.5->ydata_profiling) (2.9.0.post0)
Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in /usr/local/lib/python3.11/dist-packages (from numba<=0.61,>=0.56.0->ydata_profiling) (0.43.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas!=1.4.0,<3.0,>1.1->ydata_profiling) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas!=1.4.0,<3.0,>1.1->ydata_profiling) (2025.2)
Requirement already satisfied: joblib>=0.14.1 in /usr/local/lib/python3.11/dist-packages (from phik<0.13,>=0.11.1->ydata_profiling) (1.4.2)
Requirement already satisfied: annotated-types>=0.6.0 in /usr/local/lib/python3.11/dist-packages (from pydantic>=2->ydata_profiling) (0.7.0)
Requirement already satisfied: pydantic-core==2.33.1 in /usr/local/lib/python3.11/dist-packages (from pydantic>=2->ydata_profiling) (2.33.1)
Requirement already satisfied: typing-extensions>=4.12.2 in /usr/local/lib/python3.11/dist-packages (from pydantic>=2->ydata_profiling) (4.13.2)
Requirement already satisfied: typing-inspection>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from pydantic>=2->ydata_profiling) (0.4.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.24.0->ydata_profiling) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.24.0->ydata_profiling) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.24.0->ydata_profiling) (2.4.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.24.0->ydata_profiling) (2025.4.26)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-packages (from statsmodels<1,>=0.13.2->ydata_profiling) (1.0.1)
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.11/dist-packages (from visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling) (25.3.0)
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.11/dist-packages (from visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling) (3.4.2)
Collecting puremagic (from visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling)
  Downloading puremagic-1.29-py3-none-any.whl.metadata (5.8 kB)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib<=3.10,>=3.5->ydata_profiling) (1.17.0)
Downloading ydata_profiling-4.16.1-py2.py3-none-any.whl (400 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 400.1/400.1 kB 9.9 MB/s eta 0:00:00
Downloading ImageHash-4.3.1-py2.py3-none-any.whl (296 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 296.5/296.5 kB 5.6 MB/s eta 0:00:00
```

```
Downloading dacite-1.9.2-py3-none-any.whl (16 kB)
Downloading multimethod-1.12-py3-none-any.whl (10 kB)
Downloading phik-0.12.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (687 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 687.8/687.8 kB 22.3 MB/s eta 0:00:00
Downloading visions-0.8.1-py3-none-any.whl (105 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 105.4/105.4 kB 5.7 MB/s eta 0:00:00
Downloading puremagic-1.29-py3-none-any.whl (43 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 43.3/43.3 kB 2.1 MB/s eta 0:00:00
Downloading pywavelets-1.8.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (4.5 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 4.5/4.5 MB 36.4 MB/s eta 0:00:00
Building wheels for collected packages: htmlmin
  Building wheel for htmlmin (setup.py) ... done
  Created wheel for htmlmin: filename=htmlmin-0.1.12-py3-none-any.whl size=27081 sha256=5deb0100b3cc7ec07fb33e4748b6e4e8bc430d88e0947f2406ee672c1abcfa13
  Stored in directory: /root/.cache/pip/wheels/8d/55/1a/19cd535375ed1ede0c996405ebffe34b196d78e2d9545723a2
Successfully built htmlmin
Installing collected packages: puremagic, htmlmin, PyWavelets, multimethod, dacite, imagehash, visions, phik, ydata_profiling
Successfully installed PyWavelets-1.8.0 dacite-1.9.2 htmlmin-0.1.12 imagehash-4.3.1 multimethod-1.12 phik-0.12.4 puremagic-1.29 visions-0.8.1 ydata_profiling-4.16.1
```

Upgrade to ydata-sdk

Improve your data and profiling with ydata-sdk, featuring data quality scoring, redundancy detection, outlier identification, text validation, and synthetic data generation.

Summarize dataset: 100% 99/99 [00:10<00:00, 8.72it/s, Completed]

```
  0%|          | 0/9 [00:00<?, ?it/s]
100%|██████████| 9/9 [00:00<00:00, 54.17it/s]
```

Generate report structure: 100% 1/1 [00:03<00:00, 3.62s/it]

Render HTML: 100% 1/1 [00:02<00:00, 2.34s/it]

Export report to file: 100% 1/1 [00:00<00:00, 29.93it/s]

Summarize dataset: 100% 99/99 [00:10<00:00, 13.16it/s, Completed]

