ecg_rhythm_classification

December 12, 2024

1 ECG Rhythm Classification

The goal of this exercise is to train a neural network model to classify different cardiac rhythm from single-lead ECG signals. The ECG signals we will use are a subset of the large scale 12-lead electrocardiogram database for arrhythmia study (https://physionet.org/content/ecg-arrhythmia/1.0.0/).

The subset includes the following cardiac rhythms:

- Atrial fibrillation
- Atrial flutter
- Normal sinus rhythm
- Sinus bradycardia
- Sinus tachycardia

There are 1500 single-lead ECG signals (lead II) for each rhythm.

First, we import all required packages, define global constants, and seed the random number generators to obtain reproducible results.

[1]:
```
%matplotlib widget



import collections
import itertools
import logging
import operator
import pathlib
import warnings

import IPython.display
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pytorch_lightning as pl
import sklearn.metrics
import sklearn.model_selection
import sklearn.preprocessing
import torch
```

```
DATA_FILE = pathlib.Path('../data/ecg_rhythms.npz')
LOG_DIRECTORY = pathlib.Path('../logs/ecg_rhythm_classification')


# Disable logging for PyTorch Lightning to avoid too long outputs.
logging.getLogger('pytorch_lightning').setLevel(logging.ERROR)

# Seed random number generators for reproducible results.
pl.seed_everything(42)
```

```
Seed set to 42
```

[1]: 42

Then, we load the ECG signals and the corresponding rhythm annotations.

[2]:
```
def load_data():
    with np.load(DATA_FILE) as data:
        signals = data['signals']
        rhythms = data['rhythms']
        fs = data['fs'].item()
    return signals, rhythms, fs


signals, rhythms, fs = load_data()

IPython.display.display(pd.DataFrame(sorted(collections.Counter(rhythms).
 ↪items()), columns=['rhythm', 'count']))
```

	rhythm	count
0	atrial_fibrillation	1500
1	atrial_flutter	1500
2	normal_sinus_rhythm	1500
3	sinus_bradycardia	1500
4	sinus_tachycardia	1500

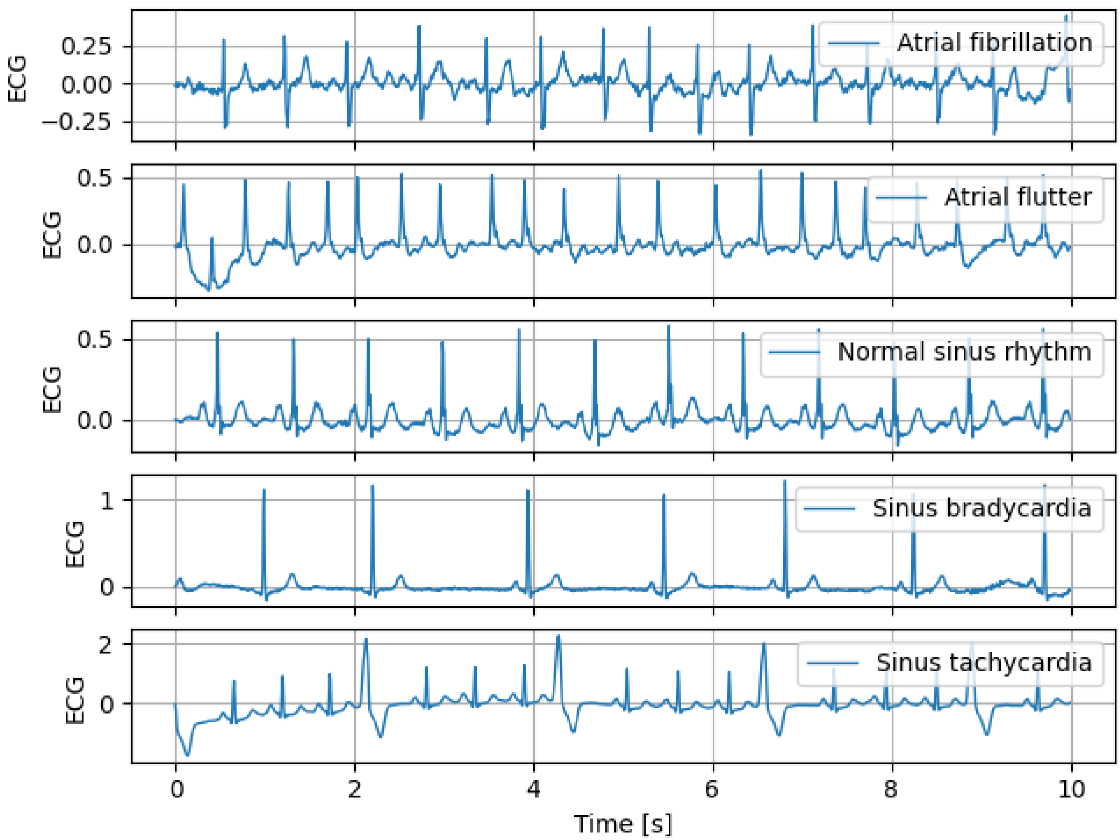
Here are a few examples of ECG signals.

