```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

DATA_PATH = "c/content/drive/MyDrive/AAI-530 Final Project Data"
```

```
DATA_PATH = "/content/drive/MyDrive/AAI-530 Final Project Data" # Corrected path
files = sorted(os.listdir(DATA_PATH))
files
```

```
['.ipynb_checkpoints',
 'CE.txt',
 'CP.txt',
 'EPS1.txt',
 'FS1.txt',
 'FS2.txt',
 'PS1.txt',
 'PS2.txt',
 'PS3.txt',
 'PS4.txt',
 'PS5.txt',
 'PS6.txt',
 'SE.txt',
 'TS1.txt',
 'TS2.txt',
 'TS3.txt',
 'TS4.txt',
 'VS1.txt',
 'cnn_predictions_with_sample_idx.csv',
 'cnn_predictions_with_sample_idx_and_targets.csv',
 'description.txt',
 'df_all.csv',
 'df_all_with_targets_and_predictions.csv',
 'documentation.txt',
 'optuna_trials.csv',
 'profile.txt',
 'tableau_predictions_and_targets.csv']
```

```
sample_path= os.path.join(DATA_PATH, files[1])
df_sample = pd.read_csv(sample_path, sep="\t", header=None)
df_sample.head()
```

{"type":"dataframe","variable_name":"df_sample"}

```
df_sample.shape
df_sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2205 entries, 0 to 2204
Data columns (total 60 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       2205 non-null   float64
 1   1       2205 non-null   float64
 2   2       2205 non-null   float64
 3   3       2205 non-null   float64
 4   4       2205 non-null   float64
 5   5       2205 non-null   float64
 6   6       2205 non-null   float64
 7   7       2205 non-null   float64
 8   8       2205 non-null   float64
 9   9       2205 non-null   float64
 10  10      2205 non-null   float64
 11  11      2205 non-null   float64
 12  12      2205 non-null   float64
 13  13      2205 non-null   float64
 14  14      2205 non-null   float64
 15  15      2205 non-null   float64
 16  16      2205 non-null   float64
 17  17      2205 non-null   float64
 18  18      2205 non-null   float64
 19  19      2205 non-null   float64
 20  20      2205 non-null   float64
 21  21      2205 non-null   float64
 22  22      2205 non-null   float64
 23  23      2205 non-null   float64
 24  24      2205 non-null   float64
 25  25      2205 non-null   float64
 26  26      2205 non-null   float64
 27  27      2205 non-null   float64
 28  28      2205 non-null   float64
 29  29      2205 non-null   float64
 30  30      2205 non-null   float64
 31  31      2205 non-null   float64
 32  32      2205 non-null   float64
 33  33      2205 non-null   float64
 34  34      2205 non-null   float64
 35  35      2205 non-null   float64
 36  36      2205 non-null   float64
```

```
 37  37      2205 non-null   float64
 38  38      2205 non-null   float64
 39  39      2205 non-null   float64
 40  40      2205 non-null   float64
 41  41      2205 non-null   float64
 42  42      2205 non-null   float64
 43  43      2205 non-null   float64
 44  44      2205 non-null   float64
 45  45      2205 non-null   float64
 46  46      2205 non-null   float64
 47  47      2205 non-null   float64
 48  48      2205 non-null   float64
 49  49      2205 non-null   float64
 50  50      2205 non-null   float64
 51  51      2205 non-null   float64
 52  52      2205 non-null   float64
 53  53      2205 non-null   float64
 54  54      2205 non-null   float64
 55  55      2205 non-null   float64
 56  56      2205 non-null   float64
 57  57      2205 non-null   float64
 58  58      2205 non-null   float64
 59  59      2205 non-null   float64
dtypes: float64(60)
memory usage: 1.0 MB
```

```
import os
import pandas as pd

SENSOR_PREFIXES = ("CE", "CP", "EPS", "FS", "PS", "SE", "TS", "VS")

sensor_files = sorted([
    f for f in os.listdir(DATA_PATH)
    if f.endswith(".txt")
    and f.startswith(SENSOR_PREFIXES)
    and os.path.isfile(os.path.join(DATA_PATH, f))
])

EXPECTED_COLS = 60

dfs = []
bad_files = []

for fname in sensor_files:
    fpath = os.path.join(DATA_PATH, fname)
```

```
    try:
        df = pd.read_csv(
            fpath,
            sep="\t",               # IMPORTANT: tab delimiter
            header=None,
            engine="python",        # more forgiving parser
            encoding="latin1"       # avoids unicode decode issues
        )
    except Exception as e:
        bad_files.append((fname, str(e)))
        continue

    # Drop completely empty columns (sometimes happen from trailing tabs)
    df = df.dropna(axis=1, how="all")

    # Force exactly 60 columns (keep first 60 if extra)
    if df.shape[1] >= EXPECTED_COLS:
        df = df.iloc[:, :EXPECTED_COLS]
    else:
        # if fewer than 60, pad with NaN (rare, but keeps shape consistent)
        for c in range(df.shape[1], EXPECTED_COLS):
            df[c] = pd.NA
        df = df.iloc[:, :EXPECTED_COLS]

    df["sensor_file"] = fname.replace(".txt", "")
    dfs.append(df)

df_all = pd.concat(dfs, ignore_index=True)

print("Sensor files found:", sensor_files)
print("Combined shape:", df_all.shape)
print("Unique sensor files:", df_all["sensor_file"].nunique())
print("Bad files:", bad_files)

df_all.head()
```

```
Sensor files found: ['CE.txt', 'CP.txt', 'EPS1.txt', 'FS1.txt', 'FS2.txt', 'PS1.txt', 'PS2.t
Combined shape: (37485, 61)
Unique sensor files: 17
Bad files: []
```