```
  0%|          | 0/9 [00:00<?, ?it/s]
100%|██████████| 9/9 [00:00<00:00, 72.93it/s]
```

Generate report structure: 100% 1/1 [00:02<00:00, 2.94s/it]

Render HTML: 100% 1/1 [00:02<00:00, 2.17s/it]

YData Profiling Report

Overview Variables Interactions Correlations Missing values Sample


A simple visualization of nullity by column.

# Sample

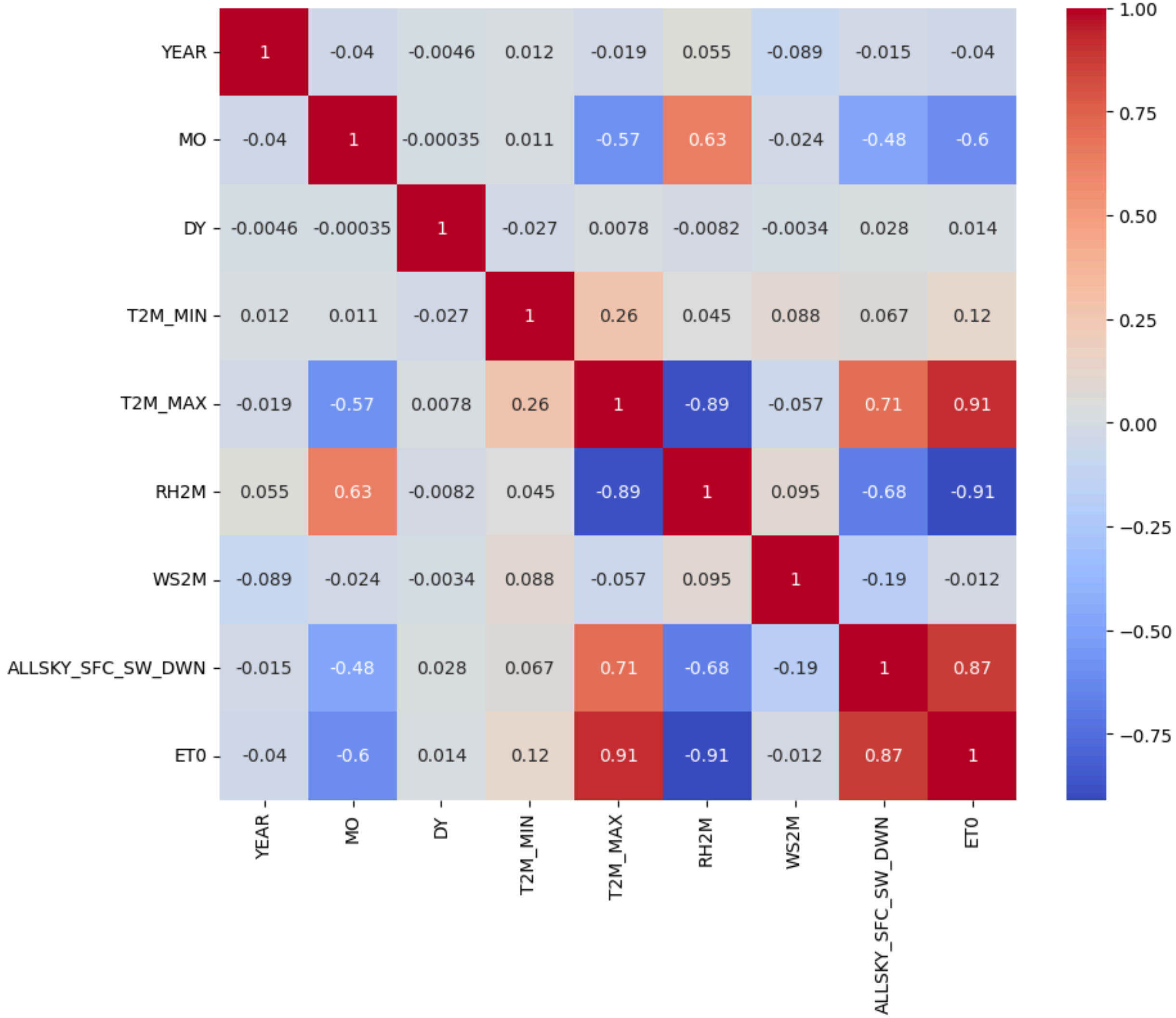
First rows Last rows

| | YEAR | MO | DY | T2M_MIN | T2M_MAX | RH2M | WS2M | ALLSKY_SFC_SW_DWN | ET0 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2010 | 1 | 1 | 17.52 | 28.38 | 72.15 | 2.89 | 17.820 | 4.778 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 2010 | 1 | 2 | 15.41 | 28.93 | 66.76 | 2.69 | 19.080 | 5.200 |
| **2** | 2010 | 1 | 3 | 15.10 | 27.57 | 70.37 | 1.95 | 19.332 | 4.814 |
| **3** | 2010 | 1 | 4 | 14.46 | 29.65 | 64.02 | 1.83 | 20.304 | 5.326 |
| **4** | 2010 | 1 | 5 | 13.64 | 30.33 | 63.20 | 1.95 | 19.908 | 5.338 |
| **5** | 2010 | 1 | 6 | 14.11 | 28.97 | 67.19 | 2.57 | 18.432 | 4.980 |
| **6** | 2010 | 1 | 7 | 15.21 | 29.06 | 68.88 | 2.52 | 17.064 | 4.682 |
| **7** | 2010 | 1 | 8 | 14.96 | 30.28 | 69.21 | 2.30 | 17.100 | 4.690 |
| **8** | 2010 | 1 | 9 | 18.18 | 29.73 | 75.17 | 2.71 | 14.292 | 4.030 |
| **9** | 2010 | 1 | 10 | 18.94 | 29.76 | 74.92 | 2.81 | 14.904 | 4.208 |

