tqwt-ecg

April 14, 2024

Importing necessary packages

[1]:

```
import os
import ast
import wfdb
import random
import numpy as np
import pandas as pd
import pywt

import seaborn as sns
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout, Conv1D, MaxPooling1D, Flatten,␣
 ↪AveragePooling1D, GlobalAveragePooling1D, BatchNormalization
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping
from keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.tree import export_graphviz
```

[2]:

```
PATH = 'ptbxl/'

ecg_df = pd.read_csv(os.path.join(PATH, 'ptbxl_database.csv'),␣
 ↪index_col='ecg_id')
ecg_df.scp_codes = ecg_df.scp_codes.apply(lambda x : ast.literal_eval(x))

agg_df = pd.read_csv(os.path.join(PATH, 'scp_statements.csv'), index_col=0)
agg_df = agg_df[agg_df.diagnostic == 1]

LEAD_NAMES = ['I', 'II', 'III', 'aVR', 'aVL', 'aVF', 'V1', 'V2', 'V3', 'V4',␣
 ↪'V5', 'V6']
```

aggregate_diagnostic() : function that takes the scp codes of a patient and returns the superclass labels for multiclass classification by mapping the scp codes to the diagnostic statements in the scp_statements csv file

[3]:
```
def aggregate_diagnostic(y_dic):
    tmp = []
    for key in y_dic.keys():
        if key in agg_df.index:
            tmp.append(agg_df.loc[key].diagnostic_class)
    return list(set(tmp))
```

[4]:
```
ecg_df['diagnostic_superclass'] = ecg_df.scp_codes.apply(aggregate_diagnostic)
```

load_raw_data() : function to load raw data from the files, wfdb package is used to read the .dat files from the PATH

[5]:
```
def load_raw_data(df, sampling_rate, path):
    if sampling_rate == 100:
        data = [wfdb.rdsamp(path+f) for f in df.filename_lr]
    else:
        data = [wfdb.rdsamp(path+f) for f in df.filename_hr]
    data = np.array([signal for signal, meta in data])
    return data
```

[6]:
```
ecg_data=np.load('ecg_data.npy')
```

[7]:
```
ecg_data = load_raw_data(ecg_df, 100, PATH)
```

[8]:
```
ecg_data.shape
```

[8]:
```
(21799, 1000, 12)
```

Initially data is loaded in the shape (21799, 1000, 12) The data is then reshaped to (21799, 12, 1000) for logical purposes. The shape (12, 1000) represents 1000 samples for each of the 12 leads attached to the patient.

[9]:
```
ecg_data = np.transpose(ecg_data, (0, 2, 1))
ecg_data.shape
```

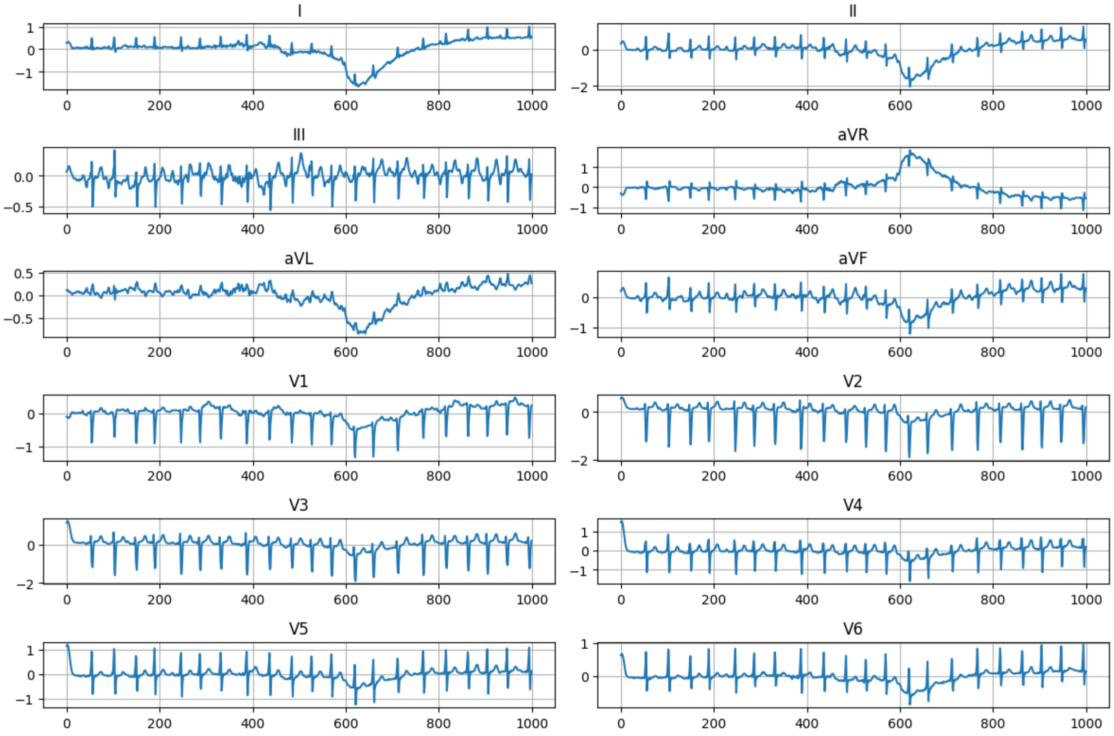
[9]:
```
(21799, 12, 1000)
```

Plotting the ECG signals for one patient for visualization purpose

[10]:
```
idx = random.randint(0, ecg_data.shape[0])
plt.figure(figsize=(20, 5))
data = ecg_data[idx]
plt.figure(figsize=(12, 8))
for i in range(12):
    plt.subplot(6, 2, i + 1)
    plt.plot(data[i])
    plt.title(LEAD_NAMES[i])
    plt.grid()
    plt.tight_layout()

# plt.suptitle(y[idx])
plt.show()
```

```
<Figure size 2000x500 with 0 Axes>
```



Feature Extraction: Tunable Q-factor Wavelet Transform (TQWT) is used to extract features from the ECG signals. The five most significant coefficients are extracted from the TQWT of the ECG signals in order to filter out the noise components and retain the essential features. Harr wavelet is used for the process.

[11]:
```
q_values = [0.5]
```

[12]:
```
def tqwt(signal, q_values, wavelet_name='haar', level=5):
    tqwt_coeffs = []
    for q in q_values:
        # Apply Discrete Wavelet Transform (DWT)
        coeffs = pywt.wavedec(signal, wavelet_name, level=level)

        # Apply the TQWT using the q value
        for i in range(1, len(coeffs)):
            coeffs[i] = np.sign(coeffs[i]) * np.power(np.abs(coeffs[i]), q)

        # Reconstruct the signal
        reconstructed_signal = pywt.waverec(coeffs, wavelet_name)

        # Store the TQWT coefficients
        tqwt_coeffs.append(reconstructed_signal)

    return np.concatenate(tqwt_coeffs)

ecg_data_tqwt = []
for patient_data in ecg_data:
    patient_coeffs = []
    for lead_data in patient_data:
        lead_coeffs = tqwt(lead_data,q_values)
        patient_coeffs.append(lead_coeffs)
    ecg_data_tqwt.append(patient_coeffs)

ecg_data_tqwt = np.array(ecg_data_tqwt)
```

Visualizing the Tqwt coefficients for one patient and one lead

[13]:
```
coeffs = pywt.wavedec(ecg_data[0][0], wavelet='haar', level=5)
cA1, cD5, cD4, cD3, cD2, cD1 = coeffs
```