{"type":"dataframe","variable_name":"df_all"}

```
print(df_all["sensor_file"].value_counts().head())
print("Any nulls?", df_all.isna().sum().sum())
print("Number of columns (should be consistent across sensors):", df_all.shape[1])
```

```
sensor_file
CE      2205
CP      2205
EPS1    2205
FS1     2205
FS2     2205
Name: count, dtype: int64
Any nulls? 0
Number of columns (should be consistent across sensors): 61
```

```python
# 1.4.1 Standardize Column Structure and Validate Consistency

# Rename signal columns (0-59) -> t0-t59
signal_cols = list(range(60))
rename_map = {i: f"t{i}" for i in signal_cols}
df_all = df_all.rename(columns=rename_map)

# Ensure signal values are numeric
for c in [f"t{i}" for i in range(60)]:
    df_all[c] = pd.to_numeric(df_all[c], errors="coerce")

# Add sample index within each sensor file (0..2204)
df_all["sample_idx"] = df_all.groupby("sensor_file").cumcount()

# Reorder columns cleanly
df_all = df_all[[f"t{i}" for i in range(60)] + ["sensor_file", "sample_idx"]]

# Sanity checks
print("Combined shape:", df_all.shape)  # should be (37485, 62)
print("Any NaNs:", int(df_all.isna().sum().sum()))
print("Rows per sensor:")
print(df_all["sensor_file"].value_counts().sort_index())

df_all.head()
```

```
Combined shape: (37485, 62)
Any NaNs: 0
Rows per sensor:
sensor_file
CE      2205
CP      2205
EPS1    2205
FS1     2205
FS2     2205
PS1     2205
PS2     2205
PS3     2205
```

```
PS4     2205
PS5     2205
PS6     2205
SE      2205
TS1     2205
TS2     2205
TS3     2205
TS4     2205
VS1     2205
Name: count, dtype: int64
```

{"type":"dataframe","variable_name":"df_all"}

```
# 1.4.2 Finalize DataFrame Schema (column order + validation)

# Put columns in a consistent, readable order
signal_cols = [f"t{i}" for i in range(60)]
meta_cols = ["sensor_file", "sample_idx"]

# (Optional) If sample_idx doesn't exist yet, create it per sensor
if "sample_idx" not in df_all.columns:
    df_all["sample_idx"] = df_all.groupby("sensor_file").cumcount()

# Reorder columns
df_all = df_all[signal_cols + meta_cols]

# Hard validations (these should all pass)
assert df_all.shape[1] == 62, f"Expected 62 columns (60 signals + sensor_file + sample_idx)
assert df_all[signal_cols].select_dtypes(exclude="number").shape[1] == 0, "Signal columns mu
assert df_all[signal_cols].isna().sum().sum() == 0, "No NaNs expected in signal columns"
assert df_all["sensor_file"].nunique() == 17, f"Expected 17 sensors, got {df_all['sensor_fil

print("  Schema finalized.")
print("Final shape:", df_all.shape)
df_all.head()
```

```
 Schema finalized.
Final shape: (37485, 62)
```

{"type":"dataframe","variable_name":"df_all"}

```
dfs_by_sensor = {}
for sensor_file in df_all['sensor_file'].unique():
    dfs_by_sensor[sensor_file] = df_all[df_all['sensor_file'] == sensor_file].copy()

print(f"Created {len(dfs_by_sensor)} DataFrames, one for each unique sensor file.")
print("Keys in dfs_by_sensor dictionary:", dfs_by_sensor.keys())
```

```python
# Display the head of one of the split dataframes
if 'CE' in dfs_by_sensor:
    print("\nHead of 'CE' sensor DataFrame:")
    print(dfs_by_sensor['CE'].head())
```

```
Created 17 DataFrames, one for each unique sensor file.
Keys in dfs_by_sensor dictionary: dict_keys(['CE', 'CP', 'EPS1', 'FS1', 'FS2', 'PS1', 'PS2',

Head of 'CE' sensor DataFrame:
       t0      t1      t2      t3      t4      t5      t6      t7      t8  \
0  47.202  47.273  47.250  47.332  47.213  47.372  47.273  47.438  46.691
1  29.208  28.822  28.805  28.922  28.591  28.643  28.216  27.812  27.514
2  23.554  23.521  23.527  23.008  23.042  23.052  22.658  22.952  22.908
3  21.540  21.419  21.565  20.857  21.052  21.039  20.926  20.912  20.989
4  20.460  20.298  20.350  19.867  19.997  19.972  19.924  19.813  19.691

       t9  ...     t52     t53     t54     t55     t56     t57     t58  \
0  46.599  ...  30.639  30.561  30.368  30.224  29.790  29.261  29.287
1  27.481  ...  24.283  23.877  23.816  23.933  23.354  23.483  23.320
2  22.359  ...  21.564  21.526  21.753  21.749  21.802  21.582  21.283
3  20.882  ...  20.295  20.482  20.600  20.547  20.708  20.708  20.574
4  19.634  ...  19.696  19.634  19.747  20.005  19.919  19.736  19.977

      t59  sensor_file  sample_idx
0  28.866           CE           0
1  23.588           CE           1
2  21.519           CE           2
3  20.403           CE           3
4  20.016           CE           4

[5 rows x 62 columns]
```

```python
target= os.path.join(DATA_PATH, 'profile.txt')
print(target)
```

```
/content/drive/MyDrive/AAI-530 Final Project Data/profile.txt
```

```python
try:
        df_target = pd.read_csv(
            target,
            sep="\t",
            header=None,
            engine="python",
            encoding="latin1"
        )
except Exception as e:
    bad_files.append((fname, str(e)))
```

```python
df_target.describe()
```

