ECG_classification-Alexandre_Bailly

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1 ECG classification

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[1]:
```
from IPython.display import HTML
```

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, log_loss
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense,␣
↪Dropout
from tensorflow.keras.utils import to_categorical
from scipy.stats import entropy
```

```
2025-01-08 23:09:27.884557: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
```

1.1 A first naive model by extracting simple features

Your environment contains variables arr, nsr, and chf which respectively contain 10-second recordings of ECG signals extracted from three datasets on PhysioNet: one from a person suffering from arrhythmia, one from a person with a normal heart rhythm, and another from a person with heart failure.

Matplotlib subplots (or any other library), display these signals on three subfigures (the subplots should be called with the parameter nrows = 3). Can you find any differences between them?

[3]:
```
arr = np.loadtxt('arr.txt')
chf = np.loadtxt('chf.txt')
nsr = np.loadtxt('nsr.txt')
```

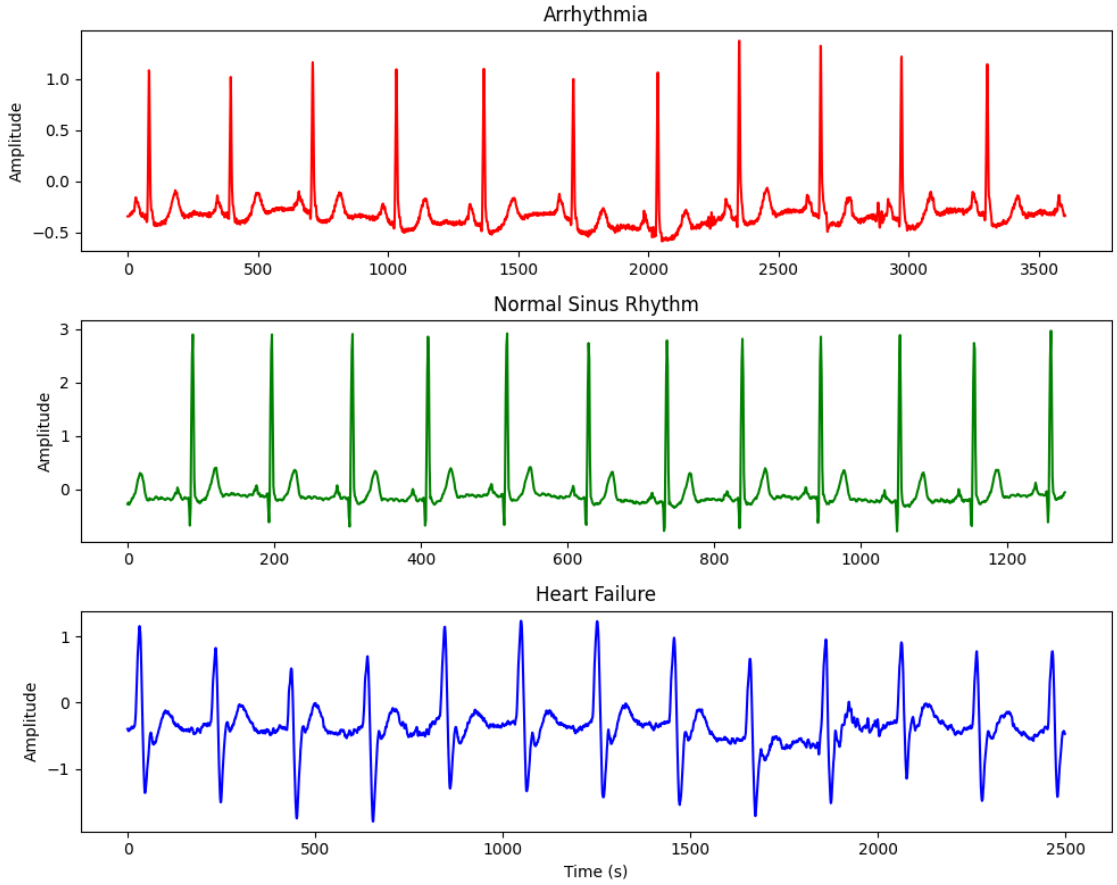
```
# Plotting the ECG signals
fig, axs = plt.subplots(nrows=3, ncols=1, figsize=(10, 8))

# arr
axs[0].plot(arr, color='r')
axs[0].set_title('Arrhythmia')
axs[0].set_ylabel('Amplitude')

#nsr
axs[1].plot(nsr, color='g')
axs[1].set_title('Normal Sinus Rhythm')
axs[1].set_ylabel('Amplitude')

# chf
axs[2].plot(chf, color='b')
axs[2].set_title('Heart Failure')
axs[2].set_ylabel('Amplitude')
axs[2].set_xlabel('Time (s)')

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



We want to extract features from the time series. For that we will use simple statistics.