[14]:
```
cA1.shape, cD5.shape, cD4.shape, cD3.shape, cD2.shape, cD1.shape
```

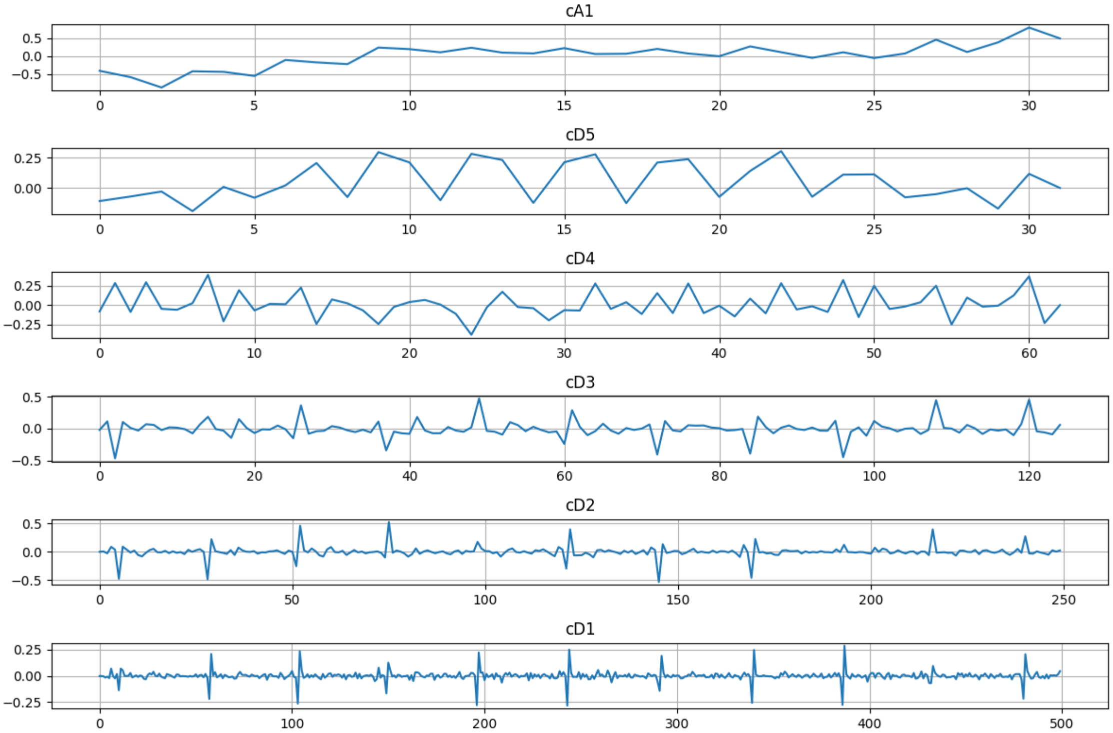
[14]:
```
((32,), (32,), (63,), (125,), (250,), (500,))
```

[15]:
```
coeffs = pywt.wavedec(ecg_data[0][0], wavelet='haar', level=5)

# extract the coeffs cA1, cD5, cD4, cD3, cD2, cD1 from the concatenated coeffs

plt.figure(figsize=(12, 8))
for i, coeff in enumerate(coeffs):
    if i == 0:
        label = 'cA1'
    else:
        label = f'cD{6-i}'
    plt.subplot(6, 1, i+1)
    plt.plot(coeff)
    plt.title(label)
    plt.grid()

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



Exploring the datafram to identify essential columns

[16]:
```
ecg_df.head()
```

[16]:
```
         patient_id   age  sex  height  weight  nurse  site     device  \
ecg_id
1           15709.0  56.0    1     NaN    63.0    2.0   0.0  CS-12   E
2           13243.0  19.0    0     NaN    70.0    2.0   0.0  CS-12   E
3           20372.0  37.0    1     NaN    69.0    2.0   0.0  CS-12   E
4           17014.0  24.0    0     NaN    82.0    2.0   0.0  CS-12   E
5           17448.0  19.0    1     NaN    70.0    2.0   0.0  CS-12   E

             recording_date                               report  …  \
ecg_id                                                            …
1       1984-11-09 09:17:34  sinusrhythmus periphere niederspannung  …
2       1984-11-14 12:55:37     sinusbradykardie sonst normales ekg  …
3       1984-11-15 12:49:10              sinusrhythmus normales ekg  …
4       1984-11-15 13:44:57              sinusrhythmus normales ekg  …
5       1984-11-17 10:43:15              sinusrhythmus normales ekg  …

        baseline_drift static_noise burst_noise electrodes_problems  \
ecg_id
1                  NaN    , I-V1,           NaN                 NaN
2                  NaN          NaN         NaN                 NaN
```

```
3                  NaN          NaN         NaN                 NaN
4         , II,III,AVF          NaN         NaN                 NaN
5        , III,AVR,AVF          NaN         NaN                 NaN

        extra_beats  pacemaker  strat_fold                filename_lr  \
ecg_id
1               NaN        NaN           3  records100/00000/00001_lr
2               NaN        NaN           2  records100/00000/00002_lr
3               NaN        NaN           5  records100/00000/00003_lr
4               NaN        NaN           3  records100/00000/00004_lr
5               NaN        NaN           4  records100/00000/00005_lr

                      filename_hr diagnostic_superclass
ecg_id
1       records500/00000/00001_hr                [NORM]
2       records500/00000/00002_hr                [NORM]
3       records500/00000/00003_hr                [NORM]
4       records500/00000/00004_hr                [NORM]
5       records500/00000/00005_hr                [NORM]

[5 rows x 28 columns]
```

Isolating the labels from the datafram for cleaner workspace and better understanding

[17]:
```
labels = ecg_df[['diagnostic_superclass']].copy()
```

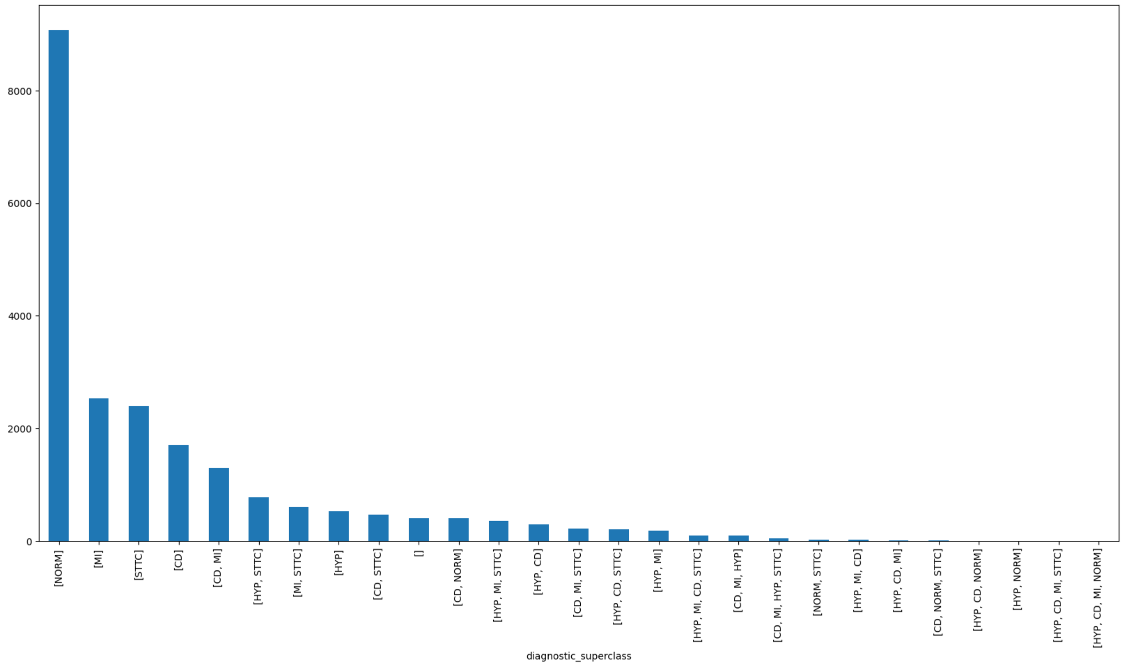
[18]:
```
# display all the unique diagnostic_superclass combinations present
labels['diagnostic_superclass'].value_counts()
```

[18]:
```
diagnostic_superclass
[NORM]                    9069
[MI]                      2532
[STTC]                    2400
[CD]                      1708
[CD, MI]                  1297
[HYP, STTC]                781
[MI, STTC]                 599
[HYP]                      535
[CD, STTC]                 471
[]                         411
[CD, NORM]                 407
[HYP, MI, STTC]            361
[HYP, CD]                  300
[CD, MI, STTC]             223
[HYP, CD, STTC]            211
[HYP, MI]                  183
[HYP, MI, CD, STTC]        102
```