{"summary":"{\n \"name\": \"df_target\",\n \"rows\": 8,\n \"fields\": [\n   {\n   \"c

```python
# id_vars = ['sensor_file', 'sample_idx']
# signal_cols = [f"t{i}" for i in range(60)]

# # Perform the melt operation
# df_tableau = df_all.melt(
#     id_vars=id_vars,
#     value_vars=signal_cols,
#     var_name='time_moment_raw',  # Temporary column name for t0, t1, etc.
#     value_name='sensor_value'
# )

# # Extract the numeric time moment from 'time_moment_raw'
# df_tableau['time_moment'] = df_tableau['time_moment_raw'].str.replace('t', '').astype(int

# # Drop the raw time moment column and reorder columns for clarity
# df_tableau = df_tableau[['sensor_file', 'sample_idx', 'time_moment', 'sensor_value']]

# # Prepare df_target by renaming columns for clarity before merging
# target_col_names = {i: f'target_var_{i}' for i in range(df_target.shape[1])}
# df_target_renamed = df_target.rename(columns=target_col_names)
# # Add sample_idx to df_target_renamed, assuming its index corresponds to sample_idx
# df_target_renamed['sample_idx'] = df_target_renamed.index

# # Merge df_tableau with df_target_renamed on 'sample_idx'
# # This will repeat target variables for each sensor_file as requested
# df_tableau = pd.merge(df_tableau, df_target_renamed, on='sample_idx', how='left')

# print("Transformed DataFrame for Tableau with target variables:")
# print(df_tableau.head())
# print(f"New DataFrame shape: {df_tableau.shape}")
```

```python
signal_cols = [f"t{i}" for i in range(60)] # Define signal_cols
arrays = [df[signal_cols].values for df in dfs_by_sensor.values()]

X = np.stack(arrays, axis=-1)
y = df_target.values

print(f"Input shape (X): {X.shape}")
print(f"Target shape (y): {y.shape}")
```

```
Input shape (X): (2205, 60, 17)
Target shape (y): (2205, 5)
```

```python
from sklearn.preprocessing import StandardScaler
X_features = X
y_target = df_target.iloc[:, 2]
original_shape = X_features.shape
X_features_reshaped = X_features.reshape(-1, original_shape[2])
scaler = StandardScaler()
X_features_scaled = scaler.fit_transform(X_features_reshaped)
X_features = X_features_scaled.reshape(original_shape)

print(f"X_features after scaling and reshaping: {X_features.shape}")
```

```
X_features after scaling and reshaping: (2205, 60, 17)
```

```python
from sklearn.model_selection import TimeSeriesSplit

# To get roughly 20% of the data as the test set in the last split, n_splits should be 4.
tscv = TimeSeriesSplit(n_splits=4)
train_index, test_index = list(tscv.split(X_features))[-1]

X_train, X_test = X_features[train_index], X_features[test_index]
y_train, y_test = y_target.iloc[train_index], y_target.iloc[test_index]
```

```python
import torch
from torch import nn
from torch.utils.data import DataLoader
from torchvision import datasets
from torchvision.transforms import ToTensor

X_train_pt = torch.from_numpy(X_train).float()
X_test_pt = torch.from_numpy(X_test).float()
y_train_pt = torch.from_numpy(y_train.values).long()
y_test_pt = torch.from_numpy(y_test.values).long()

print(f"X_train_pt shape: {X_train_pt.shape}, dtype: {X_train_pt.dtype}")
print(f"X_test_pt shape: {X_test_pt.shape}, dtype: {X_test_pt.dtype}")
print(f"y_train_pt shape: {y_train_pt.shape}, dtype: {y_train_pt.dtype}")
print(f"y_test_pt shape: {y_test_pt.shape}, dtype: {y_test_pt.dtype}")
```

```
X_train_pt shape: torch.Size([1764, 60, 17]), dtype: torch.float32
X_test_pt shape: torch.Size([441, 60, 17]), dtype: torch.float32
y_train_pt shape: torch.Size([1764]), dtype: torch.int64
y_test_pt shape: torch.Size([441]), dtype: torch.int64
```

```
pip install optuna
```

```
Collecting optuna
  Downloading optuna-4.7.0-py3-none-any.whl.metadata (17 kB)
Requirement already satisfied: alembic>=1.5.0 in /usr/local/lib/python3.12/dist-packages (fr
Collecting colorlog (from optuna)
```

```
  Downloading colorlog-6.10.1-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages (from optuna
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/dist-packages (f
Requirement already satisfied: sqlalchemy>=1.4.2 in /usr/local/lib/python3.12/dist-packages
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-packages (from optuna)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.12/dist-packages (from optun
Requirement already satisfied: Mako in /usr/local/lib/python3.12/dist-packages (from alembic
Requirement already satisfied: typing-extensions>=4.12 in /usr/local/lib/python3.12/dist-pac
Requirement already satisfied: greenlet>=1 in /usr/local/lib/python3.12/dist-packages (from
Requirement already satisfied: MarkupSafe>=0.9.2 in /usr/local/lib/python3.12/dist-packages
Downloading optuna-4.7.0-py3-none-any.whl (413 kB)
                      413.9/413.9 kB 10.4 MB/s eta 0:00:00
```

```
from sklearn.utils.class_weight import compute_class_weight
import numpy as np

y_train_np = y_train_pt.numpy()
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=np.unique(y_train_np),
    y=y_train_np
)


weights_tensor = torch.tensor(class_weights, dtype=torch.float)
```

```
import optuna
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split

def objective(trial):

    seq_length = X_train_pt.shape[1]
    num_features = X_train_pt.shape[2]
    num_classes = len(torch.unique(y_train_pt))
    lr = trial.suggest_float('lr', 1e-5, 1e-1, log=True)
    num_filters = trial.suggest_int('num_filters', 8, 64, step=8)
    fc_units = trial.suggest_int('fc_units', 64, 256, step=32)
    batch_size = trial.suggest_categorical('batch_size', [32, 64, 128])


    class TunableCNN(nn.Module):
        def __init__(self, num_features, seq_length, num_classes, num_filters, fc_units):
            super(TunableCNN, self).__init__()
            self.conv1 = nn.Conv1d(num_features, num_filters, kernel_size=3, padding=1)
```

```
        self.bn1 = nn.BatchNorm1d(num_filters)
        self.relu = nn.ReLU()
        self.pool = nn.MaxPool1d(kernel_size=2)

        flattened_size = num_filters * (seq_length // 2)

        self.fc1 = nn.Linear(flattened_size, fc_units)
        self.fc2 = nn.Linear(fc_units, num_classes)

    def forward(self, x):
        x = x.permute(0, 2, 1)

        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu(x)
        x = self.pool(x)

        x = x.view(x.size(0), -1)

        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x

model = TunableCNN(num_features, seq_length, num_classes, num_filters, fc_units)


criterion = nn.CrossEntropyLoss(weight=weights_tensor)
optimizer = optim.Adam(model.parameters(), lr=lr)


train_size = int(0.8 * len(X_train_pt))
val_size = len(X_train_pt) - train_size
train_dataset, val_dataset = random_split(
    TensorDataset(X_train_pt, y_train_pt), [train_size, val_size]
)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

num_epochs = 10
for epoch in range(num_epochs):
    model.train()
    for data, target in train_loader:
        optimizer.zero_grad()
        outputs = model(data)
```

```
            loss = criterion(outputs, target)
            loss.backward()
            optimizer.step()

    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for data, target in val_loader:
            outputs = model(data)
            _, predicted = torch.max(outputs.data, 1)
            total += target.size(0)
            correct += (predicted == target).sum().item()

    validation_accuracy = correct / total
    return validation_accuracy

print("Optuna objective function 'objective' updated with Batch Norm and Weighted Loss.")
```

```
Optuna objective function 'objective' updated with Batch Norm and Weighted Loss.
```

```
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=50)

print("Number of finished trials:", len(study.trials))
print("Best trial:")
trial = study.best_trial

print("  Value: ", trial.value)
print("  Params: ")
for key, value in trial.params.items():
    print(f"    {key}: {value}")
```

```
[I 2026-02-21 19:15:37,176] A new study created in memory with name: no-name-35305a37-eb9c-4
[I 2026-02-21 19:15:42,196] Trial 0 finished with value: 0.9291784702549575 and parameters:
[I 2026-02-21 19:15:43,847] Trial 1 finished with value: 0.7082152974504249 and parameters:
[I 2026-02-21 19:15:45,946] Trial 2 finished with value: 0.7620396600566572 and parameters:
[I 2026-02-21 19:15:49,910] Trial 3 finished with value: 0.9065155807365439 and parameters:
[I 2026-02-21 19:15:55,819] Trial 4 finished with value: 0.7592067988668555 and parameters:
[I 2026-02-21 19:15:56,842] Trial 5 finished with value: 0.7082152974504249 and parameters:
[I 2026-02-21 19:15:58,688] Trial 6 finished with value: 0.7818696883852692 and parameters:
[I 2026-02-21 19:16:00,184] Trial 7 finished with value: 0.8101983002832861 and parameters:
[I 2026-02-21 19:16:03,593] Trial 8 finished with value: 0.7932011331444759 and parameters:
[I 2026-02-21 19:16:07,541] Trial 9 finished with value: 0.8583569405099151 and parameters:
[I 2026-02-21 19:16:11,014] Trial 10 finished with value: 0.9263456090651558 and parameters
[I 2026-02-21 19:16:15,025] Trial 11 finished with value: 0.943342776203966 and parameters:
[I 2026-02-21 19:16:22,820] Trial 12 finished with value: 0.9490084985835694 and parameters
```

```
[I 2026-02-21 19:16:25,740] Trial 13 finished with value: 0.9320113314447592 and parameters:
[I 2026-02-21 19:16:28,510] Trial 14 finished with value: 0.8895184135977338 and parameters:
[I 2026-02-21 19:16:32,084] Trial 15 finished with value: 0.8838526912181303 and parameters:
[I 2026-02-21 19:16:37,319] Trial 16 finished with value: 0.41359773371104813 and parameters
[I 2026-02-21 19:16:41,813] Trial 17 finished with value: 0.9008498583569405 and parameters:
[I 2026-02-21 19:16:45,679] Trial 18 finished with value: 0.9320113314447592 and parameters:
[I 2026-02-21 19:16:46,496] Trial 19 finished with value: 0.8640226628895185 and parameters:
[I 2026-02-21 19:16:49,781] Trial 20 finished with value: 0.9121813031161473 and parameters:
[I 2026-02-21 19:16:53,010] Trial 21 finished with value: 0.9405099150141643 and parameters:
[I 2026-02-21 19:16:55,913] Trial 22 finished with value: 0.9150141643059491 and parameters:
[I 2026-02-21 19:16:58,711] Trial 23 finished with value: 0.9235127478753541 and parameters:
[I 2026-02-21 19:17:02,724] Trial 24 finished with value: 0.8838526912181303 and parameters:
[I 2026-02-21 19:17:07,405] Trial 25 finished with value: 0.9320113314447592 and parameters:
[I 2026-02-21 19:17:10,548] Trial 26 finished with value: 0.7790368271954674 and parameters:
[I 2026-02-21 19:17:13,159] Trial 27 finished with value: 0.9150141643059491 and parameters:
[I 2026-02-21 19:17:15,046] Trial 28 finished with value: 0.830028328611898 and parameters:
[I 2026-02-21 19:17:19,585] Trial 29 finished with value: 0.8526912181303116 and parameters:
[I 2026-02-21 19:17:23,146] Trial 30 finished with value: 0.8725212464589235 and parameters:
[I 2026-02-21 19:17:26,065] Trial 31 finished with value: 0.9065155807365439 and parameters:
[I 2026-02-21 19:17:28,980] Trial 32 finished with value: 0.9065155807365439 and parameters:
[I 2026-02-21 19:17:32,745] Trial 33 finished with value: 0.9093484419263456 and parameters:
[I 2026-02-21 19:17:36,457] Trial 34 finished with value: 0.9461756373937678 and parameters:
[I 2026-02-21 19:17:38,792] Trial 35 finished with value: 0.886685552407932 and parameters:
[I 2026-02-21 19:17:43,158] Trial 36 finished with value: 0.7563739376770539 and parameters:
[I 2026-02-21 19:17:47,826] Trial 37 finished with value: 0.9291784702549575 and parameters:
[I 2026-02-21 19:17:51,636] Trial 38 finished with value: 0.9405099150141643 and parameters:
[I 2026-02-21 19:17:54,503] Trial 39 finished with value: 0.8781869688385269 and parameters:
[I 2026-02-21 19:17:57,000] Trial 40 finished with value: 0.7903682719546742 and parameters:
[I 2026-02-21 19:18:01,209] Trial 41 finished with value: 0.8611898016997167 and parameters:
[I 2026-02-21 19:18:06,004] Trial 42 finished with value: 0.5779036827195467 and parameters:
[I 2026-02-21 19:18:08,936] Trial 43 finished with value: 0.7677053824362606 and parameters:
[I 2026-02-21 19:18:13,383] Trial 44 finished with value: 0.8640226628895185 and parameters:
[I 2026-02-21 19:18:17,012] Trial 45 finished with value: 0.8923512747875354 and parameters:
[I 2026-02-21 19:18:21,508] Trial 46 finished with value: 0.9518413597733711 and parameters:
[I 2026-02-21 19:18:23,537] Trial 47 finished with value: 0.9518413597733711 and parameters:
[I 2026-02-21 19:18:25,598] Trial 48 finished with value: 0.9348441926345609 and parameters:
[I 2026-02-21 19:18:27,727] Trial 49 finished with value: 0.8441926345609065 and parameters:

Number of finished trials: 50
Best trial:
  Value:  0.9518413597733711
  Params:
    lr: 0.0013041687829088002
    num_filters: 48
    fc_units: 224
    batch_size: 32
```

```python
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

best_hps = study.best_trial.params
lr = best_hps['lr']
num_filters = best_hps['num_filters']
fc_units = best_hps['fc_units']
batch_size = best_hps['batch_size']

seq_length = X_train_pt.shape[1]
num_features = X_train_pt.shape[2]
num_classes = len(torch.unique(y_train_pt))

class TunableCNN(nn.Module):
    def __init__(self, num_features, seq_length, num_classes, num_filters, fc_units):
        super(TunableCNN, self).__init__()
        self.conv1 = nn.Conv1d(num_features, num_filters, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm1d(num_filters)
        self.relu = nn.ReLU()
        self.pool = nn.MaxPool1d(kernel_size=2)

        flattened_size = num_filters * (seq_length // 2)

        self.fc1 = nn.Linear(flattened_size, fc_units)
        self.fc2 = nn.Linear(fc_units, num_classes)

    def forward(self, x):
        x = x.permute(0, 2, 1)

        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu(x)
        x = self.pool(x)

        x = x.view(x.size(0), -1)

        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x

final_model = TunableCNN(num_features, seq_length, num_classes, num_filters, fc_units)

criterion = nn.CrossEntropyLoss(weight=weights_tensor)
optimizer = optim.Adam(final_model.parameters(), lr=lr)
```

```python
train_dataset_final = TensorDataset(X_train_pt, y_train_pt)
train_loader_final = DataLoader(train_dataset_final, batch_size=batch_size, shuffle=True)

num_epochs_final = 20
print(f"Training final model for {num_epochs_final} epochs...")

for epoch in range(num_epochs_final):
    final_model.train()
    running_loss = 0.0
    for data, target in train_loader_final:
        optimizer.zero_grad()
        outputs = final_model(data)
        loss = criterion(outputs, target)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

    if (epoch + 1) % 5 == 0:
        avg_loss = running_loss / len(train_loader_final)
        print(f'Epoch [{epoch+1}/{num_epochs_final}], Average Loss: {avg_loss:.4f}')

final_model.eval()
with torch.no_grad():
    outputs_test = final_model(X_test_pt)
    test_loss = criterion(outputs_test, y_test_pt)

    _, predicted = torch.max(outputs_test.data, 1)
    total = y_test_pt.size(0)
    correct = (predicted == y_test_pt).sum().item()
    test_accuracy = correct / total

print('\n--- Final Model Evaluation ---')
print(f'Test Loss: {test_loss.item():.4f}')
print(f'Test Accuracy: {test_accuracy:.4f}')
```