Create a function named calculate_stats_features(x) that calculates some statistical features of a signal x using standard numpy functions: nanpercentile, nanmean, etc. calculate_stats_features will return a list of features in this order:

0. Max
1. Min
2. Mean
3. Median
4. Variance

[4]:
```python
# Function to calculate statistical features
def calculate_stats_features(x):
    return [
        np.nanmax(x),         # Max
        np.nanmin(x),         # Min
        np.nanmean(x),        # Mean
        np.nanmedian(x),      # Median
        np.nanvar(x)          # Variance
    ]
```

```
# Calculate features for each signal
features_arr = calculate_stats_features(arr)
features_nsr = calculate_stats_features(nsr)
features_chf = calculate_stats_features(chf)

print("arr:", features_arr)
print("nsr:", features_nsr)
print("chf:", features_chf)
```

```
arr: [1.375, -0.59, -0.3120111111111112, -0.335, 0.039663552654320984]
nsr: [2.965, -0.785, -0.035453124999999995, -0.145, 0.21755463842773434]
chf: [1.235, -1.79, -0.363622, -0.375, 0.15541165111599997]
```

Create a function named `calculate_zero_crossing(x)` that calculates the Zero Crossing of a signal x.

The zero crossing is defined as the number of times the signal changes sign. For this, you can use the signbit, diff, and nonzero functions from numpy.

[5]:
```
def calculate_zero_crossing(x):
    sign_x = np.sign(x)
    sign_diff = np.diff(sign_x)
    zero_crossings = np.count_nonzero(sign_diff)

    return zero_crossings
```

Create a function named **calculate_rms(x)** that returns the Root Mean Square (RMS) of a signal x. We will use the nanmean function instead of the mean function from numpy.

[6]:
```
def calculate_rms(x):
    squared_x = np.square(x)
    mean_squared = np.nanmean(squared_x)
    rms = np.sqrt(mean_squared)
    return rms
```

Create a function named calculate_entropy(x) that calculates the Shannon entropy of a signal x using the entropy function from scipy.stats.

[7]:
```
def calculate_entropy(x):
    v, c = np.unique(x, return_counts=True)
    p = c/len(x)
    return  entropy(p)
```

Create a function get_features(x) that combines the features calculated by all previous functions including caculate_stats_features.

[8]:
```
def get_features(x):
    # Calculate each feature
    stats_features = calculate_stats_features(x)
    zero_crossings = calculate_zero_crossing(x)
    rms = calculate_rms(x)
    entropy_val = calculate_entropy(x)

    # Put in one list
    features = stats_features + [zero_crossings, rms, entropy_val]

    return features
```

Load the small ecg dataset Use your fonction get_features create a new dataframe where you have all the feature as X and y as the label. Train a random forest on it after doing a train test split if the dataset is not too small

[9]:
```
# Load dataset
df = pd.read_csv('ecg_small_dataset.csv')
X, y = [], []

# process data
for _, row in df.iterrows():
    ts = row[2:].values
    lbl = row[1]
    X.append(get_features(ts))
    y.append(lbl)

# df
X = pd.DataFrame(X, columns=['Max', 'Min', 'Mean', 'Med', 'Var', 'ZC', 'RMS',␣
 ↪'Ent'])
y = pd.Series(y, name='Lbl')

# Train and test split
X_tr, X_te, y_tr, y_te = train_test_split(X, y, test_size=0.3, random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_tr, y_tr)

# Pred
y_te_pred = clf.predict(X_te)

# Result
print("Result:")
print(classification_report(y_te, y_te_pred))
```

```
Result:
              precision    recall  f1-score   support
```

```
           1       0.00      0.00      0.00       2.0
           2       0.00      0.00      0.00       0.0

    accuracy                           0.00       2.0
   macro avg       0.00      0.00      0.00       2.0
weighted avg       0.00      0.00      0.00       2.0
```

```
/tmp/ipykernel_33831/3954723016.py:8: FutureWarning: Series.__getitem__ treating
keys as positions is deprecated. In a future version, integer keys will always
be treated as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  lbl = row[1]
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Now you have a first pipeline, do the same on the full dataset Report the train and test loss

[10]:
```
# Load dataset
df = pd.read_csv('ECG-laurent.csv')
X, y = [], []

# process data
for _, row in df.iterrows():
    ts = row[2:].values
    lbl = row[1]
    X.append(get_features(ts))
    y.append(lbl)

# df
X = pd.DataFrame(X, columns=['Max', 'Min', 'Mean', 'Median', 'Variance',␣
 ↪'ZeroCrossings', 'RMS', 'Entropy'])
y = pd.Series(y, name='Lbl')

# Train and test split
X_tr, X_te, y_tr, y_te = train_test_split(X, y, test_size=0.3, random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_tr, y_tr)

# Pred
y_te_pred = clf.predict(X_te)

# Result
print("Result:")
print(classification_report(y_te, y_te_pred))
```

```
/tmp/ipykernel_33831/997142380.py:2: DtypeWarning: Columns (0) have mixed types.
Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('ECG-laurent.csv')
/tmp/ipykernel_33831/997142380.py:8: FutureWarning: Series.__getitem__ treating
keys as positions is deprecated. In a future version, integer keys will always
be treated as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  lbl = row[1]
```