```
[CD, MI, HYP]           93
[CD, MI, HYP, STTC]     52
[NORM, STTC]            28
[HYP, MI, CD]           18
[HYP, CD, MI]            6
[CD, NORM, STTC]         5
[HYP, CD, NORM]          2
[HYP, NORM]              2
[HYP, CD, MI, STTC]      2
[HYP, CD, MI, NORM]      1
Name: count, dtype: int64
```

Plotting the distribuiton of data for each superclass and it's combinations

[19]:
```
# plot the count of every diagnostic superclass
plt.figure(figsize=(20, 10))
labels.diagnostic_superclass.value_counts().plot(kind='bar')
plt.show()
```



Filter out the labels and the ecg data for five class classification The data belonging to the individual superclasses "NORM", "STTC", "MI", "CD", "HYP" are filtered out by going through the entire dataframe and extracting the data that belongs to the respective superclass.

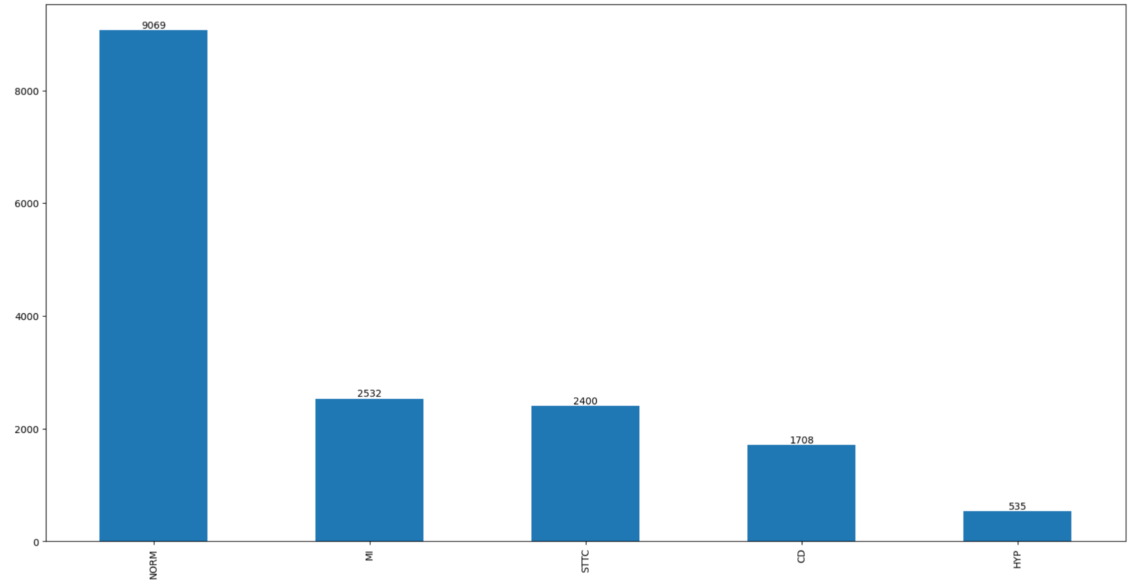
[20]:

```
# filter out only datas and corresponding labels with diagnostic superclass of␣
 ↪'NORM' , 'MI', 'STTC', 'CD' and 'HYP'
ecg_data_filtered = []
labels_filtered = []
for i in range(len(labels)):
    list = labels.iloc[i].diagnostic_superclass
    if (list == ['NORM'] or list == ['MI'] or list == ['STTC'] or list ==␣
 ↪['CD'] or list == ['HYP']):
        ecg_data_filtered.append(ecg_data_tqwt[i])
        labels_filtered.append(list)
```

```
[21]: ecg_data_filtered = np.array(ecg_data_filtered)
      labels_filtered = np.array(labels_filtered)
      ecg_data_filtered.shape, labels_filtered.shape
```

```
[21]: ((16244, 12, 1000), (16244, 1))
```

```
[22]: # plot the filtered labels count in a bar graph
      plt.figure(figsize=(20, 10))
      ax = pd.Series(labels_filtered.flatten()).value_counts().plot(kind='bar')
      for p in ax.patches:
          ax.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
       ↪get_height()), ha='center', va='bottom')
      plt.show()
```



Creating a separate label set for binary classification among the classes "NORM" (0) and "ABNORM" (1)

[23]:

```
Y_binary = []
for list in labels_filtered:
        if list == ['NORM']:
            Y_binary.append(0)
        else:
            Y_binary.append(1)
```

Encoding the labels from string to categorical classes for training and testing purposes

[24]:

```
labelEncoder = LabelEncoder()
Y_multiclass = labelEncoder.fit_transform(labels_filtered)
Y_multiclass = to_categorical(Y_multiclass)
```

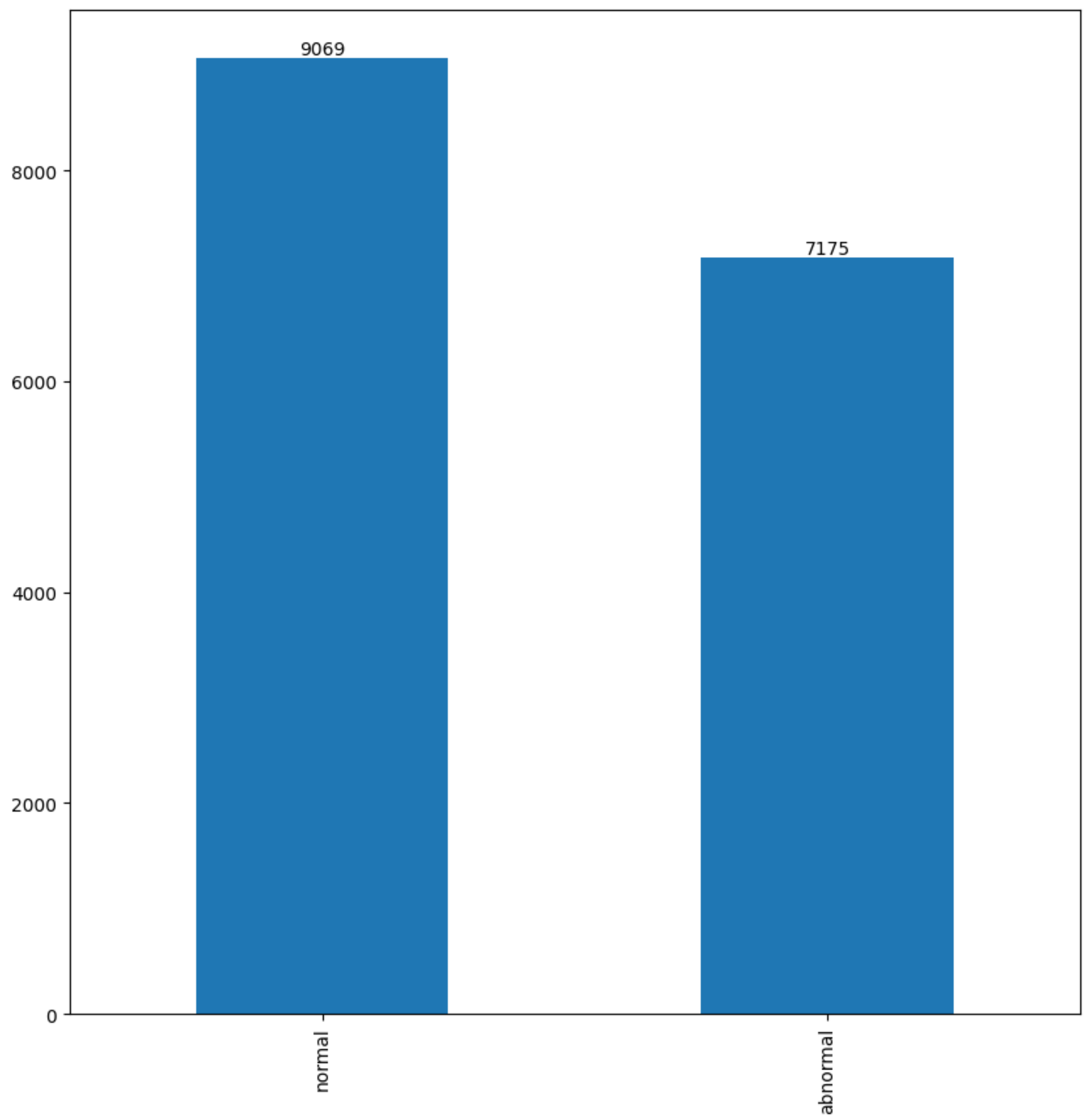
```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\preprocessing\_label.py:114: DataConversionWarning: A column-
vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

Visualizing the distribution of normal and abnormal data

[25]:

```
plt.figure(figsize=(10, 10))
ax = pd.Series(Y_binary).value_counts().plot(kind='bar')
for p in ax.patches:
    ax.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
  ↪get_height()), ha='center', va='bottom')
plt.xticks([0, 1], ['normal', 'abnormal'])
plt.show()

pd.Series(Y_binary).value_counts()
```