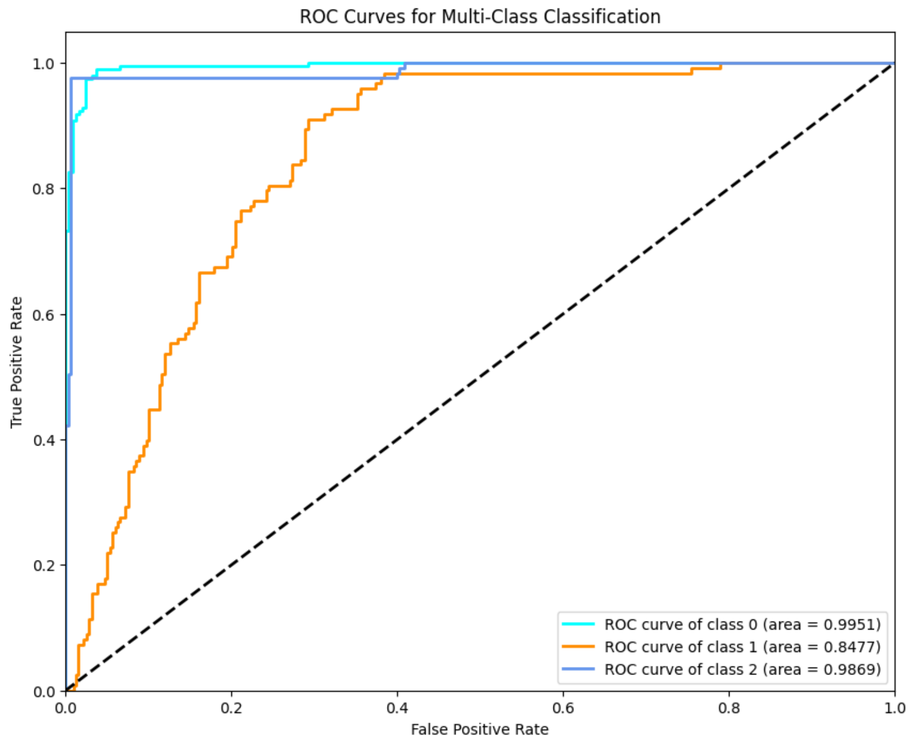
```
Training final model for 20 epochs...
Epoch [5/20], Average Loss: 0.3137
Epoch [10/20], Average Loss: 0.3111
Epoch [15/20], Average Loss: 0.3133
Epoch [20/20], Average Loss: 0.2257

--- Final Model Evaluation ---
Test Loss: 0.4345
Test Accuracy: 0.7211
```

```python
#torch.save(final_model.state_dict(), 'hydraulic_leak_model.pth')
```

```python
# import torch.nn as nn
# import torch.optim as optim
# from torch.utils.data import DataLoader, TensorDataset
# # To load it back later:
# class TunableCNN(nn.Module):
#     def __init__(self, num_features, seq_length, num_classes, num_filters, fc_units):
#         super(TunableCNN, self).__init__()
#         # Matches the architecture used in the objective function
#         self.conv1 = nn.Conv1d(num_features, num_filters, kernel_size=3, padding=1)
#         self.bn1 = nn.BatchNorm1d(num_filters)
#         self.relu = nn.ReLU()
#         self.pool = nn.MaxPool1d(kernel_size=2)

#         # Output length stays 60 after Conv (padding=1), then becomes 30 after Pool
#         flattened_size = num_filters * (seq_length // 2)

#         self.fc1 = nn.Linear(flattened_size, fc_units)
#         self.fc2 = nn.Linear(fc_units, num_classes)

#     def forward(self, x):
#         # Shape: [Batch, Time, Sensors] -> [Batch, Sensors, Time]
#         x = x.permute(0, 2, 1)

#         # Feature Extraction: Conv -> BN -> ReLU -> Pool
#         x = self.conv1(x)
#         x = self.bn1(x)
#         x = self.relu(x)
#         x = self.pool(x)

#         # Transition: Flatten for Linear Layers
#         x = x.view(x.size(0), -1)

#         # Classification
#         x = self.fc1(x)
#         x = self.relu(x)
#         x = self.fc2(x)
#         return x

# model = TunableCNN(num_features, seq_length, num_classes, num_filters, fc_units)
# model.load_state_dict(torch.load('hydraulic_leak_model (1).pth'))
# model.eval()

from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np
```

```python
import torch

final_model.eval()

with torch.no_grad():
    outputs_test_logits = final_model(X_test_pt)
    y_pred_proba = torch.nn.functional.softmax(outputs_test_logits, dim=1).numpy()

y_test_np = y_test_pt.numpy()
y_test_binarized = np.eye(num_classes)[y_test_np]

fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(num_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarized[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

fpr["micro"], tpr["micro"], _ = roc_curve(y_test_binarized.ravel(), y_pred_proba.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

all_fpr = np.unique(np.concatenate([fpr[i] for i in range(num_classes)]))

mean_tpr = np.zeros_like(all_fpr)
for i in range(num_classes):
    mean_tpr += np.interp(all_fpr, fpr[i], tpr[i])

mean_tpr /= num_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

plt.figure(figsize=(10, 8))

colors = ['aqua', 'darkorange', 'cornflowerblue']
for i, color in zip(range(num_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'ROC curve of class {i} (area = {roc_auc[i]:.4f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Multi-Class Classification')
```

```
plt.legend(loc='lower right')
plt.show()

print("AUC scores per class:")
for i in range(num_classes):
    print(f"Class {i}: {roc_auc[i]:.4f}")
print(f"Micro-average AUC: {roc_auc['micro']:.4f}")
print(f"Macro-average AUC: {roc_auc['macro']:.4f}")
```