```
df_cleaned.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(df_cleaned.corr(), annot=True, cmap='coolwarm')
```

```
<Axes: >
```




```
df_cleaned.drop(columns=['YEAR', 'DY', 'MO'], inplace=True)
```

```
# from sklearn.preprocessing import MinMaxScaler
# scaler = MinMaxScaler()
# df_scaled = scaler.fit_transform(df_cleaned)
# df_scaled = pd.DataFrame(df_scaled, columns=df_cleaned.columns)
```

```
# df_scaled.head()
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_cleaned)
df_scaled = pd.DataFrame(df_scaled, columns=df_cleaned.columns)
df_scaled.head()
```

| | T2M_MIN | T2M_MAX | RH2M | WS2M | ALLSKY_SFC_SW_DWN | ET0 |
|---|---|---|---|---|---|---|
| **0** | -0.455899 | -0.629694 | 0.287135 | 0.099587 | -0.480752 | -0.486189 |
| **1** | -1.267821 | -0.474509 | -0.056696 | -0.084756 | -0.165699 | -0.241519 |
| **2** | -1.387109 | -0.858239 | 0.173588 | -0.766825 | -0.102689 | -0.465317 |
| **3** | -1.633379 | -0.271357 | -0.231482 | -0.877431 | 0.140352 | -0.168466 |
| **4** | -1.948913 | -0.079492 | -0.283790 | -0.766825 | 0.041335 | -0.161508 |

```
from sklearn.model_selection import train_test_split
X = df_scaled.drop(columns=['ET0'])
y = df_scaled['ET0']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_score
```

```
model_LR = LinearRegression()
model_LR.fit(X_train, y_train)
y_pred_LR = model_LR.predict(X_test)
mse_LR = mean_squared_error(y_test, y_pred_LR)
r2_LR = r2_score(y_test, y_pred_LR)
print("Linear Regression MSE:", mse_LR)
print("Linear Regression R2:", r2_LR)
```

```
Linear Regression MSE: 0.019221886354103167
Linear Regression R2: 0.9801178170726929
```

```
best_features = ['T2M_MAX', 'RH2M', 'ALLSKY_SFC_SW_DWN']
```

```
df_new = df_scaled[best_features]
df_new['ET0'] = df_scaled['ET0']
df_new.head()
```

```
<ipython-input-12-629fe5febc3a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_new['ET0'] = df_scaled['ET0']
```

| | T2M_MAX | RH2M | ALLSKY_SFC_SW_DWN | ET0 |
|---|---|---|---|---|
| 0 | -0.629694 | 0.287135 | -0.480752 | -0.486189 |
| 1 | -0.474509 | -0.056696 | -0.165699 | -0.241519 |
| 2 | -0.858239 | 0.173588 | -0.102689 | -0.465317 |
| 3 | -0.271357 | -0.231482 | 0.140352 | -0.168466 |
| 4 | -0.079492 | -0.283790 | 0.041335 | -0.161508 |

```
X_train1, X_test1, y_train1, y_test1 = train_test_split(df_new.drop(columns=['ET0']), df_new['ET0'], test_size=0.2, random_state=42)
```

```
model_LR1 = LinearRegression()
model_LR.fit(X_train1, y_train1)
y_pred_LR = model_LR.predict(X_test1)
mse_LR = mean_squared_error(y_test1, y_pred_LR)
r2_LR = r2_score(y_test1, y_pred_LR)
print("Linear Regression MSE:", mse_LR)
print("Linear Regression R2:", r2_LR)
```

```
Linear Regression MSE: 0.03694636610222275
Linear Regression R2: 0.9618963672174179
```