[25]:
```
0    9069
1    7175
Name: count, dtype: int64
```

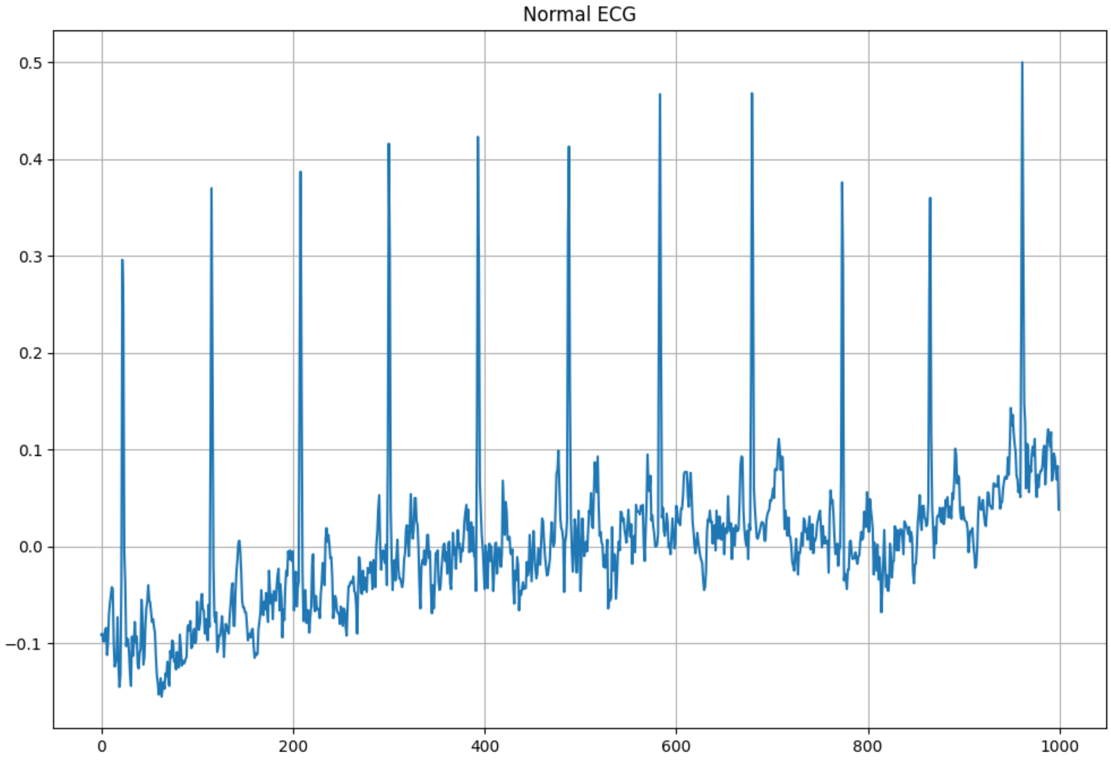
[26]:
```
Y_binary = np.array(Y_binary)
Y_binary.shape
```

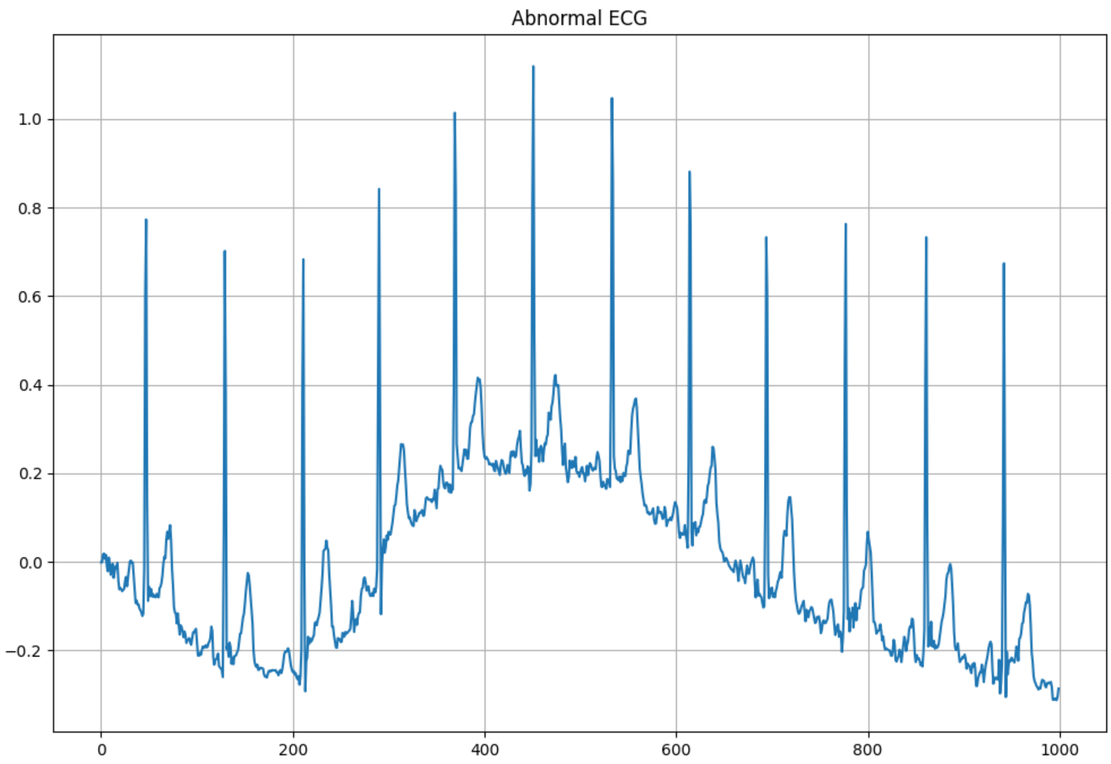
[26]:
```
(16244,)
```

[27]:
```
# plot one normal and one abnormal signal
normal_idx = np.where(Y_binary == 0)[0]
abnormal_idx = np.where(Y_binary == 1)[0]
```

```
plt.figure(figsize=(12, 8))
plt.plot(ecg_data[normal_idx[0]][4])
plt.title('Normal ECG')
plt.grid()
plt.show()

plt.figure(figsize=(12, 8))
plt.plot(ecg_data[abnormal_idx[0]][4])
plt.title('Abnormal ECG')
plt.grid()
plt.show()
```





Splitting the data into training and testing sets

[28]:
```
x_train_binary, x_test_binary, y_train_binary, y_test_binary =␣
↪train_test_split(ecg_data_filtered, Y_binary, test_size=0.2, random_state=42)
x_valid_binary, y_valid_binary = x_test_binary, y_test_binary
```

Validation sets used in training are same as testing sets

[29]:
```
x_train_binary.shape, x_test_binary.shape, y_train_binary.shape, y_test_binary.
↪shape
```

[29]:
```
((12995, 12, 1000), (3249, 12, 1000), (12995,), (3249,))
```

[30]:
```
x_train_multiclass, x_test_multiclass, y_train_multiclass, y_test_multiclass =␣
↪train_test_split(ecg_data_filtered, Y_multiclass, test_size=0.2,␣
↪random_state=42)
x_valid_multiclass, y_valid_multiclass = x_test_multiclass, y_test_multiclass
```

[31]:
```
x_train_multiclass.shape, x_valid_multiclass.shape, y_train_multiclass.shape,␣
↪y_valid_multiclass.shape
```

[31]:
```
((12995, 12, 1000), (3249, 12, 1000), (12995, 5), (3249, 5))
```

Visualizing the train - test split for the binary classification and the five class classification

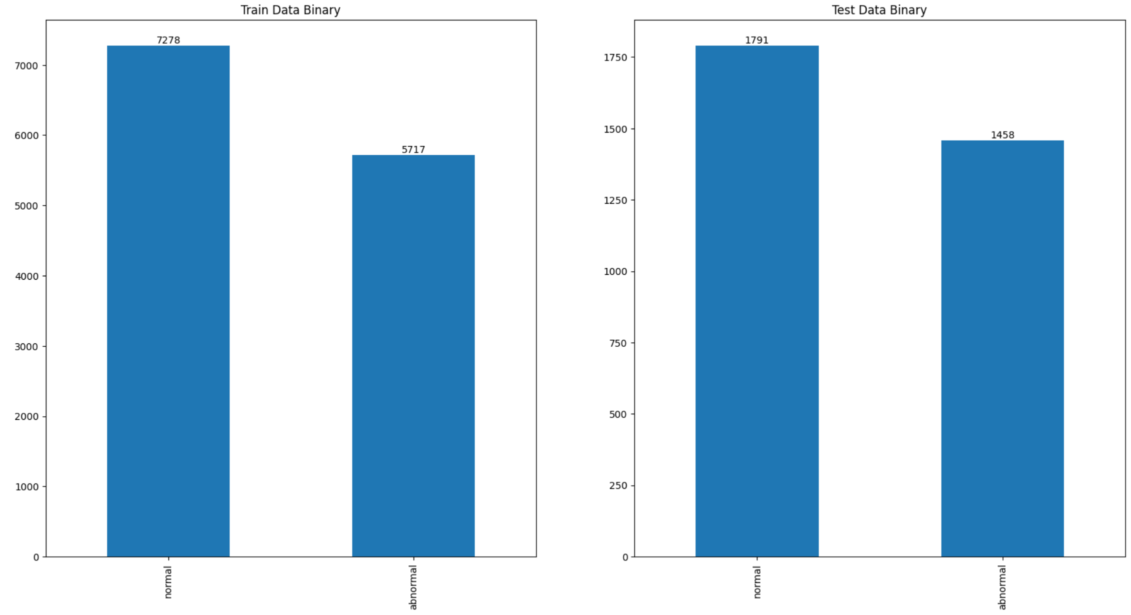
[32]:

```
plt.figure(figsize=(20, 10))

# Plot train data
plt.subplot(1, 2, 1)
ax_train = pd.Series(y_train_binary).value_counts().plot(kind='bar')
for p in ax_train.patches:
    ax_train.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
 ↪get_height()), ha='center', va='bottom')
plt.xticks([0, 1], ['normal', 'abnormal'])
plt.title(f'Train Data Binary')

# Plot test data
plt.subplot(1, 2, 2)
ax_test = pd.Series(y_test_binary).value_counts().plot(kind='bar')
for p in ax_test.patches:
    ax_test.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
 ↪get_height()), ha='center', va='bottom')
plt.xticks([0, 1], ['normal', 'abnormal'])
plt.title(f'Test Data Binary')

plt.show()
```