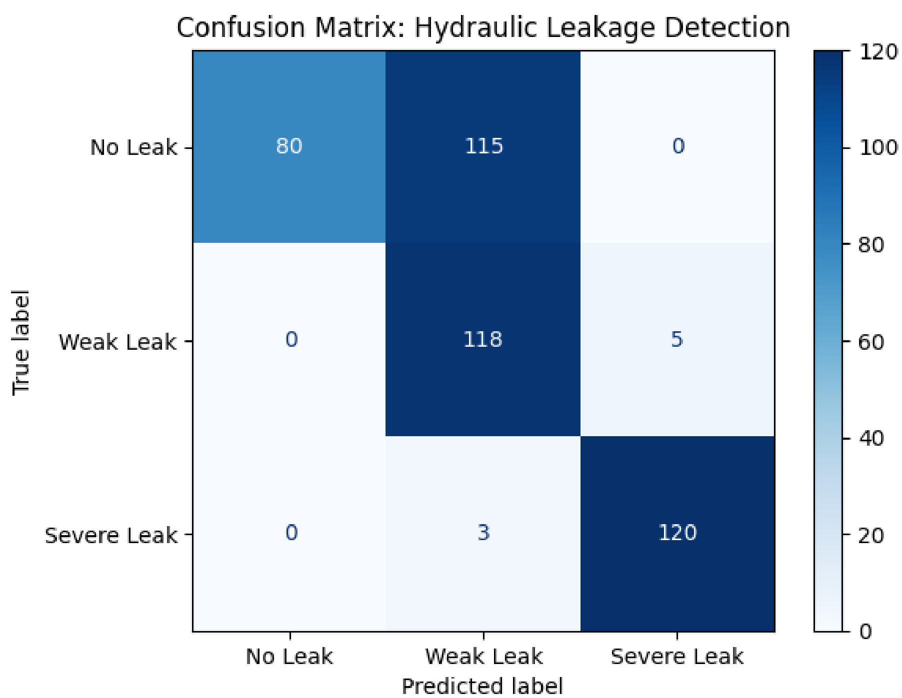



```
AUC scores per class:
Class 0: 0.9951
Class 1: 0.8477
Class 2: 0.9869
Micro-average AUC: 0.8850
Macro-average AUC: 0.9451
```