```
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score

Model1_SVR_df_new = SVR()
Model1_SVR_df_new.fit(X_train1, y_train1)
y_pred_SVR = Model1_SVR_df_new.predict(X_test1)
mse_SVR = mean_squared_error(y_test1, y_pred_SVR)
r2_SVR = r2_score(y_test1, y_pred_SVR)
print("Support Vector Regressor MSE:", mse_SVR)
print("Support Vector Regressor R2:", r2_SVR)
```

```
Support Vector Regressor MSE: 0.031656185785660554
Support Vector Regressor R2: 0.9673522512298908
```

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

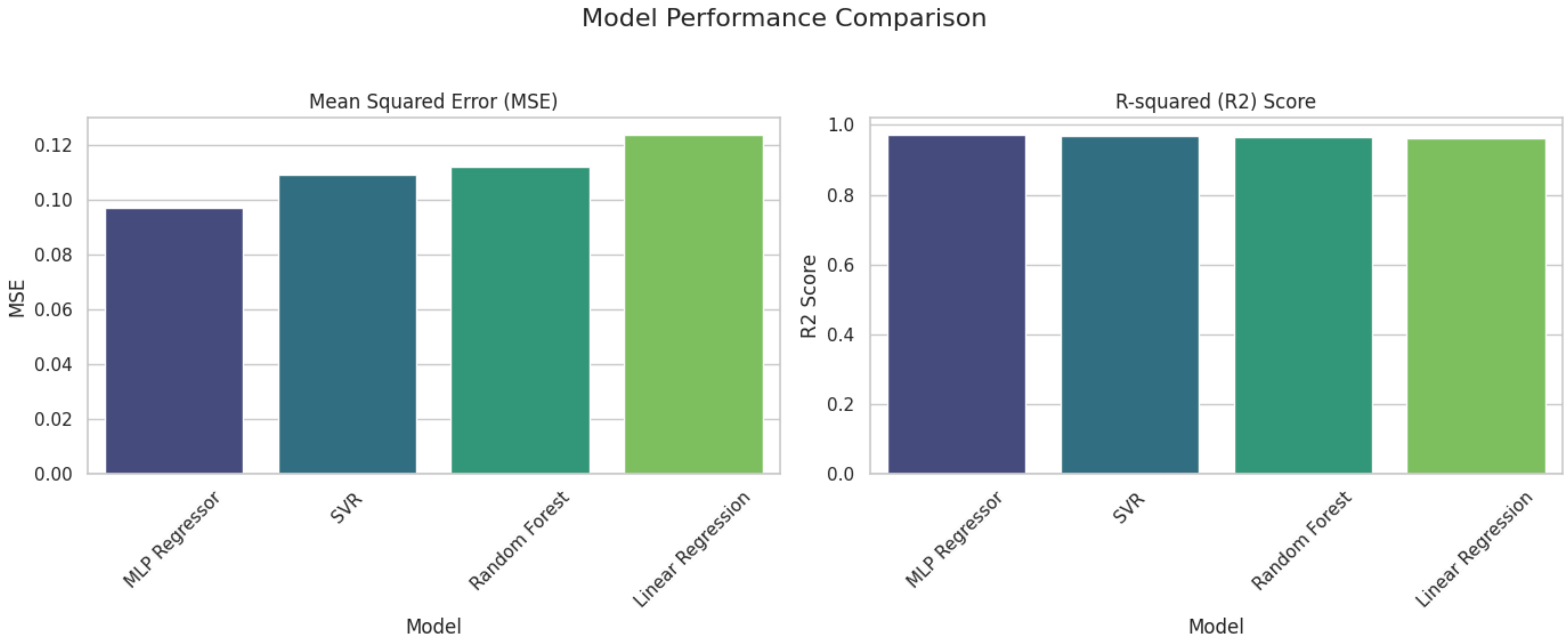
```
import seaborn as sns

# --- Function to estimate MLP model size ---
def estimate_mlp_size(model, dtype_size=8):
    """
    Estimate memory size of a trained MLPRegressor in bytes.
    Parameters:
        model: Trained sklearn.neural_network.MLPRegressor model
        dtype_size: Size of each parameter in bytes (default 8 for float64)
    Returns:
        Total size in bytes
    """
    total_params = 0
    for coef in model.coefs_:
        total_params += coef.size
    for intercept in model.intercepts_:
        total_params += intercept.size

    total_size_bytes = total_params * dtype_size
    total_size_kb = total_size_bytes / 1024
    total_size_mb = total_size_kb / 1024

    print(f"MLP Model Parameter Count: {total_params}")
    print(f"Estimated Model Size: {total_size_bytes:.2f} bytes ({total_size_kb:.2f} KB / {total_size_mb:.2f} MB)")
    return total_size_bytes