```
Result:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.76      0.97      0.85        29
           2       0.50      0.10      0.17        10

    accuracy                           0.80        49
   macro avg       0.75      0.69      0.67        49
```

```
weighted avg       0.75      0.80      0.74        49
```

try to tweak the model hyperparameter to see if it works

[11]:
```
param_grid = {
    'n_estimators': [50, 100, 200, 300],  # Number of trees in the forest
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the tree
    'min_samples_split': [2, 3, 10, 20],  # Minimum number of samples required␣
 ↪to split an internal node
    'min_samples_leaf': [1, 2, 4, 6],  # Minimum number of samples required to␣
 ↪be at a leaf node
}

clf = RandomForestClassifier(random_state=42)

grid_search = GridSearchCV(estimator=clf, param_grid=param_grid,
                           cv=3, n_jobs=-1, verbose=0)

grid_search.fit(X_tr, y_tr)

# Get the best parameters and best model
best_params = grid_search.best_params_
best_clf = grid_search.best_estimator_

print("Best parameters: ", best_params)

y_test_pred = best_clf.predict(X_te)

print("\nResult with best modell:")
print(classification_report(y_te, y_test_pred))
```

```
Best parameters:  {'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 3, 'n_estimators': 100}

Result with best modell:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.80      0.97      0.88        29
           2       0.75      0.30      0.43        10

    accuracy                           0.84        49
   macro avg       0.85      0.76      0.77        49
weighted avg       0.83      0.84      0.81        49
```

1.2 Fourier transform features

We want now to see if a model using only fourier transform could work.

create a function get_fourier_coefficients(ecg)

[12]:
```
def get_fourier_coefficients(ecg, n_coefficients=10):
    fft_result = np.fft.fft(ecg)
    fft_magnitude = np.abs(fft_result)
    fft_coefficients = fft_magnitude[1:n_coefficients+1]
    return fft_coefficients.tolist()
```

Using this function create a dataframe df_fourrier containing the fourrier transform coefficients and the label

[13]:
```
fourier_features_list = []
labels = []

for index, row in df.iterrows():
    time_series = row[2:].values
    label = row[1]
    fourier_features = get_fourier_coefficients(time_series)
    fourier_features_list.append(fourier_features)
    labels.append(label)

n_coefficients = len(fourier_features_list[0])
columns = [f'Fourier_Coeff_{i+1}' for i in range(n_coefficients)]

# df
df_fourrier = pd.DataFrame(fourier_features_list, columns=columns)

# Add the label
df_fourrier['Label'] = labels


print(df_fourrier)
```

```
/tmp/ipykernel_33831/259185693.py:6: FutureWarning: Series.__getitem__ treating
keys as positions is deprecated. In a future version, integer keys will always
be treated as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  label = row[1]

     Fourier_Coeff_1  Fourier_Coeff_2  Fourier_Coeff_3  Fourier_Coeff_4  \
0        1850.171567       295.333800      1185.545859       926.385162
1        4137.499334      2152.391165      2520.424900      2066.642615
2         400.463461       481.532272       729.461562       964.923609
3         313.204866       531.520312       667.082007       647.502832
4         303.329945       596.020424       609.179346       380.981983
..               …                …                …                …
```

```
157       593.412836       760.985169      1294.411838      1341.284484
158       378.721372       408.463206       581.751509       276.486875
159      1434.196761      2603.621630       769.678837      1109.373133
160       289.587563       621.209385       322.026792       332.194610
161       683.773983      1434.478998      2887.008289       976.316846

     Fourier_Coeff_5  Fourier_Coeff_6  Fourier_Coeff_7  Fourier_Coeff_8  \
0          538.293366       828.133738       689.752202      1559.152560
1         1640.749953      1579.574817       945.659290      1648.125085
2          946.182174       618.667927      1231.230068        82.521093
3          600.576281       620.723292       409.162029      2237.361623
4          272.183845      1134.805832       111.595226       865.347508
..                ...              ...              ...              ...
157        913.092712       421.080003      1230.467798       495.875861
158        177.656101       818.958481       415.362422       791.562387
159        479.235405       778.097122      1163.406930       628.928545
160        843.567029       683.896537       939.492166      1015.935540
161        847.116245      1962.896372       718.249410       608.238326

     Fourier_Coeff_9  Fourier_Coeff_10  Label
0          545.466498       1161.365509      1
1         1195.160663        537.355100      1
2          910.135298        745.443443      1
3          501.455323       1011.333733      1
4          194.837216        590.579985      1
..                ...              ...    ...
157        310.455683        415.697032      2
158        313.919207        231.886252      2
159        715.623275        450.295608      2
160        648.703645        635.155569      2
161        585.244309       1375.340407      2

[162 rows x 11 columns]
```

Try to train a model using the Fourrier coefficient

[14]:
```
# Train-test split
X = df_fourrier.drop(columns=['Label'])
y = df_fourrier['Label']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.18,␣
 ↪random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict
y_test_pred = clf.predict(X_test)
```

```python
# Result
print("\nResult:")
print(classification_report(y_test, y_test_pred))
```

```
Result:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.77      1.00      0.87        17
           2       0.00      0.00      0.00         5

    accuracy                           0.83        30
   macro avg       0.59      0.67      0.62        30
weighted avg       0.70      0.83      0.76        30


/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Try to learn a model using both fourrier coefficient and the features from the previous sections. Does it work ?