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

final_model.eval()
#model.eval()
with torch.no_grad():
```

```
    #test_outputs= model(X_test_pt)
    test_outputs = final_model(X_test_pt)
    _, y_pred = torch.max(test_outputs, 1)

y_true = y_test_pt.numpy()
y_pred = y_pred.numpy()

cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(8, 6))
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=['No Leak', 'Weak Leak', 'Severe Leak'])
disp.plot(cmap=plt.cm.Blues, values_format='d')
plt.title('Confusion Matrix: Hydraulic Leakage Detection')
plt.show()
print(cm)
```

```
<Figure size 800x600 with 0 Axes>
```




```
[[ 80 115   0]
 [  0 118   5]
 [  0   3 120]]
```

```
# # To load it back later:
```

```
# # Best trial:
# #   Value:  0.9518413597733711
# #   Params:
# #     lr: 0.0013041687829088002
# #     num_filters: 48
# #     fc_units: 224
# #     batch_size: 32
# # best_hps = study.best_trial.params
# # lr = 0.0013041687829088002
# import optuna
# import torch
# import torch.nn as nn
# import torch.optim as optim
# from torch.utils.data import DataLoader, TensorDataset, random_split

# num_filters = 48
# fc_units = 224
# batch_size = 32
# class TunableCNN(nn.Module):
#     def __init__(self, num_features, seq_length, num_classes, num_filters, fc_units):
#         super(TunableCNN, self).__init__()
#         # Matches the architecture used in the objective function
#         self.conv1 = nn.Conv1d(num_features, num_filters, kernel_size=3, padding=1)
#         self.bn1 = nn.BatchNorm1d(num_filters)
#         self.relu = nn.ReLU()
#         self.pool = nn.MaxPool1d(kernel_size=2)

#         # Output length stays 60 after Conv (padding=1), then becomes 30 after Pool
#         flattened_size = num_filters * (seq_length // 2)

#         self.fc1 = nn.Linear(flattened_size, fc_units)
#         self.fc2 = nn.Linear(fc_units, num_classes)

#     def forward(self, x):
#         # Shape: [Batch, Time, Sensors] -> [Batch, Sensors, Time]
#         x = x.permute(0, 2, 1)

#         # Feature Extraction: Conv -> BN -> ReLU -> Pool
#         x = self.conv1(x)
#         x = self.bn1(x)
#         x = self.relu(x)
#         x = self.pool(x)