# --- Data Preparation ---
try:
    df = pd.read_csv('https://raw.githubusercontent.com/AYRUS06/Edge_AI_based_precision_irrigation/refs/heads/main/output_data_with_ET0.csv')

    print("--- Raw Data Head ---")
    print(df.head())
    print("\n--- Raw Data Info ---")
    df.info()
    print("\n")

    best_features = ['T2M_MAX', 'RH2M', 'ALLSKY_SFC_SW_DWN']
    target_variable = 'ET0'
    required_columns = best_features + [target_variable]
    if not all(col in df.columns for col in required_columns):
        missing_cols = [col for col in required_columns if col not in df.columns]
        raise ValueError(f"Missing required columns in CSV: {missing_cols}")

    X = df[best_features].copy()
    y = df[target_variable].copy()

    print("--- Scaling Features ---")
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    X = pd.DataFrame(X_scaled, columns=best_features, index=X.index)
    print("Features scaled using StandardScaler.\n")

    X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.2, random_state=42)
    print(f"Training set size: {X_train1.shape[0]} samples")
    print(f"Test set size: {X_test1.shape[0]} samples\n")
```

```
results = {}

# 1. Linear Regression
print("--- Training Linear Regression ---")
model_LR = LinearRegression()
model_LR.fit(X_train1, y_train1)
y_pred_LR = model_LR.predict(X_test1)
mse_LR = mean_squared_error(y_test1, y_pred_LR)
r2_LR = r2_score(y_test1, y_pred_LR)
results['Linear Regression'] = {'MSE': mse_LR, 'R2': r2_LR}
print(f"Linear Regression MSE: {mse_LR:.4f}")
print(f"Linear Regression R2: {r2_LR:.4f}\n")

# 2. Support Vector Regressor (SVR)
print("--- Training Support Vector Regressor (SVR) ---")
model_SVR = SVR()
model_SVR.fit(X_train1, y_train1)
y_pred_SVR = model_SVR.predict(X_test1)
mse_SVR = mean_squared_error(y_test1, y_pred_SVR)
r2_SVR = r2_score(y_test1, y_pred_SVR)
results['SVR'] = {'MSE': mse_SVR, 'R2': r2_SVR}
print(f"Support Vector Regressor MSE: {mse_SVR:.4f}")
print(f"Support Vector Regressor R2: {r2_SVR:.4f}\n")

# 3. Random Forest Regressor
print("--- Training Random Forest Regressor ---")
model_RF = RandomForestRegressor(n_estimators=100, random_state=42)
model_RF.fit(X_train1, y_train1)
y_pred_RF = model_RF.predict(X_test1)
mse_RF = mean_squared_error(y_test1, y_pred_RF)
r2_RF = r2_score(y_test1, y_pred_RF)
results['Random Forest'] = {'MSE': mse_RF, 'R2': r2_RF}
print(f"Random Forest Regressor MSE: {mse_RF:.4f}")
print(f"Random Forest Regressor R2: {r2_RF:.4f}\n")

# 4. MLP Regressor
print("--- Training MLP Regressor ---")
model_MLP = MLPRegressor(hidden_layer_sizes=(64, 32), max_iter=1000, random_state=42, early_stopping=True, n_iter_no_change=10)
model_MLP.fit(X_train1, y_train1)
y_pred_MLP = model_MLP.predict(X_test1)
mse_MLP = mean_squared_error(y_test1, y_pred_MLP)
r2_MLP = r2_score(y_test1, y_pred_MLP)
results['MLP Regressor'] = {'MSE': mse_MLP, 'R2': r2_MLP}
print(f"MLP Regressor MSE: {mse_MLP:.4f}")
print(f"MLP Regressor R2: {r2_MLP:.4f}")

print("--- Estimating MLP Regressor Model Size ---")
original_size_bytes = estimate_mlp_size(model_MLP)

# Simulated compression techniques:
# 1. Quantization to 8-bit (1 byte per parameter)
quantized_size_bytes = original_size_bytes / 8