[33]:

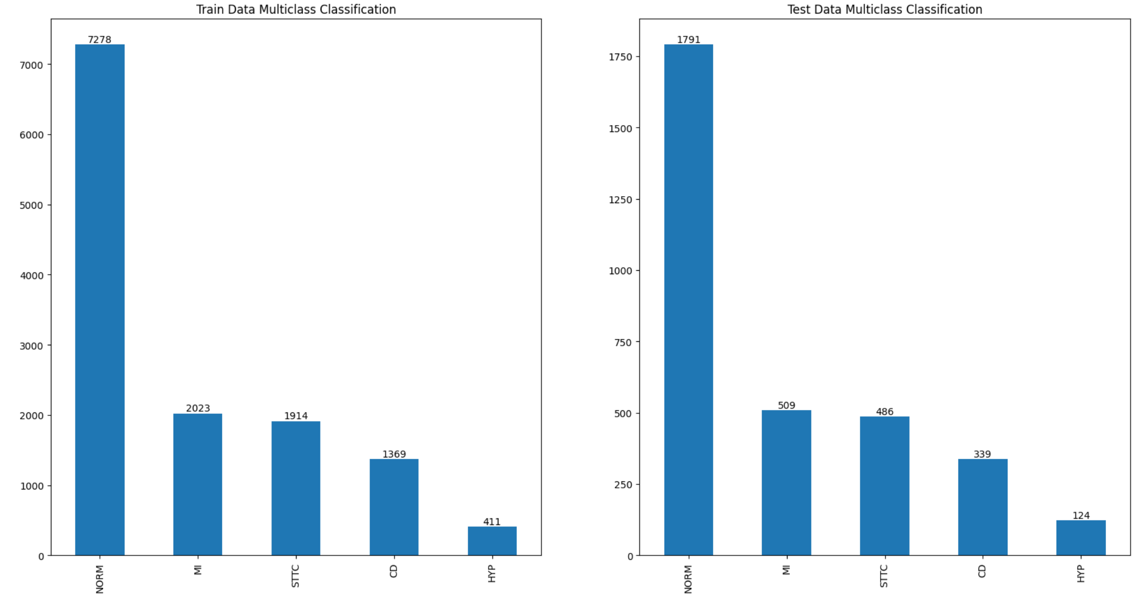
```
plt.figure(figsize=(20, 10))

# Plot train data
```

```
plt.subplot(1, 2, 1)
ax_train = pd.Series(y_train_multiclass.argmax(axis=1)).value_counts().
 ↪plot(kind='bar')
for p in ax_train.patches:
    ax_train.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
 ↪get_height()), ha='center', va='bottom')
plt.xticks([0, 1, 2, 3, 4], ['NORM', 'MI', 'STTC', 'CD', 'HYP'])
plt.title('Train Data Multiclass Classification')

# Plot test data
plt.subplot(1, 2, 2)
ax_test = pd.Series(y_test_multiclass.argmax(axis=1)).value_counts().
 ↪plot(kind='bar')
for p in ax_test.patches:
    ax_test.annotate(str(p.get_height()), (p.get_x() + p.get_width() / 2, p.
 ↪get_height()), ha='center', va='bottom')
plt.xticks([0, 1, 2, 3, 4], ['NORM', 'MI', 'STTC', 'CD', 'HYP'])
plt.title('Test Data Multiclass Classification')

plt.show()
```



0.0.1 Training and testing the models

1D CNN model for five class classification

```
[34]: def build_model_cnn_multiclass(input_shape):
          model = Sequential()
          model.add(Conv1D(filters=256, kernel_size=6, activation='relu',
                          padding='same', input_shape=input_shape))
          model.add(BatchNormalization())
          model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

          model.add(Conv1D(filters=128, kernel_size=6, activation='relu',
                          padding='same'))
          model.add(BatchNormalization())
          model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

          model.add(Conv1D(filters=64, kernel_size=6, activation='relu',
                          padding='same'))
          model.add(BatchNormalization())
          model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

          model.add(Flatten())
          model.add(Dense(64, activation='relu'))
          model.add(Dropout(0.5))
          model.add(Dense(64, activation='relu'))
          model.add(Dropout(0.5))
          model.add(Dense(5, activation='softmax'))

          model.compile(loss='categorical_crossentropy',␣
        ↪optimizer=Adam(learning_rate=0.0001), metrics=['accuracy'])

          return model;
```

0.1 Classification using 1 lead ECG signal

[35]:
```
x_train_single_lead = x_train_multiclass[:, 0, :]
x_train_single_lead.shape
```

[35]:
```
(12995, 1000)
```

[36]:
```
x_train_single_lead = x_train_multiclass[:, 0, :]
x_train_single_lead = x_train_single_lead.reshape(x_train_single_lead.shape[0],␣
  ↪x_train_single_lead.shape[1], 1)
x_valid_single_lead = x_valid_multiclass[:, 0, :]
x_valid_single_lead = x_valid_single_lead.reshape(x_valid_single_lead.shape[0],␣
  ↪x_valid_single_lead.shape[1], 1)
x_test_single_lead = x_test_multiclass[:, 0, :]
x_test_single_lead = x_test_single_lead.reshape(x_test_single_lead.shape[0],␣
  ↪x_test_single_lead.shape[1], 1)
```

[37]:
```
x_train_single_lead.shape
```

[37]:
```
(12995, 1000, 1)
```

[38]:

```
model_cnn_single_lead = build_model_cnn_multiclass((x_train_single_lead.
 ↪shape[1], x_train_single_lead.shape[2]))
model_cnn_single_lead.summary()
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Model: "sequential"


 Layer (type)                     Output Shape                  Param #

 conv1d (Conv1D)                  (None, 1000, 256)               1,792

 batch_normalization              (None, 1000, 256)               1,024
 (BatchNormalization)

 max_pooling1d (MaxPooling1D)     (None, 500, 256)                    0

 conv1d_1 (Conv1D)                (None, 500, 128)              196,736

 batch_normalization_1            (None, 500, 128)                  512
 (BatchNormalization)

 max_pooling1d_1 (MaxPooling1D)   (None, 250, 128)                    0

 conv1d_2 (Conv1D)                (None, 250, 64)                49,216

 batch_normalization_2            (None, 250, 64)                   256
 (BatchNormalization)

 max_pooling1d_2 (MaxPooling1D)   (None, 125, 64)                     0

 flatten (Flatten)                (None, 8000)                        0

 dense (Dense)                    (None, 64)                    512,064

 dropout (Dropout)                (None, 64)                          0

 dense_1 (Dense)                  (None, 64)                      4,160

 dropout_1 (Dropout)              (None, 64)                          0
 dense_2 (Dense)                  (None, 5)                        325


  Total params: 766,085 (2.92 MB)

  Trainable params: 765,189 (2.92 MB)

  Non-trainable params: 896 (3.50 KB)
```

[39]:
```
model=model_cnn_single_lead.fit(x_train_single_lead, y_train_multiclass,␣
 ↪validation_data=(x_valid_single_lead, y_valid_multiclass), epochs=20,␣
 ↪batch_size=32, callbacks=[EarlyStopping(patience=5)])
```

```
Epoch 1/4
407/407             118s 280ms/step -
accuracy: 0.3686 - loss: 1.6983 - val_accuracy: 0.4537 - val_loss: 1.3729
Epoch 2/4
407/407             107s 263ms/step -
accuracy: 0.5092 - loss: 1.3198 - val_accuracy: 0.5543 - val_loss: 1.1890
Epoch 3/4
407/407             111s 272ms/step -
accuracy: 0.5429 - loss: 1.2490 - val_accuracy: 0.5586 - val_loss: 1.2098
Epoch 4/4
407/407             119s 293ms/step -
accuracy: 0.5516 - loss: 1.2127 - val_accuracy: 0.5777 - val_loss: 1.1726
```

[40]:
```
from sklearn.metrics import precision_score, recall_score, confusion_matrix,␣
 ↪f1_score, ConfusionMatrixDisplay
```