#         # Transition: Flatten for Linear Layers
#         x = x.view(x.size(0), -1)
```

```
#         # Classification
#         x = self.fc1(x)
#         x = self.relu(x)
#         x = self.fc2(x)
#         return x
# # Define model parameters that are derived from the data
# seq_length = X_train_pt.shape[1]  # e.g., 60
# num_features = X_train_pt.shape[2] # e.g., 17
# num_classes = len(torch.unique(y_train_pt)) # e.g., 3
# final_model = TunableCNN(num_features, seq_length, num_classes, num_filters, fc_units)
# final_model.load_state_dict(torch.load('hydraulic_leak_model (1).pth'))
# final_model.eval()

# Save the model weights
#torch.save(final_model.state_dict(), 'hydraulic_leak_model.pth')

# To load it back later:
# Best trial:
#   Value:  0.9518413597733711
#   Params:
#     lr: 0.0013041687829088002
#     num_filters: 48
#     fc_units: 224
#     batch_size: 32
# best_hps = study.best_trial.params
# lr = 0.0013041687829088002
# num_filters = 48
# fc_units = 224
# batch_size = 32


# # Define model parameters that are derived from the data
# seq_length = X_train_pt.shape[1]  # e.g., 60
# num_features = X_train_pt.shape[2] # e.g., 17
# num_classes = len(torch.unique(y_train_pt)) # e.g., 3
# model = TunableCNN(num_features, seq_length, num_classes, num_filters, fc_units)
# model.load_state_dict(torch.load('hydraulic_leak_model.pth'))
# model.eval()

# def predict_leakage(sensor_data_window, model):
#     """
#     sensor_data_window: A numpy array or tensor of shape [60, num_features]
#     model: Your trained final_model
#     """
#     model.eval()
#     with torch.no_grad():
#         # 1. Convert to tensor if it's numpy
#         if isinstance(sensor_data_window, np.ndarray):
```

```
#             input_tensor = torch.tensor(sensor_data_window, dtype=torch.float32)
#         else:
#             input_tensor = sensor_data_window

#         # 2. Add batch dimension: [1, 60, 17]
#         input_tensor = input_tensor.unsqueeze(0)

#         # 3. Get raw logits and convert to probabilities
#         logits = model(input_tensor)
#         probs = torch.nn.functional.softmax(logits, dim=1)

#         # 4. Get the winning class and the confidence
#         conf, pred_class = torch.max(probs, 1)

#     labels = ['No Leak', 'Weak Leak', 'Severe Leak']
#     result = labels[pred_class.item()]
#     confidence = conf.item() * 100

#     print(f"Prediction: {result} ({confidence:.2f}% confidence)")
#     return pred_class.item(), confidence

# # Example usage:
# # sample_idx = 10
# # predict_leakage(X_test_pt[sample_idx], final_model)
# import numpy as np
# import torch

# def get_last_cycle(X_data):
#     """
#     Extracts the final 60-second cycle from the dataset.
#     Assumes X_data is shaped (Total_Cycles, Time_Steps, Num_Sensors)
#     """
#     # 1. Get the last row (the last full cycle)
#     # Shape will be (1, Time_Steps, Num_Sensors)
#     last_window = X_data[-1:]

#     # 2. Ensure it's a PyTorch tensor for the model
#     if not isinstance(last_window, torch.Tensor):
#         last_window_pt = torch.tensor(last_window, dtype=torch.float32)
#     else:
#         last_window_pt = last_window.clone().detach()

#     return last_window_pt

# # Execute
```

```
# last_window = get_last_cycle(X_test_pt)

# print(f"Extracted Window Shape: {last_window.shape}")
# # Expected: torch.Size([1, 60, 17]) -> [Batch, Time, Sensors]

# # Now pass it to the prediction function we made earlier
# # (Note: the function needs to handle the batch dimension properly)
# final_model.eval()
# with torch.no_grad():
#     # The model's forward method handles the permutation internally
#     prediction = final_model(last_window)
#     _, predicted_class = torch.max(prediction, 1)

# labels = ['No Leak', 'Weak Leak', 'Severe Leak']
# print(f"Status of the latest cycle: {labels[predicted_class.item()]}")
# print("Head of final model predictions (probabilities):")
# print(y_pred_proba[:5])
# import numpy as np

# # Get the predicted class labels by taking the argmax of the probabilities
# y_pred_labels = np.argmax(y_pred_proba, axis=1)

# print("Head of final model predicted class labels:")
# print(y_pred_labels)
# print(y_pred_labels.shape)
# import torch
# import numpy as np

# # The model was trained on sequences of 60 timesteps.
# # To predict, we should use the data in the format the model expects.
# # X_features already has the shape (samples, timesteps, sensors) = (2205, 60, 17)

# # Convert the full X_features to a PyTorch tensor for prediction
# X_full_features_pt = torch.from_numpy(X_features).float()

# print(f"Shape of data for prediction: {X_full_features_pt.shape}")
# # Ensure the model is in evaluation mode
# final_model.eval()

# # Make predictions on the full dataset (as the model was trained for 60 timesteps)
# with torch.no_grad():
#     outputs_logits = final_model(X_full_features_pt)
#     # Apply softmax to get probabilities
```

```
#     y_pred_proba_full_data = torch.nn.functional.softmax(outputs_logits, dim=1).numpy()
#     # Get predicted class labels
#     y_pred_labels_full_data = np.argmax(y_pred_proba_full_data, axis=1)

# print("Head of predicted probabilities for the full data:")
# print(y_pred_proba_full_data[:5])

# print("\nHead of predicted class labels for the full data:")
# print(y_pred_labels_full_data[:10])

# print(f"Shape of predicted probabilities: {y_pred_proba_full_data.shape}")
# print(f"Shape of predicted labels: {y_pred_labels_full_data.shape}")

# # Create a DataFrame for CNN predictions, indexed by sample_idx
# df_cnn_predictions = pd.DataFrame({
#     'sample_idx': np.arange(len(y_pred_labels_full_data)),
#     'CNN Prediction': y_pred_labels_full_data
# })

# # Drop existing 'CNN Prediction' columns from df_tableau if they exist
# # This prevents the MergeError if the cell is run multiple times or if a 'CNN Prediction'
# if 'CNN Prediction' in df_tableau.columns:
#     df_tableau = df_tableau.drop(columns=['CNN Prediction'])
# if 'CNN Prediction_x' in df_tableau.columns:
#     df_tableau = df_tableau.drop(columns=['CNN Prediction_x'])
# if 'CNN Prediction_y' in df_tableau.columns:
#     df_tableau = df_tableau.drop(columns=['CNN Prediction_y'])