# 2. Example pruning - assume 30% of weights are pruned
pruned_size_bytes = original_size_bytes * 0.7
```

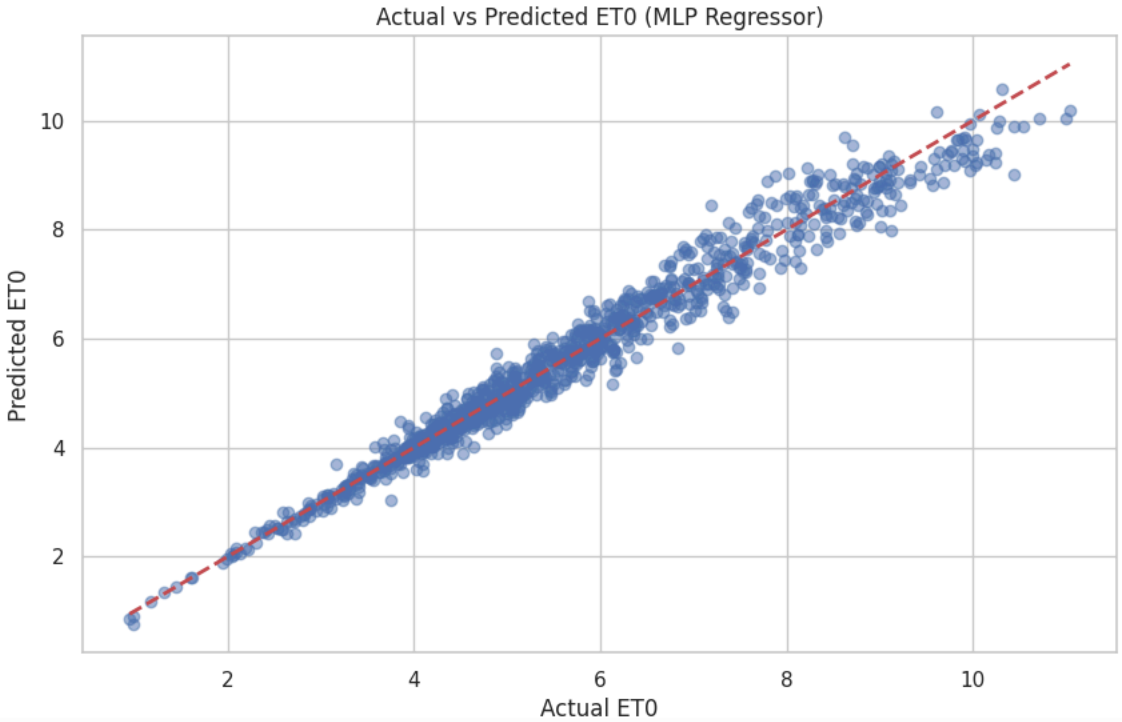
```
        print(f"\nSimulated Quantized Model Size (8-bit): {quantized_size_bytes:.2f} bytes ({quantized_size_bytes/1024:.2f} KB)")
        print(f"Simulated Pruned Model Size (30% smaller): {pruned_size_bytes:.2f} bytes ({pruned_size_bytes/1024:.2f} KB)")

        # --- Model Comparison ---
        print("--- Model Comparison Results ---")
        results_df = pd.DataFrame(results).T
        print(results_df)
        print("\n")

        # --- Visualization ---
        print("--- Generating Comparison Plots ---")
        sns.set(style="whitegrid")
        fig, axes = plt.subplots(1, 2, figsize=(14, 6))
        fig.suptitle('Model Performance Comparison', fontsize=16)

        mse_sorted = results_df.sort_values('MSE')
        sns.barplot(x=mse_sorted.index, y='MSE', data=mse_sorted, ax=axes[0], palette='viridis')
        axes[0].set_title('Mean Squared Error (MSE)')
        axes[0].set_ylabel('MSE')
        axes[0].set_xlabel('Model')
        axes[0].tick_params(axis='x', rotation=45)

        r2_sorted = results_df.sort_values('R2', ascending=False)
        sns.barplot(x=r2_sorted.index, y='R2', data=r2_sorted, ax=axes[1], palette='viridis')
        axes[1].set_title('R-squared (R2) Score')
        axes[1].set_ylabel('R2 Score')
        axes[1].set_xlabel('Model')
        axes[1].tick_params(axis='x', rotation=45)
        axes[1].axhline(0, color='grey', lw=1, linestyle='--')

        plt.tight_layout(rect=[0, 0.03, 1, 0.95])
        plt.show()

    except FileNotFoundError:
        print("Error: The file 'output_data_with_ET0.csv' was not found.")
    except ValueError as ve:
        print(f"Data Error: {ve}")
    except Exception as e:
        print(f"An unexpected error occurred: {e}")

    print("--- Finished ---")
```

```
--- Raw Data Head ---
   YEAR  MO  DY  T2M_MIN  T2M_MAX   RH2M  WS2M  ALLSKY_SFC_SW_DWN    ET0
0  2010   1   1    17.52    28.38  72.15  2.89             17.820  4.778
1  2010   1   2    15.41    28.93  66.76  2.69             19.080  5.200
2  2010   1   3    15.10    27.57  70.37  1.95             19.332  4.814
3  2010   1   4    14.46    29.65  64.02  1.83             20.304  5.326
4  2010   1   5    13.64    30.33  63.20  1.95             19.908  5.338