[41]:
```
y_pred = model_cnn_single_lead.predict(x_test_single_lead)
y_pred = np.argmax(y_pred, axis=1)
y_true = np.argmax(y_test_multiclass, axis=1)

accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred, average='weighted')
recall = recall_score(y_true, y_pred, average='weighted')
f1_score = f1_score(y_true,y_pred,average='weighted')
print(f'Accuracy: {accuracy}')
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'f1_score: {f1_score}')
```

```
102/102             8s 77ms/step
Accuracy: 0.5777162203755002
Precision: 0.452582152588447
```

```
Recall: 0.5777162203755002
f1_score: 0.46329031066174897
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

[42]:

```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
  ↪ConfusionMatrixDisplay
```

[43]:

```
# write a function to perform the operation of the above 3 cells for all the␣
  ↪leads and store the loss and accuracy in a list
def train_model_for_all_leads(x_train, y_train, x_valid, y_valid, x_test,␣
  ↪y_test):
    loss_list = []
    accuracy_list = []
    precision_list = []
    recall_list = []
    f1score_list = []

    for i in range(x_train.shape[1]):
        x_train_single_lead = x_train[:, i, :]
        x_train_single_lead = x_train_single_lead.reshape(x_train_single_lead.
  ↪shape[0], x_train_single_lead.shape[1], 1)
        x_valid_single_lead = x_valid[:, i, :]
        x_valid_single_lead = x_valid_single_lead.reshape(x_valid_single_lead.
  ↪shape[0], x_valid_single_lead.shape[1], 1)
        x_test_single_lead = x_test[:, i, :]
        x_test_single_lead = x_test_single_lead.reshape(x_test_single_lead.
  ↪shape[0], x_test_single_lead.shape[1], 1)

        model_cnn_single_lead = build_model_cnn_multiclass((x_train_single_lead.
  ↪shape[1], x_train_single_lead.shape[2]))
        model_cnn_single_lead.fit(x_train_single_lead, y_train,␣
  ↪validation_data=(x_valid_single_lead, y_valid), epochs=20, batch_size=32,␣
  ↪callbacks=[EarlyStopping(patience=5)])
        y_pred = model_cnn_single_lead.predict(x_test_single_lead)
        y_pred = np.argmax(y_pred, axis=1)
        y_true = np.argmax(y_test, axis=1)

        accuracy = accuracy_score(y_true, y_pred)
        precision = precision_score(y_true, y_pred, average='weighted')
        recall = recall_score(y_true, y_pred, average='weighted')
        f1score = f1_score(y_true, y_pred, average='weighted')
        results = model_cnn_single_lead.evaluate(x_test_single_lead, y_test)
        loss_list.append(results[0])
        accuracy_list.append(accuracy)
        precision_list.append(precision)
        recall_list.append(recall)
        f1score_list.append(f1score)
    return loss_list, accuracy_list, precision_list, recall_list , f1score_list
```

[44]:

```
loss_list, accuracy_list, precision_list, recall_list, f1score_list =␣
  ↪train_model_for_all_leads(x_train_multiclass, y_train_multiclass,␣
  ↪x_valid_multiclass, y_valid_multiclass, x_test_multiclass, y_test_multiclass)
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             120s 286ms/step -
accuracy: 0.3663 - loss: 1.7090 - val_accuracy: 0.0674 - val_loss: 2.4506
Epoch 2/2
407/407             107s 262ms/step -
accuracy: 0.5181 - loss: 1.3437 - val_accuracy: 0.5512 - val_loss: 1.1957
102/102             6s 59ms/step
  2/102             5s 51ms/step - accuracy:
0.4688 - loss: 1.4151
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             6s 58ms/step -
accuracy: 0.5365 - loss: 1.2235
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             111s 266ms/step -
accuracy: 0.4557 - loss: 1.5865 - val_accuracy: 0.1114 - val_loss: 2.7542
Epoch 2/2
407/407             108s 265ms/step -
```

```
accuracy: 0.5298 - loss: 1.2947 - val_accuracy: 0.5534 - val_loss: 1.1489
102/102            7s 67ms/step
  1/102            10s 100ms/step - accuracy:
0.4688 - loss: 1.3109
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102            7s 68ms/step -
accuracy: 0.5392 - loss: 1.1719
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407            109s 260ms/step -
accuracy: 0.3907 - loss: 1.6506 - val_accuracy: 0.5516 - val_loss: 2.9060
Epoch 2/2
407/407            113s 278ms/step -
accuracy: 0.5088 - loss: 1.3278 - val_accuracy: 0.5522 - val_loss: 1.2241
102/102            7s 67ms/step
  1/102            8s 80ms/step - accuracy:
0.4375 - loss: 1.4553
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102            6s 62ms/step -
accuracy: 0.5380 - loss: 1.2506
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407            126s 302ms/step -
accuracy: 0.3449 - loss: 1.7518 - val_accuracy: 0.1579 - val_loss: 2.1497
Epoch 2/2
407/407            122s 300ms/step -
```

```
accuracy: 0.5167 - loss: 1.3053 - val_accuracy: 0.5759 - val_loss: 1.1040
102/102             8s 78ms/step
  1/102             9s 96ms/step - accuracy:
0.4688 - loss: 1.2649

c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))

102/102             7s 72ms/step -
accuracy: 0.5623 - loss: 1.1338

c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(

Epoch 1/2
407/407             116s 274ms/step -
accuracy: 0.4060 - loss: 1.7070 - val_accuracy: 0.5245 - val_loss: 1.9195
Epoch 2/2
407/407             116s 284ms/step -
accuracy: 0.5256 - loss: 1.3565 - val_accuracy: 0.5512 - val_loss: 1.2322
102/102             10s 95ms/step

c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))

102/102             9s 88ms/step -
accuracy: 0.5365 - loss: 1.2608

c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(

Epoch 1/2
407/407             117s 279ms/step -
accuracy: 0.4068 - loss: 1.6718 - val_accuracy: 0.5235 - val_loss: 1.3474
Epoch 2/2
407/407             126s 310ms/step -
accuracy: 0.5314 - loss: 1.3025 - val_accuracy: 0.5559 - val_loss: 1.1780
102/102             9s 81ms/step
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             8s 79ms/step -
accuracy: 0.5401 - loss: 1.2021
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             118s 282ms/step -
accuracy: 0.3856 - loss: 1.7231 - val_accuracy: 0.2204 - val_loss: 1.6831
Epoch 2/2
407/407             113s 277ms/step -
accuracy: 0.5129 - loss: 1.3862 - val_accuracy: 0.5503 - val_loss: 1.2276
102/102             9s 89ms/step
  1/102             10s 106ms/step - accuracy:
0.4375 - loss: 1.5400
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             8s 75ms/step -
accuracy: 0.5352 - loss: 1.2592
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             110s 261ms/step -
accuracy: 0.2820 - loss: 1.8707 - val_accuracy: 0.5328 - val_loss: 1.4517
Epoch 2/2
407/407             109s 268ms/step -
accuracy: 0.4757 - loss: 1.4115 - val_accuracy: 0.5719 - val_loss: 1.2041
102/102             8s 80ms/step
  1/102             10s 100ms/step - accuracy:
0.4375 - loss: 1.4047
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102            7s 71ms/step -
accuracy: 0.5557 - loss: 1.2257
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407            119s 286ms/step -
accuracy: 0.4173 - loss: 1.7049 - val_accuracy: 0.5519 - val_loss: 3.8803
Epoch 2/2
407/407            112s 274ms/step -
accuracy: 0.5331 - loss: 1.3369 - val_accuracy: 0.5737 - val_loss: 1.1985
102/102            6s 61ms/step
  1/102            9s 95ms/step - accuracy:
0.4688 - loss: 1.4071
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102            6s 60ms/step -
accuracy: 0.5603 - loss: 1.2176
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407            107s 256ms/step -
accuracy: 0.4366 - loss: 1.5636 - val_accuracy: 0.5679 - val_loss: 1.2214
Epoch 2/2
407/407            118s 290ms/step -
accuracy: 0.5368 - loss: 1.2881 - val_accuracy: 0.5845 - val_loss: 1.1440
102/102            9s 84ms/step
  1/102            11s 112ms/step - accuracy:
0.5000 - loss: 1.2593
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             9s 86ms/step -
accuracy: 0.5734 - loss: 1.1597
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             118s 280ms/step -
accuracy: 0.3084 - loss: 1.7882 - val_accuracy: 0.1496 - val_loss: 3.4570
Epoch 2/2
407/407             114s 281ms/step -
accuracy: 0.4927 - loss: 1.3531 - val_accuracy: 0.5771 - val_loss: 1.1233
102/102             8s 75ms/step
  1/102             10s 100ms/step - accuracy:
0.5000 - loss: 1.1762
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             8s 77ms/step -
accuracy: 0.5609 - loss: 1.1362
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

```
Epoch 1/2
407/407             113s 268ms/step -
accuracy: 0.4147 - loss: 1.6115 - val_accuracy: 0.5512 - val_loss: 3.2603
Epoch 2/2
407/407             114s 280ms/step -
accuracy: 0.5360 - loss: 1.2689 - val_accuracy: 0.5722 - val_loss: 1.1044
102/102             7s 69ms/step
  1/102             10s 105ms/step - accuracy:
0.4688 - loss: 1.1961
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
102/102             7s 69ms/step -
accuracy: 0.5612 - loss: 1.1274
```