[15]:
```python
def get_combined_featuresandF(x):
    stats_features = calculate_stats_features(x)
    zero_crossings = calculate_zero_crossing(x)
    rms = calculate_rms(x)
    entropy_val = calculate_entropy(x)
    fourier_features = get_fourier_coefficients(x)
    features = stats_features + [zero_crossings, rms, entropy_val] + fourier_features
    return features
```

```
combined_features_list = []
labels = []


for index, row in df.iterrows():
    time_series = row[2:].values
    label = row[1]


    combined_features = get_combined_featuresandF(time_series)


    combined_features_list.append(combined_features)
    labels.append(label)

# Create DataFrame with combined features and labels
n_combined_features = len(combined_features_list[0])
columns = ['Max', 'Min', 'Mean', 'Median', 'Variance', 'ZeroCrossings', 'RMS',␣
 ↪'Entropy'] + \
          [f'Fourier_Coeff_{i+1}' for i in range(len(fourier_features))]

df_combined = pd.DataFrame(combined_features_list, columns=columns)
df_combined['Label'] = labels

# Train-test split
X = df_combined.drop(columns=['Label'])
y = df_combined['Label']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.18,␣
 ↪random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict
y_test_pred = clf.predict(X_test)

# Result
print("\nResult:")
print(classification_report(y_test, y_test_pred))
```

```
/tmp/ipykernel_33831/1085781370.py:17: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  label = row[1]
```

```
Result:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.77      1.00      0.87        17
           2       0.00      0.00      0.00         5

    accuracy                           0.83        30
   macro avg       0.59      0.67      0.62        30
weighted avg       0.70      0.83      0.76        30

/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

[16]:
```
#It is not better but it works
```

1.3 Wavelets

We now wants to use another signal decomposition which are called wavelet. Wavelet are a multi-scale function decomposition on a familly of functions generated from what is called a mother wavelet.

Using PyWavelet make a function get_wavelet_coefficients(ecg) that returns the wavelet coefficient of a given ECG

[17]:
```
pip install pywavelets
```

```
Requirement already satisfied: pywavelets in /home/floflo/Documents/epita/epita-
ml-scia/lib/python3.12/site-packages (1.7.0)
Requirement already satisfied: numpy<3,>=1.23 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
pywavelets) (1.26.4)
Note: you may need to restart the kernel to use updated packages.
```

[18]:
```
import pywt


def get_wavelet_coefficients(ecg, wavelet='db4', level=4):
    coeffs = pywt.wavedec(ecg, wavelet, level=level)
    wavelet_coefficients = np.concatenate(coeffs).tolist()
    return wavelet_coefficients
```

Using the get_wavelet_coefficients, create a dataframe when the features are the coefficients and include the label

[19]:
```
wavelet_features_list = []
labels = []

for index, row in df.iterrows():
    time_series = row[2:].values
    label = row[1]

    wavelet_features = get_wavelet_coefficients(time_series)

    wavelet_features_list.append(wavelet_features)
    labels.append(label)

# df
n_coefficients = len(wavelet_features_list[0])
columns = [f'Wavelet_Coeff_{i+1}' for i in range(n_coefficients)]

df_wavelet = pd.DataFrame(wavelet_features_list, columns=columns)

df_wavelet['Label'] = labels

print(df_wavelet)
```

```
/tmp/ipykernel_33831/3371426252.py:6: FutureWarning: Series.__getitem__ treating
keys as positions is deprecated. In a future version, integer keys will always
be treated as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  label = row[1]
```

	Wavelet_Coeff_1	Wavelet_Coeff_2	Wavelet_Coeff_3	Wavelet_Coeff_4	\
0	-0.228740	-0.190008	-0.179619	-0.226580	
1	-2.284291	-2.311781	-2.299607	-2.283637	
2	-0.821863	-0.796012	-0.774485	-0.775475	
3	0.348926	0.375198	0.371578	0.332356	
4	-1.643063	-1.666765	-1.676780	-1.630421	
..	…	…	…	…	
157	-1.256411	-1.176086	-1.000601	-1.271352	
158	-1.547153	-1.558670	-1.539930	-1.546184	

```
159        -0.365921        -0.357162        -0.362281        -0.369334
160         0.731175         0.785912         0.819470         0.593377
161         0.690330         0.747722         0.748915         0.634233

     Wavelet_Coeff_5  Wavelet_Coeff_6  Wavelet_Coeff_7  Wavelet_Coeff_8  \
0          -0.031340        -1.018605        -0.444753        -2.368966
1          -2.467491        -1.493960        -3.442873        -4.733150
2          -0.978186        -0.179384        -0.315090        -1.138809
3           0.535287        -0.082380         2.922918         0.238627
4          -1.849698        -0.928686         0.243894        -1.045281
..               …                …                …                …
157        -0.768256        -2.578013         0.597282         0.373866
158        -1.587573        -1.424208        -1.299591        -1.291218
159        -0.313935        -0.525250        -0.576419        -0.590355
160         1.540172        -1.551643        -0.743050        -3.033243
161         1.083086        -0.216203        -2.680500        -1.776808