--- Raw Data Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5569 entries, 0 to 5568
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   YEAR               5569 non-null   int64  
 1   MO                 5569 non-null   int64  
 2   DY                 5569 non-null   int64  
 3   T2M_MIN            5569 non-null   float64
 4   T2M_MAX            5569 non-null   float64
 5   RH2M               5569 non-null   float64
 6   WS2M               5569 non-null   float64
 7   ALLSKY_SFC_SW_DWN  5569 non-null   float64
 8   ET0                5569 non-null   float64
dtypes: float64(6), int64(3)
memory usage: 391.7 KB


--- Scaling Features ---
Features scaled using StandardScaler.

Training set size: 4455 samples
Test set size: 1114 samples

--- Training Linear Regression ---
Linear Regression MSE: 0.1237
Linear Regression R2: 0.9632

--- Training Support Vector Regressor (SVR) ---
Support Vector Regressor MSE: 0.1093
Support Vector Regressor R2: 0.9675

--- Training Random Forest Regressor ---
Random Forest Regressor MSE: 0.1120
Random Forest Regressor R2: 0.9667

--- Training MLP Regressor ---
MLP Regressor MSE: 0.0971
MLP Regressor R2: 0.9711
--- Estimating MLP Regressor Model Size ---
MLP Model Parameter Count: 2369
Estimated Model Size: 18952.00 bytes (18.51 KB / 0.02 MB)

Simulated Quantized Model Size (8-bit): 2369.00 bytes (2.31 KB)
Simulated Pruned Model Size (30% smaller): 13266.40 bytes (12.96 KB)
--- Model Comparison Results ---
                        MSE        R2
Linear Regression  0.123728  0.963197
SVR                0.109338  0.967477
Random Forest      0.111998  0.966686
MLP Regressor      0.097086  0.971122
```

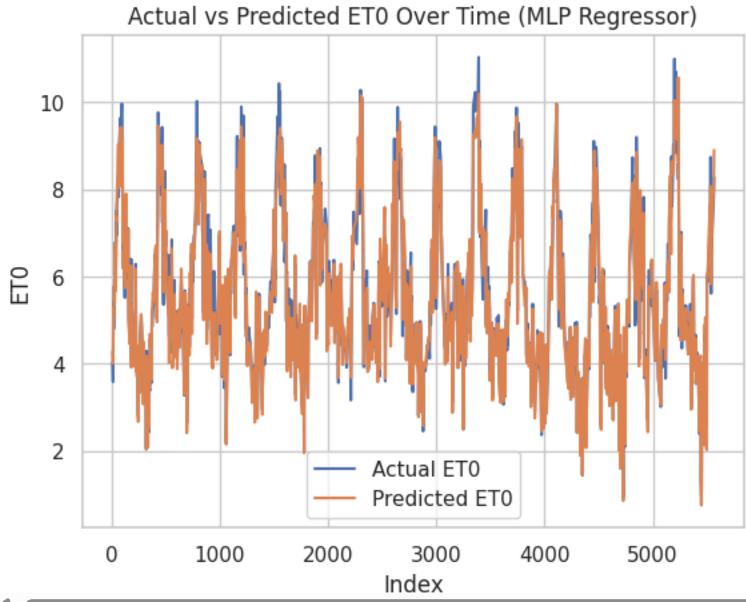
```
--- Generating Comparison Plots ---
<ipython-input-16-8e2b9b9c5404>:139: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=mse_sorted.index, y='MSE', data=mse_sorted, ax=axes[0], palette='viridis')
<ipython-input-16-8e2b9b9c5404>:146: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=r2_sorted.index, y='R2', data=r2_sorted, ax=axes[1], palette='viridis')
```



```
plt.figure(figsize=(10, 6))
plt.scatter(y_test1, y_pred_MLP, alpha=0.5)
plt.plot([y_test1.min(), y_test1.max()], [y_test1.min(), y_test1.max()], 'r--', lw=2)
plt.xlabel('Actual ET0')
plt.ylabel('Predicted ET0')
plt.title('Actual vs Predicted ET0 (MLP Regressor)')
plt.show()
```




```
sns.lineplot(x=y_test1.index, y=y_test1, label='Actual ET0')
sns.lineplot(x=y_test1.index, y=y_pred_MLP, label='Predicted ET0')
plt.xlabel('Index')
plt.ylabel('ET0')
plt.title('Actual vs Predicted ET0 Over Time (MLP Regressor)')
plt.legend()
plt.show()
```




```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import StandardScaler
import warnings