[45]:

```
result_df = pd.DataFrame({'Lead Names': LEAD_NAMES, 'Accuracy': accuracy_list,␣
 ↪'Loss': loss_list, 'Precision': precision_list, 'Recall': recall_list,␣
 ↪'f1_score': f1score_list})
result_df
```

[45]:

```
   Lead Names  Accuracy      Loss  Precision    Recall  f1_score
0           I  0.551247  1.195680   0.303966  0.551247  0.391857
1          II  0.553401  1.148934   0.621890  0.553401  0.397701
2         III  0.552170  1.224057   0.409014  0.552170  0.394230
3         aVR  0.575869  1.104027   0.562215  0.575869  0.446633
4         aVL  0.551247  1.232233   0.303873  0.551247  0.391779
5         aVF  0.555863  1.177992   0.427647  0.555863  0.412932
6          V1  0.550323  1.227649   0.303831  0.550323  0.391511
7          V2  0.571868  1.204092   0.429075  0.571868  0.435839
8          V3  0.573715  1.198460   0.472331  0.573715  0.444801
9          V4  0.584488  1.144003   0.455242  0.584488  0.463417
10         V5  0.577101  1.123338   0.447050  0.577101  0.457404
11         V6  0.572176  1.104450   0.532613  0.572176  0.443422
```

Using RandomForest Classifier for the same task

[46]:

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(x_train_single_lead.reshape(x_train_single_lead.shape[0],␣
 ↪x_train_single_lead.shape[1]), y_train_multiclass)
```

[46]:

```
RandomForestClassifier(random_state=42)
```

[47]:

```
Y_pred = rf.predict(x_test_single_lead.reshape(x_test_single_lead.shape[0],␣
 ↪x_test_single_lead.shape[1]))
```

[48]:

```
from sklearn.metrics import f1_score
```

[49]:

```
accuracy = accuracy_score(y_test_multiclass, Y_pred)
precision = precision_score(y_test_multiclass, Y_pred, average='weighted')
recall = recall_score(y_test_multiclass, Y_pred, average='weighted')
print("Random Forest Accuracy for single lead testing: ", accuracy)
print("Random Forest Precision for single lead testing: ", precision)
print("Random Forest Recall for single lead testing: ", recall)
```

```
Random Forest Accuracy for single lead testing:  0.4115112342259157
Random Forest Precision for single lead testing:  0.343437381406624
Random Forest Recall for single lead testing:  0.4115112342259157
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

random_forest_for_all_leads() : function to train the model for all the 12 leads individually and output a table of validation/testing accuracy values obtained from each lead. The function performs the exact same operation as the above three cells for one lead - five class classification, but iterates through all the 12 leads.

[50]:
```
# write a function to perfom random forest classification for all the leads and␣
 ↪return the accuracy
def random_forest_classification_all_leads(x_train, y_train, x_test, y_test):
    accuracy_list = []
    precision_score_list = []
    recall_score_list = []
    f1score_list = []
    for i in range(x_train.shape[1]):
        rf = RandomForestClassifier(n_estimators=100, random_state=42)
        rf.fit(x_train[:, i, :], y_train)
        Y_pred = rf.predict(x_test[:, i, :])
        accuracy = accuracy_score(y_test, Y_pred)
        accuracy_list.append(accuracy)

        precision = precision_score(y_test, Y_pred, average='weighted')
        precision_score_list.append(precision)

        recall = recall_score(y_test, Y_pred, average='weighted')
        recall_score_list.append(recall)

        f1score = f1_score(y_test, Y_pred, average='weighted')
        f1score_list.append(f1score)
    return accuracy_list, precision_score_list, recall_score_list, f1score_list
```

[51]:
```
accuracy_list_rf, precision_list_rf, recall_list_rf, f1score_list_rf =␣
 ↪random_forest_classification_all_leads(x_train_multiclass,␣
 ↪y_train_multiclass, x_test_multiclass, y_test_multiclass)
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

```
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samples. Use `zero_division` parameter to control this behavior.
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samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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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))
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packages\sklearn\metrics\_classification.py:1509: 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))
```

[52]:

```
output_df_rf = pd.DataFrame({'Lead Names': LEAD_NAMES, 'Accuracy':␣
  ↪accuracy_list_rf, 'Precision': precision_list_rf, 'Recall': recall_list_rf,␣
  ↪'f1_score': f1score_list_rf})

# display the dataframe with the specified title
print("Accuracy and performance of single lead under Random Forest␣
  ↪Classification")
output_df_rf
```

```
Accuracy and performance of single lead under Random Forest Classification
```

[52]:

```
   Lead Names  Accuracy  Precision    Recall  f1_score
0           I  0.411511   0.343437  0.411511  0.374405
1          II  0.446907   0.356054  0.446907  0.396341
2         III  0.393660   0.362491  0.393660  0.377433
3         aVR  0.439212   0.352274  0.439212  0.390969
4         aVL  0.385349   0.354110  0.385349  0.369070
5         aVF  0.420129   0.354763  0.420129  0.384689
6          V1  0.413666   0.455951  0.413666  0.387435
7          V2  0.411511   0.447326  0.411511  0.375585
8          V3  0.436750   0.470804  0.436750  0.399017
9          V4  0.445060   0.526121  0.445060  0.404238
10         V5  0.453370   0.368415  0.453370  0.406501
11         V6  0.449369   0.357857  0.449369  0.398426
```

0.2 Subproblem - 2 : Using leads (2, 4, 6, 12)

Using the leads 2, 4, 6 and 12 together for five class classification to compare if the model performs better with more than one lead for classification.

[53]:

```
x_train_4lead = x_train_multiclass[:, [1, 3, 5, 11], :]
x_train_4lead = x_train_4lead.reshape(x_train_4lead.shape[0], 4, x_train_4lead.
  ↪shape[2])
x_valid_4lead = x_valid_multiclass[:, [1, 3, 5, 11], :]
x_valid_4lead = x_valid_4lead.reshape(x_valid_4lead.shape[0], 4, x_valid_4lead.
  ↪shape[2])
x_test_4lead = x_test_multiclass[:, [1, 3, 5, 11], :]
x_test_4lead = x_test_4lead.reshape(x_test_4lead.shape[0], 4, x_test_4lead.
  ↪shape[2])
```

Using CNN for (2, 4, 6, 12) leads

[54]:

```
model_cnn_4_lead = build_model_cnn_multiclass((x_train_4lead.shape[1],␣
  ↪x_train_4lead.shape[2]))
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

[55]:

```
history = model_cnn_4_lead.fit(x_train_4lead, y_train_multiclass,␣
  ↪validation_data=(x_valid_4lead, y_valid_multiclass), epochs=20,␣
  ↪batch_size=20, callbacks=[EarlyStopping(patience=5)])
```

```
Epoch 1/20
650/650              26s 33ms/step -
accuracy: 0.3497 - loss: 1.7092 - val_accuracy: 0.5494 - val_loss: 1.3125
Epoch 2/20
650/650              22s 34ms/step -
accuracy: 0.4936 - loss: 1.3915 - val_accuracy: 0.5509 - val_loss: 1.2920
Epoch 3/20
650/650              24s 37ms/step -
accuracy: 0.5296 - loss: 1.2863 - val_accuracy: 0.5519 - val_loss: 1.2843
Epoch 4/20
650/650              25s 39ms/step -
accuracy: 0.5434 - loss: 1.2222 - val_accuracy: 0.5531 - val_loss: 1.2688
Epoch 5/20
650/650              34s 52ms/step -
accuracy: 0.5710 - loss: 1.1394 - val_accuracy: 0.5494 - val_loss: 1.2594
Epoch 6/20
650/650              30s 46ms/step -
accuracy: 0.5971 - loss: 1.0365 - val_accuracy: 0.5436 - val_loss: 1.3012
Epoch 7/20
650/650              18s 27ms/step -
accuracy: 0.6297 - loss: 0.9303 - val_accuracy: 0.5254 - val_loss: 1.3677
Epoch 8/20
650/650              18s 28ms/step -
accuracy: 0.6864 - loss: 0.8217 - val_accuracy: 0.5300 - val_loss: 1.4492
Epoch 9/20
650/650              19s 29ms/step -
accuracy: 0.7203 - loss: 0.7172 - val_accuracy: 0.5159 - val_loss: 1.5346
Epoch 10/20
650/650              21s 32ms/step -
accuracy: 0.7449 - loss: 0.6477 - val_accuracy: 0.5155 - val_loss: 1.7184
```