# # Merge df_tableau with the CNN predictions on 'sample_idx'
# df_tableau = pd.merge(df_tableau, df_cnn_predictions, on='sample_idx', how='left')

# print("Head of df_tableau with cleaned CNN Prediction:")
# print(df_tableau.tail())
# print(f"New DataFrame shape: {df_tableau.shape}")

# output_path = os.path.join(DATA_PATH, 'df_all.csv')
# df_tableau.to_csv(output_path, index=False)
# print(f"DataFrame exported to: {output_path}")

# output_path_predictions = os.path.join(DATA_PATH, 'cnn_predictions_with_sample_idx.csv')
# df_cnn_predictions.to_csv(output_path_predictions, index=False)
# print(f"Predictions and sample indices exported to: {output_path_predictions}")

# import pandas as pd
# import os

# # Define the path to the existing CNN predictions CSV
# predictions_path = os.path.join(DATA_PATH, 'cnn_predictions_with_sample_idx.csv')
```

```
# # Load the CNN predictions
# df_cnn_predictions_loaded = pd.read_csv(predictions_path)

# # Merge df_cnn_predictions_loaded with df_target_renamed on 'sample_idx'
# # df_target_renamed is available from cell B84qC-HUgipd and contains 'sample_idx' and all
# df_combined_predictions_targets = pd.merge(df_cnn_predictions_loaded, df_target_renamed, 

# # Define the output path for the new combined CSV
# output_path_combined_pred_targets = os.path.join(DATA_PATH, 'cnn_predictions_with_sample_

# # Save the combined DataFrame to CSV
# df_combined_predictions_targets.to_csv(output_path_combined_pred_targets, index=False)

# print(f"Combined predictions and targets exported to: {output_path_combined_pred_targets}
# print("Head of combined DataFrame:")
# print(df_combined_predictions_targets.head())

# output_path_tableau_predictions = os.path.join(DATA_PATH, 'tableau_predictions_and_target
# df_tableau_output = df_tableau[['sample_idx', 'CNN Prediction', 'target_var_2']]
# df_tableau_output.to_csv(output_path_tableau_predictions, index=False)
# print(f"Selected data exported to: {output_path_tableau_predictions}")

# import pandas as pd
# import os

# # Prepare the target values for merging
# df_target_merged = pd.DataFrame({
#     'sample_idx': y_target.index,
#     'target_value': y_target.values
# })

# # Prepare the prediction values for merging
# df_predictions_merged = pd.DataFrame({
#     'sample_idx': np.arange(len(y_pred_labels_full_data)),
#     'CNN_prediction': y_pred_labels_full_data
# })

# # Merge with df_all on 'sample_idx'
# df_all_combined = df_all.merge(df_target_merged, on='sample_idx', how='left')
# df_all_combined = df_all_combined.merge(df_predictions_merged, on='sample_idx', how='left

# # Define the output path and save to CSV
# output_path_combined = os.path.join(DATA_PATH, 'df_all_with_targets_and_predictions.csv')
# df_all_combined.to_csv(output_path_combined, index=False)

# print(f"Combined DataFrame saved to: {output_path_combined}")
```

```
# print("Head of combined DataFrame:")
# print(df_all_combined.head())

# trials_df = study.trials_dataframe()
# output_path_trials = os.path.join(DATA_PATH, 'optuna_trials.csv')
# trials_df.to_csv(output_path_trials, index=False)
# print(f"Optuna trials DataFrame exported to: {output_path_trials}")

# df_temp=pd.read_csv(os.path.join(DATA_PATH, '/content/temperature_predictions_v2.csv'))

# import pandas as pd
# import numpy as np

# # --- STEP 1: Create the Mapping ---
# total_cycles = 2205
# total_ts_points = len(df_temp) # Corrected: Get total_ts_points from df_temp length
# points_per_cycle = total_ts_points // total_cycles

# # Assign a Cycle ID to every one of your partner's timesteps
# # This creates: 0,0,0... (points_per_cycle times), 1,1,1... (points_per_cycle times), etc
# cycle_ids = np.repeat(np.arange(total_cycles), points_per_cycle)

# # Handle any rounding remainders if necessary
# if len(cycle_ids) < total_ts_points:
#     padding = np.full(total_ts_points - len(cycle_ids), total_cycles - 1)
#     cycle_ids = np.concatenate([cycle_ids, padding])

# # --- STEP 2: Aggregate Partner's Data ---
# # Assuming df_temp has columns ['Predicted_Temperature', 'Actual_Temperature']
# df_temp['cycle_id'] = cycle_ids

# # Group by cycle_id to get one row per cycle
# df_temp_summarized = df_temp.groupby('cycle_id').agg({
#     'Predicted_Temperature': ['mean', 'max'],
#     'Actual_Temperature': ['mean', 'max']
# })

# # Flatten the multi-index columns (e.g., 'Predicted_Temperature_mean', 'Predicted_Tempera
# df_temp_summarized.columns = ['_'.join(col).strip() for col in df_temp_summarized.columns
# df_temp_summarized.reset_index(inplace=True)

# # --- STEP 3: Create the Master Dashboard Dataframe ---
# # Let's assume 'y_test_labels' and 'y_pred_labels' are your results
# # NOTE: y_test_labels and y_pred_labels are from a subset of data (test set),
# # but total_cycles refers to the full dataset. This will cause a mismatch.
# # We need to use y_pred_labels_full_data (predictions on all samples).
# # Also, prediction_probs is not defined globally. Using a placeholder for now if needed, 
```

```
# # Assuming y_pred_labels_full_data is available and corresponds to total_cycles
# master_df = pd.DataFrame({
#     'cycle_id': np.arange(total_cycles),
#     'predicted_condition': y_pred_labels_full_data # Your CNN output for all samples
# })

# # To add actual_condition, we need to map y_target (which is for full data) to cycles
# # Since y_target is also 2205 rows, we can add it directly.
# master_df['actual_condition'] = y_target.values # Assuming y_target contains the target fo

# # If you also need 'prediction_confidence', you would need to store that for all 2205 samp
# # For now, I'll omit it as it's not globally available for all 2205 cycles.

# # Merge your CNN results with his Temperature summaries
# master_df = pd.merge(master_df, df_temp_summarized, on='cycle_id', how='left')

# print(master_df.head())

# output_path_master_df = os.path.join(DATA_PATH, 'master_dashboard_data.csv')
# master_df.to_csv(output_path_master_df, index=False)
# print(f"Master DataFrame exported to: {output_path_master_df}")
```