# Suppress ConvergenceWarning for cleaner output during extraction focus
from sklearn.exceptions import ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)

# --- Configuration ---
CSV_FILE = 'https://raw.githubusercontent.com/AYRUS06/Edge_AI_based_precision_irrigation/refs/heads/main/output_data_with_ET0.csv'
BEST_FEATURES = ['T2M_MAX', 'RH2M', 'ALLSKY_SFC_SW_DWN']
TARGET_VARIABLE = 'ET0'
TEST_SIZE = 0.2
RANDOM_STATE = 42
# MLP Parameters (Keep it relatively simple for Pico)
# You might need to experiment with smaller layers if memory is still an issue
HIDDEN_LAYER_SIZES = (16, 8) # Reduced layers for Pico suitability
MAX_ITER = 1500 # Increased iterations might be needed for smaller networks
EARLY_STOPPING = True
N_ITER_NO_CHANGE = 15

# --- Data Preparation ---
print(f"--- Loading Data from {CSV_FILE} ---")
try:
    df = pd.read_csv(CSV_FILE)
    print("Data loaded successfully.")
```

```
    # Check for required columns
    required_columns = BEST_FEATURES + [TARGET_VARIABLE]
    if not all(col in df.columns for col in required_columns):
        missing_cols = [col for col in required_columns if col not in df.columns]
        raise ValueError(f"Missing required columns in CSV: {missing_cols}")

    X = df[BEST_FEATURES].copy()
    y = df[TARGET_VARIABLE].copy()

    # Handle potential NaN values (replace with mean, or choose another strategy)
    if X.isnull().values.any():
        print("Warning: NaN values found in features. Filling with mean.")
        X = X.fillna(X.mean())
    if y.isnull().values.any():
        print("Warning: NaN values found in target. Filling with mean.")
        y = y.fillna(y.mean())


    # --- Feature Scaling ---
    print("--- Scaling Features ---")
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    print("Features scaled using StandardScaler.")
    # Keep X_scaled as numpy array for training

    # --- Train/Test Split ---
    X_train, X_test, y_train, y_test = train_test_split(
        X_scaled, y, test_size=TEST_SIZE, random_state=RANDOM_STATE
    )
    print(f"Training set size: {X_train.shape[0]}, Test set size: {X_test.shape[0]}\n")

    # --- Train MLP Regressor ---
    print(f"--- Training MLP Regressor {HIDDEN_LAYER_SIZES} ---")
    model_MLP = MLPRegressor(
        hidden_layer_sizes=HIDDEN_LAYER_SIZES,
        activation='relu', # Standard activation, easy to implement
        solver='adam',
        max_iter=MAX_ITER,
        random_state=RANDOM_STATE,
        early_stopping=EARLY_STOPPING,
        n_iter_no_change=N_ITER_NO_CHANGE,
        learning_rate_init=0.001 # Default, adjust if needed
    )
    model_MLP.fit(X_train, y_train)
    print("MLP Model training complete.")

    # --- Evaluate (Optional but recommended) ---
    from sklearn.metrics import mean_squared_error, r2_score
    y_pred_MLP = model_MLP.predict(X_test)
    mse_MLP = mean_squared_error(y_test, y_pred_MLP)
    r2_MLP = r2_score(y_test, y_pred_MLP)
    print(f"\n--- Model Evaluation ---")
    print(f"MLP Regressor MSE: {mse_MLP:.4f}")
    print(f"MLP Regressor R2: {r2_MLP:.4f}\n")
```

```
# --- Extract Parameters ---
print("--- Extracting Model Parameters for MicroPython ---")

# 1. Scaler Parameters
scaler_mean = scaler.mean_.tolist()
scaler_scale = scaler.scale_.tolist() # Use scale_ (standard deviation)

# 2. MLP Weights and Biases
# Coefs are weights, Intercepts are biases
weights = [coef.tolist() for coef in model_MLP.coefs_]
biases = [intercept.tolist() for intercept in model_MLP.intercepts_]

# --- Print Parameters in MicroPython Format ---
# Clear instructions for the user
print("\n" + "="*50)
print("COPY THE FOLLOWING PARAMETERS INTO YOUR MicroPython SCRIPT")
print("="*50 + "\n")

print("# --- Scaler Parameters ---")
print(f"SCALER_MEAN = {scaler_mean}")
print(f"SCALER_SCALE = {scaler_scale}\n")

print("# --- MLP Parameters ---")
# Print weights layer by layer
for i, w in enumerate(weights):
    print(f"# Weights: Layer {i} (Input/Previous Layer -> Layer {i+1})")
    print(f"WEIGHTS_{i} = [")
    for row in w:
```