     Wavelet_Coeff_9  Wavelet_Coeff_10  …  Wavelet_Coeff_65554  \
0          -1.634749         -0.977731  …             0.020990
1          -1.800736         -0.455900  …             0.016427
2          -0.368271          0.456424  …            -0.109406
3           0.597085          1.542039  …             0.037289
4          -0.736337         -0.233167  …             0.263982
..               …                …  …                  …
157         0.595444         -1.932390  …             0.007585
158        -1.166278         -1.821944  …             0.007847
159        -0.647901         -0.987933  …             0.000326
160        -1.141369         -0.903578  …             0.016191
161        -0.004091          0.030515  …             0.000801

     Wavelet_Coeff_65555  Wavelet_Coeff_65556  Wavelet_Coeff_65557  \
0              -0.037387             0.028253             0.002237
1               0.000257            -0.018340            -0.019976
2               0.154508             0.025962            -0.032860
3               0.045591             0.031034             0.009156
4              -0.425948             0.128538            -0.049629
..                   …                    …                    …
157            -0.010335             0.009463             0.001435
158            -0.012782            -0.000983            -0.008603
159             0.000340             0.011216             0.009061
160             0.002240             0.005429             0.021204
161             0.009888             0.001010             0.038516

     Wavelet_Coeff_65558  Wavelet_Coeff_65559  Wavelet_Coeff_65560  \
0              -0.000266            -0.028554             0.014615
1               0.006214            -0.063029             0.020517
2               0.056736            -0.031413             0.009088
3              -0.016872             0.045184            -0.008458
```

```
4              -0.076230            -0.007552            -0.001764
..                   …                    …                    …
157             0.001654             0.022055            -0.007558
158            -0.008715            -0.017159             0.005511
159             0.001568             0.008229            -0.002588
160             0.028493             0.039656            -0.012011
161             0.006706             0.002083            -0.000744

     Wavelet_Coeff_65561  Wavelet_Coeff_65562  Label
0               0.031316            -0.027797      1
1               0.055184            -0.012997      1
2               0.012298            -0.058915      1
3              -0.029453             0.015599      1
4               0.022396             0.089177      1
..                   …                    …    …
157            -0.020769             0.006174      2
158             0.017860             0.006525      2
159            -0.008707            -0.001065      2
160            -0.042655            -0.025372      2
161             0.001390            -0.027506      2

[162 rows x 65563 columns]
```

Train a random forest classifier with such features. DOes the model work

[20]:
```
#Split
X = df_wavelet.drop(columns=['Label'])
y = df_wavelet['Label']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.18,␣
 ↪random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict
y_test_pred = clf.predict(X_test)

# Result
print("\nResult:")
print(classification_report(y_test, y_test_pred))
```

```
Result:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         8
```

```
           1       0.57      1.00      0.72        17
           2       0.00      0.00      0.00         5

    accuracy                           0.57        30
   macro avg       0.19      0.33      0.24        30
weighted avg       0.32      0.57      0.41        30
```

```
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

[21]:
```
#It works but it is worse
```

Add one or several of the previous feature functions and try to train another model

[22]:
```
def get_combined_features(x):
    stats_features = calculate_stats_features(x)
    wavelet_features = get_wavelet_coefficients(x)
    combined_features = stats_features + wavelet_features
    return combined_features
```

[23]:
```
combined_features_list = []
labels = []

for index, row in df.iterrows():
    time_series = row[2:].values
    label = row[1]

    combined_features = get_combined_features(time_series)

    combined_features_list.append(combined_features)
    labels.append(label)

n_wavelet_coefficients = len(get_wavelet_coefficients(time_series))
```

```
columns = ['Max', 'Min', 'Mean', 'Median', 'Variance'] +␣
 ↪[f'Wavelet_Coeff_{i+1}' for i in range(n_wavelet_coefficients)]

df_combined = pd.DataFrame(combined_features_list, columns=columns)
df_combined['Label'] = labels

print(df_combined)
```

```
/tmp/ipykernel_33831/3471101090.py:6: FutureWarning: Series.__getitem__ treating
keys as positions is deprecated. In a future version, integer keys will always
be treated as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  label = row[1]
```

	Max	Min	Mean	Median	Variance	Wavelet_Coeff_1	\
0	3.006143	-2.460911	-0.268554	-0.346791	0.420271	-0.228740	
1	2.527708	-3.550697	-0.221014	-0.106818	0.536639	-2.284291	
2	2.264555	-3.929179	-0.163022	-0.153941	0.182135	-0.821863	
3	3.055421	-1.906982	0.053962	0.051409	0.158568	0.348926	
4	2.035001	-1.575197	-0.148872	-0.174830	0.111417	-1.643063	
..	…	…	…	…	…	…	
157	0.635837	-2.036593	-0.217742	-0.113975	0.165278	-1.256411	
158	2.777683	-1.408466	-0.270539	-0.258593	0.023627	-1.547153	
159	0.919894	-1.070185	-0.172078	-0.164195	0.018569	-0.365921	
160	7.078177	-5.961910	-0.343730	-0.390100	0.545255	0.731175	
161	4.478441	-4.748514	-0.264106	-0.214821	0.213515	0.690330	