[56]:

```
y_pred = model_cnn_4_lead.predict(x_test_4lead)
y_pred = np.argmax(y_pred, axis=1)
y_true = np.argmax(y_test_multiclass, axis=1)

accuracy = accuracy_score(y_true, y_pred)
precision = precision_score(y_true, y_pred, average='weighted')
recall = recall_score(y_true, y_pred, average='weighted')
f1_score = f1_score(y_true,y_pred,average='weighted')
print(f'Accuracy: {accuracy}')
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'f1_score: {f1_score}')
```

```
102/102              2s 14ms/step
Accuracy: 0.5155432440751
Precision: 0.4586109738570126
Recall: 0.5155432440751
f1_score: 0.48164582859773347
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\sklearn\metrics\_classification.py:1509: 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))
```

[ ]:

```
# plot the history of the model
plt.figure(figsize=(20, 10))
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.legend()
plt.show()
```

Using Random Forest Classification for (2, 4, 6, 12) leads

[58]:

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(x_train_4lead.reshape(x_train_4lead.shape[0], x_train_4lead.shape[1] *␣
  ↪x_train_4lead.shape[2]), y_train_binary)
```

[58]:

```
RandomForestClassifier(random_state=42)
```

[59]:

```
Y_pred = rf.predict(x_test_4lead.reshape(x_test_4lead.shape[0], x_test_4lead.
  ↪shape[1] * x_test_4lead.shape[2]))
```

[60]:

```
from sklearn.metrics import f1_score
```

[61]:

```
accuracy = accuracy_score(y_test_binary, Y_pred)
precision = precision_score(y_test_binary, Y_pred, average='weighted')
recall = recall_score(y_test_binary, Y_pred, average='weighted')
```

```
f1score = f1_score(y_test_binary, y_pred, average='weighted')
print("Random Forest Accuracy for single lead testing: ", accuracy)
print("Random Forest Precision for single lead testing: ", precision)
print("Random Forest Recall for single lead testing: ", recall)
print("Random Forest f1_score for single lead testing: ", f1score)
```

```
Random Forest Accuracy for single lead testing:  0.6620498614958449
Random Forest Precision for single lead testing:  0.6919893753655412
Random Forest Recall for single lead testing:  0.6620498614958449
Random Forest f1_score for single lead testing:  0.05065803159865547
```

0.3 All 12 leads

[62]:

```
def build_model_cnn_binary(input_shape):
    model = Sequential()
    model.add(Conv1D(filters=128, kernel_size=6, activation='relu',
                    padding='same', input_shape=input_shape))
    model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

    model.add(Conv1D(filters=64, kernel_size=6, activation='relu',
                    padding='same'))
    model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

    model.add(Conv1D(filters=32, kernel_size=6, activation='relu',
                    padding='same'))
    model.add(MaxPooling1D(pool_size=(3), strides=2, padding='same'))

    model.add(Flatten())
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(32, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(1, activation='softmax'))

    model.compile(loss='binary_crossentropy', optimizer=Adam(learning_rate=0.
 ↪00001), metrics=['accuracy'])

    return model;
```

[63]:

```
model_cnn_12_leads = build_model_cnn_binary((x_train_binary.shape[1],␣
 ↪x_train_binary.shape[2]))
```

```
c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\layers\convolutional\base_conv.py:99: 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__(
```

[64]:

```
model_cnn_12_leads.fit(x_train_binary, y_train_binary,␣
 ↪validation_data=(x_valid_binary, y_valid_binary), epochs=20, batch_size=12)
```

```
Epoch 1/20

c:\Users\goura\Downloads\ptbxl_main\ptbxl\venv\Lib\site-
packages\keras\src\ops\nn.py:545: UserWarning: You are using a softmax over axis
-1 of a tensor of shape (None, 1). This axis has size 1. The softmax operation
will always return the value 1, which is likely not what you intended. Did you
mean to use a sigmoid instead?
  warnings.warn(

1083/1083            29s 21ms/step -
accuracy: 0.4425 - loss: 0.7055 - val_accuracy: 0.4488 - val_loss: 0.6915
Epoch 2/20
1083/1083            23s 21ms/step -
accuracy: 0.4393 - loss: 0.6933 - val_accuracy: 0.4488 - val_loss: 0.6909
Epoch 3/20
1083/1083            27s 25ms/step -
accuracy: 0.4419 - loss: 0.6919 - val_accuracy: 0.4488 - val_loss: 0.6906
Epoch 4/20
1083/1083            31s 29ms/step -
accuracy: 0.4340 - loss: 0.6863 - val_accuracy: 0.4488 - val_loss: 0.6903
Epoch 5/20
1083/1083            31s 29ms/step -
accuracy: 0.4419 - loss: 0.6847 - val_accuracy: 0.4488 - val_loss: 0.6897
Epoch 6/20
1083/1083            20s 18ms/step -
accuracy: 0.4450 - loss: 0.6837 - val_accuracy: 0.4488 - val_loss: 0.6888
Epoch 7/20
1083/1083            21s 20ms/step -
accuracy: 0.4447 - loss: 0.6798 - val_accuracy: 0.4488 - val_loss: 0.6882
Epoch 8/20
1083/1083            24s 22ms/step -
accuracy: 0.4430 - loss: 0.6729 - val_accuracy: 0.4488 - val_loss: 0.6873
Epoch 9/20
1083/1083            28s 26ms/step -
accuracy: 0.4368 - loss: 0.6685 - val_accuracy: 0.4488 - val_loss: 0.6858
Epoch 10/20
1083/1083            30s 28ms/step -
accuracy: 0.4399 - loss: 0.6603 - val_accuracy: 0.4488 - val_loss: 0.6841
Epoch 11/20
1083/1083            28s 26ms/step -
accuracy: 0.4385 - loss: 0.6503 - val_accuracy: 0.4488 - val_loss: 0.6817
Epoch 12/20
1083/1083            20s 19ms/step -
accuracy: 0.4348 - loss: 0.6376 - val_accuracy: 0.4488 - val_loss: 0.6794
Epoch 13/20
```

```
1083/1083              21s 20ms/step -
accuracy: 0.4397 - loss: 0.6190 - val_accuracy: 0.4488 - val_loss: 0.6745
Epoch 14/20
1083/1083              24s 22ms/step -
accuracy: 0.4468 - loss: 0.5920 - val_accuracy: 0.4488 - val_loss: 0.6718
Epoch 15/20
1083/1083              25s 23ms/step -
accuracy: 0.4429 - loss: 0.5622 - val_accuracy: 0.4488 - val_loss: 0.6717
Epoch 16/20
1083/1083              44s 40ms/step -
accuracy: 0.4382 - loss: 0.5271 - val_accuracy: 0.4488 - val_loss: 0.6675
Epoch 17/20
1083/1083              21s 19ms/step -
accuracy: 0.4443 - loss: 0.4848 - val_accuracy: 0.4488 - val_loss: 0.6702
Epoch 18/20
1083/1083              21s 20ms/step -
accuracy: 0.4358 - loss: 0.4241 - val_accuracy: 0.4488 - val_loss: 0.6903
Epoch 19/20
1083/1083              24s 22ms/step -
accuracy: 0.4382 - loss: 0.3751 - val_accuracy: 0.4488 - val_loss: 0.7099
Epoch 20/20
1083/1083              28s 26ms/step -
accuracy: 0.4286 - loss: 0.3134 - val_accuracy: 0.4488 - val_loss: 0.7734
```

[64]:

```
<keras.src.callbacks.history.History at 0x1e565d75a50>
```

[71]:

```python
loss, accuracy = model_cnn_12_leads.evaluate(x_test_binary, y_test_binary)
print(f'Loss: {loss}, Accuracy: {accuracy}')
```

```
102/102              1s 9ms/step -
accuracy: 0.4635 - loss: 0.7858
Loss: 0.773271918296814, Accuracy: 0.4487534761428833
```

Using Random Forest for binary classification using all 12 leads

[66]:

```python
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(x_train_binary.reshape(x_train_binary.shape[0], x_train_binary.shape[1]␣
  ↪* x_train_binary.shape[2]), y_train_binary)
```

[66]:

```
RandomForestClassifier(random_state=42)
```

[67]:

```python
Y_pred = rf.predict(x_test_binary.reshape(x_test_binary.shape[0], x_test_binary.
  ↪shape[1] * x_test_binary.shape[2]))
```

[68]:

```python
accuracy = accuracy_score(y_test_binary, Y_pred)
print("Random Forest Accuracy for all leads (Binary Classification): ",␣
  ↪accuracy)
```

```
Random Forest Accuracy for all leads (Binary Classification):  0.688211757463835
```