	Wavelet_Coeff_2	Wavelet_Coeff_3	Wavelet_Coeff_4	Wavelet_Coeff_5	…	\
0	-0.190008	-0.179619	-0.226580	-0.031340	…	
1	-2.311781	-2.299607	-2.283637	-2.467491	…	
2	-0.796012	-0.774485	-0.775475	-0.978186	…	
3	0.375198	0.371578	0.332356	0.535287	…	
4	-1.666765	-1.676780	-1.630421	-1.849698	…	
..	…	…	…	…	…	
157	-1.176086	-1.000601	-1.271352	-0.768256	…	
158	-1.558670	-1.539930	-1.546184	-1.587573	…	
159	-0.357162	-0.362281	-0.369334	-0.313935	…	
160	0.785912	0.819470	0.593377	1.540172	…	
161	0.747722	0.748915	0.634233	1.083086	…	

	Wavelet_Coeff_65554	Wavelet_Coeff_65555	Wavelet_Coeff_65556	\
0	0.020990	-0.037387	0.028253	
1	0.016427	0.000257	-0.018340	
2	-0.109406	0.154508	0.025962	
3	0.037289	0.045591	0.031034	
4	0.263982	-0.425948	0.128538	
..	…	…	…	
157	0.007585	-0.010335	0.009463	

```
158              0.007847            -0.012782            -0.000983
159              0.000326             0.000340             0.011216
160              0.016191             0.002240             0.005429
161              0.000801             0.009888             0.001010

     Wavelet_Coeff_65557  Wavelet_Coeff_65558  Wavelet_Coeff_65559  \
0               0.002237            -0.000266            -0.028554
1              -0.019976             0.006214            -0.063029
2              -0.032860             0.056736            -0.031413
3               0.009156            -0.016872             0.045184
4              -0.049629            -0.076230            -0.007552
..                   …                    …                    …
157             0.001435             0.001654             0.022055
158            -0.008603            -0.008715            -0.017159
159             0.009061             0.001568             0.008229
160             0.021204             0.028493             0.039656
161             0.038516             0.006706             0.002083

     Wavelet_Coeff_65560  Wavelet_Coeff_65561  Wavelet_Coeff_65562  Label
0               0.014615             0.031316            -0.027797      1
1               0.020517             0.055184            -0.012997      1
2               0.009088             0.012298            -0.058915      1
3              -0.008458            -0.029453             0.015599      1
4              -0.001764             0.022396             0.089177      1
..                   …                    …                    …    …
157            -0.007558            -0.020769             0.006174      2
158             0.005511             0.017860             0.006525      2
159            -0.002588            -0.008707            -0.001065      2
160            -0.012011            -0.042655            -0.025372      2
161            -0.000744             0.001390            -0.027506      2

[162 rows x 65568 columns]
```

[24]:
```python
X = df_combined.drop(columns=['Label'])
y = df_combined['Label']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.18,␣
 ↪random_state=42)

# Train
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict
y_test_pred = clf.predict(X_test)
```

```
# Result
print("\nResult")
print(classification_report(y_test, y_test_pred))
```

```
Result
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         8
           1       0.59      1.00      0.74        17
           2       1.00      0.20      0.33         5

    accuracy                           0.60        30
   macro avg       0.53      0.40      0.36        30
weighted avg       0.50      0.60      0.47        30

/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Specify the methodology you used to train the model and report the various attempts results into a table

1.4 Deep learning (1D CNN)

Now we want to see if we can skip all theses feature engineering techniques ! Design and train a multi-layer one dimensional CNN using the raw ECG signal as features.

Could you reach or surpass the feature based models ?

[25]:
```
pip install tensorflow
```

```
Requirement already satisfied: tensorflow in /home/floflo/Documents/epita/epita-
ml-scia/lib/python3.12/site-packages (2.18.0)
Requirement already satisfied: absl-py>=1.0.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (2.1.0)
```

```
Requirement already satisfied: astunparse>=1.6.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (3.4.0)
Requirement already satisfied: packaging in /home/floflo/Documents/epita/epita-
ml-scia/lib/python3.12/site-packages (from tensorflow) (24.1)
Requirement already satisfied:
protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3
in /home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (4.25.5)
Requirement already satisfied: requests<3,>=2.21.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /home/floflo/Documents/epita/epita-
ml-scia/lib/python3.12/site-packages (from tensorflow) (75.1.0)
Requirement already satisfied: six>=1.12.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (4.12.2)
Requirement already satisfied: wrapt>=1.11.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (1.16.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (1.66.1)
Requirement already satisfied: tensorboard<2.19,>=2.18 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in
```

```
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (3.5.0)
Requirement already satisfied: numpy<2.1.0,>=1.26.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (1.26.4)
Requirement already satisfied: h5py>=3.11.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (3.12.1)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorflow) (0.4.1)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
astunparse>=1.6.0->tensorflow) (0.44.0)
Requirement already satisfied: rich in /home/floflo/Documents/epita/epita-ml-
scia/lib/python3.12/site-packages (from keras>=3.5.0->tensorflow) (13.7.1)
Requirement already satisfied: namex in /home/floflo/Documents/epita/epita-ml-
scia/lib/python3.12/site-packages (from keras>=3.5.0->tensorflow) (0.0.8)
Requirement already satisfied: optree in /home/floflo/Documents/epita/epita-ml-
scia/lib/python3.12/site-packages (from keras>=3.5.0->tensorflow) (0.12.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
requests<3,>=2.21.0->tensorflow) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
requests<3,>=2.21.0->tensorflow) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
requests<3,>=2.21.0->tensorflow) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
requests<3,>=2.21.0->tensorflow) (2024.8.30)
Requirement already satisfied: markdown>=2.6.8 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.5.2)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorboard<2.19,>=2.18->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.0.4)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
werkzeug>=1.0.1->tensorboard<2.19,>=2.18->tensorflow) (2.1.5)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
rich->keras>=3.5.0->tensorflow) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
```

```
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-packages (from
rich->keras>=3.5.0->tensorflow) (2.18.0)
Requirement already satisfied: mdurl~=0.1 in /home/floflo/Documents/epita/epita-
ml-scia/lib/python3.12/site-packages (from markdown-it-
py>=2.2.0->rich->keras>=3.5.0->tensorflow) (0.1.2)
Note: you may need to restart the kernel to use updated packages.
```

[26]:
```
X = df.iloc[:, 2:].values
y = df.iloc[:, 1].values

# Normalize dta
X = (X - np.mean(X, axis=1, keepdims=True)) / np.std(X, axis=1, keepdims=True)

label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# One-hot encoding
y_categorical = to_categorical(y_encoded)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y_categorical,␣
 ↪test_size=0.18, random_state=42)

# Reshape
X_train = X_train[..., np.newaxis]
X_test = X_test[..., np.newaxis]

print(f"Training data shape: {X_train.shape}")
print(f"Test data shape: {X_test.shape}")
```

```
Training data shape: (132, 65536, 1)
Test data shape: (30, 65536, 1)
```

[27]:
```
# Male model
def create_1d_cnn_model(input_shape, num_classes):
    model = Sequential()

    model.add(Conv1D(filters=64, kernel_size=5, activation='relu',␣
 ↪input_shape=input_shape))
    model.add(MaxPooling1D(pool_size=2))

    model.add(Conv1D(filters=128, kernel_size=5, activation='relu'))
    model.add(MaxPooling1D(pool_size=2))

    model.add(Conv1D(filters=128, kernel_size=5, activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
```

```
    model.add(Flatten())

    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5))

    model.add(Dense(num_classes, activation='softmax'))

    return model

input_shape = (X_train.shape[1], X_train.shape[2])
num_classes = y_train.shape[1]

# Create the model
model = create_1d_cnn_model(input_shape, num_classes)

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

model.summary()
```

```
/home/floflo/Documents/epita/epita-ml-scia/lib/python3.12/site-
packages/keras/src/layers/convolutional/base_conv.py:107: 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__(activity_regularizer=activity_regularizer, **kwargs)
2025-01-08 23:11:05.289414: W
external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
536608768 exceeds 10% of free system memory.
2025-01-08 23:11:05.392888: W
external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
536608768 exceeds 10% of free system memory.
2025-01-08 23:11:05.447107: W
external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
536608768 exceeds 10% of free system memory.
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 65532, 64)	384
max_pooling1d (MaxPooling1D)	(None, 32766, 64)	0
conv1d_1 (Conv1D)	(None, 32762, 128)	41,088

max_pooling1d_1 (MaxPooling1D)	(None, 16381, 128)	0
conv1d_2 (Conv1D)	(None, 16377, 128)	82,048
max_pooling1d_2 (MaxPooling1D)	(None, 8188, 128)	0
flatten (Flatten)	(None, 1048064)	0
dense (Dense)	(None, 128)	134,152,320
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387

Total params: 134,276,227 (512.22 MB)

Trainable params: 134,276,227 (512.22 MB)

Non-trainable params: 0 (0.00 B)

[28]:
```
# Train
history = model.fit(X_train, y_train, epochs=30, batch_size=32,␣
↪validation_split=0.1, verbose=2)
```

```
Epoch 1/30
2025-01-08 23:11:06.558562: W
external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
536608768 exceeds 10% of free system memory.
2025-01-08 23:11:07.203408: W
external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
536838144 exceeds 10% of free system memory.
4/4 - 15s - 4s/step - accuracy: 0.4407 - loss: 52.0255 - val_accuracy: 0.5000 -
val_loss: 3.1575
Epoch 2/30
4/4 - 13s - 3s/step - accuracy: 0.4068 - loss: 2.3035 - val_accuracy: 0.3571 -
val_loss: 1.2781
Epoch 3/30
4/4 - 13s - 3s/step - accuracy: 0.6949 - loss: 0.8412 - val_accuracy: 0.4286 -
val_loss: 1.0249
Epoch 4/30
4/4 - 13s - 3s/step - accuracy: 0.8814 - loss: 0.5414 - val_accuracy: 0.5000 -
val_loss: 1.2335
Epoch 5/30
```

```
4/4 - 14s - 3s/step - accuracy: 0.8559 - loss: 0.3457 - val_accuracy: 0.7143 -
val_loss: 0.9949
Epoch 6/30
4/4 - 13s - 3s/step - accuracy: 0.9068 - loss: 0.1944 - val_accuracy: 0.7143 -
val_loss: 1.1693
Epoch 7/30
4/4 - 13s - 3s/step - accuracy: 0.9831 - loss: 0.0751 - val_accuracy: 0.7143 -
val_loss: 1.4961
Epoch 8/30
4/4 - 13s - 3s/step - accuracy: 0.9831 - loss: 0.0927 - val_accuracy: 0.7143 -
val_loss: 1.5022
Epoch 9/30
4/4 - 14s - 3s/step - accuracy: 1.0000 - loss: 0.0274 - val_accuracy: 0.7143 -
val_loss: 1.6846
Epoch 10/30
4/4 - 13s - 3s/step - accuracy: 0.9831 - loss: 0.0346 - val_accuracy: 0.7143 -
val_loss: 2.0474
Epoch 11/30
4/4 - 13s - 3s/step - accuracy: 0.9915 - loss: 0.0484 - val_accuracy: 0.7143 -
val_loss: 1.5477
Epoch 12/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0226 - val_accuracy: 0.7143 -
val_loss: 1.0207
Epoch 13/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0087 - val_accuracy: 0.7143 -
val_loss: 0.9946
Epoch 14/30
4/4 - 13s - 3s/step - accuracy: 0.9915 - loss: 0.0122 - val_accuracy: 0.7143 -
val_loss: 1.3413
Epoch 15/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0031 - val_accuracy: 0.7143 -
val_loss: 1.7805
Epoch 16/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0048 - val_accuracy: 0.7143 -
val_loss: 2.2286
Epoch 17/30
4/4 - 13s - 3s/step - accuracy: 0.9915 - loss: 0.0141 - val_accuracy: 0.7143 -
val_loss: 2.3197
Epoch 18/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0032 - val_accuracy: 0.7143 -
val_loss: 2.3287
Epoch 19/30
4/4 - 13s - 3s/step - accuracy: 0.9915 - loss: 0.0150 - val_accuracy: 0.7143 -
val_loss: 2.1151
Epoch 20/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0060 - val_accuracy: 0.7143 -
val_loss: 1.4564
Epoch 21/30
```

```
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0016 - val_accuracy: 0.7857 -
val_loss: 1.1299
Epoch 22/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0017 - val_accuracy: 0.7857 -
val_loss: 1.0143
Epoch 23/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0019 - val_accuracy: 0.7857 -
val_loss: 1.1353
Epoch 24/30
4/4 - 13s - 3s/step - accuracy: 0.9915 - loss: 0.0072 - val_accuracy: 0.7143 -
val_loss: 1.4766
Epoch 25/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0029 - val_accuracy: 0.7143 -
val_loss: 1.9155
Epoch 26/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 4.0114e-04 - val_accuracy: 0.7143
- val_loss: 2.2017
Epoch 27/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 4.0061e-04 - val_accuracy: 0.7143
- val_loss: 2.4349
Epoch 28/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 9.6793e-04 - val_accuracy: 0.7143
- val_loss: 2.6217
Epoch 29/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 2.9135e-04 - val_accuracy: 0.7143
- val_loss: 2.7803
Epoch 30/30
4/4 - 13s - 3s/step - accuracy: 1.0000 - loss: 0.0017 - val_accuracy: 0.7143 -
val_loss: 2.9471
```

[31]:
```python
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)
print(f"\nTest Accuracy: {test_acc:.4f}")

y_test_pred_prob = model.predict(X_test)
y_test_pred = np.argmax(y_test_pred_prob, axis=1)
y_test_true = np.argmax(y_test, axis=1)

print("\nRes:")
# Ensure target_names is a list of strings
target_names = label_encoder.classes_.astype(str)
print(classification_report(y_test_true, y_test_pred,␣
 ↪target_names=target_names))
```

```
Test Accuracy: 0.8000
1/1             1s 767ms/step

Res:
```

	precision	recall	f1-score	support
0	1.00	0.25	0.40	8
1	0.74	1.00	0.85	17
2	1.00	1.00	1.00	5
accuracy			0.80	30
macro avg	0.91	0.75	0.75	30
weighted avg	0.85	0.80	0.76	30

[ ]:
```
#I could not surpass the base feature model
```