[3]:
```
def plot_ecg_examples(signals, rhythms, fs):
    time = np.arange(signals.shape[-1]) / fs
    labels = np.unique(rhythms)
    indices = [np.random.choice(np.flatnonzero(rhythms == label)) for label in␣
 ↪labels]

    fig, axes = plt.subplots(len(labels), 1, sharex='all',␣
 ↪constrained_layout=True)
    for ax, index in zip(axes.flat, indices):
        label = rhythms[index].replace('_', ' ').capitalize()
        plt.sca(ax)
```

```
        plt.plot(time, signals[index].T, linewidth=1, label=label)
        plt.grid()
        plt.ylabel('ECG')
        plt.legend(loc='upper right')
    plt.xlabel('Time [s]')


plot_ecg_examples(signals, rhythms, fs)
```



Question 1

Visually, what are the differences between the different rhythms?

Answer

Atrial fibrillation, as it has been shown many times in the other lab sessions, shows a lot of irregularities in its PR-intervals and a shift of R and S points : instead of being respectively around 0.5 and -0.1, their values are around 0.25 and -0.25. There is also an increase in heartbeat frequency.

The *atrial flutter* signal shows a huge increase in heartbeat frequency (much bigger than the one in atrial fibrillation, nearly twice the one of the normal signal).

Sinus bradycardia is the opposite and shows a decrease in frequency. There is also an increase in amplitude of the R-peaks.

Sinus tachycardia has a signal frequency slightly lower than the *atrial flutter* one, with one every four PQRST complexes showing really extreme behaviours (extreme amplitudes of R and S points).

Then, we split that data into subsets for training, validation, and testing stratified by rhythms.

[4]:
```
def split_data(rhythms):
    n = rhythms.size
    splitter = sklearn.model_selection.StratifiedKFold(n_splits=5)
    indices = list(map(operator.itemgetter(1), splitter.split(np.zeros((n, 1)),␣
 ↪rhythms)))
    i_train = np.hstack(indices[:-2])
    i_val = indices[-2]
    i_test = indices[-1]

    assert np.intersect1d(i_train, i_val).size == 0
    assert np.intersect1d(i_train, i_test).size == 0
    assert np.intersect1d(i_val, i_test).size == 0
    assert np.all(np.sort(np.hstack((i_train, i_val, i_test))) == np.arange(n))

    return i_train, i_val, i_test


i_train, i_val, i_test = split_data(rhythms)


def build_summary(rhythms, indices):
    labels = np.unique(rhythms)
    data = []
    for subset, i in indices:
        y = rhythms[i]
        data.append({'subset': subset, 'total_count': y.size})
        for label in labels:
            data[-1][f'{label}_count'] = np.sum(y == label)
    return pd.DataFrame(data)


IPython.display.display(build_summary(rhythms, (('train', i_train), ('val',␣
 ↪i_val), ('test', i_test))))
```

```
  subset  total_count  atrial_fibrillation_count  atrial_flutter_count  \
0  train         4500                        900                   900
1    val         1500                        300                   300
2   test         1500                        300                   300

   normal_sinus_rhythm_count  sinus_bradycardia_count  sinus_tachycardia_count
0                        900                      900                      900
1                        300                      300                      300
```

2	300	300	300

The final preprocessing steps are to scale the ECG signals so that they have approximiately unit variance and to encode the rhythm labels with one-hot encoding.

[5]:
```python
def compute_scaling(signals):
    sigma = np.std(signals)
    return 1.0 / sigma


alpha = compute_scaling(signals[i_train])
signals *= alpha


def encode_rhythms(rhythms):
    categories = [np.unique(rhythms)]
    encoder = sklearn.preprocessing.OneHotEncoder(categories=categories,␣
 ↪sparse_output=False)
    return encoder.fit_transform(rhythms[:, None])


encoded_rhythms = encode_rhythms(rhythms)


def print_encoded_rhythms(rhythms, encoded_rhythms, n=10):
    df = pd.DataFrame(encoded_rhythms, columns=np.unique(rhythms))
    df.insert(0, 'rhythm', rhythms)
    IPython.display.display(df.head(n))


print_encoded_rhythms(rhythms, encoded_rhythms)
```

```
                rhythm  atrial_fibrillation  atrial_flutter  \
0  atrial_fibrillation                  1.0             0.0
1    sinus_bradycardia                  0.0             0.0
2    sinus_bradycardia                  0.0             0.0
3       atrial_flutter                  0.0             1.0
4    sinus_bradycardia                  0.0             0.0
5  atrial_fibrillation                  1.0             0.0
6  normal_sinus_rhythm                  0.0             0.0
7    sinus_bradycardia                  0.0             0.0
8    sinus_bradycardia                  0.0             0.0
9    sinus_bradycardia                  0.0             0.0

   normal_sinus_rhythm  sinus_bradycardia  sinus_tachycardia
0                  0.0                0.0                0.0
1                  0.0                1.0                0.0
2                  0.0                1.0                0.0
```

3	0.0	0.0	0.0
4	0.0	1.0	0.0
5	0.0	0.0	0.0
6	1.0	0.0	0.0
7	0.0	1.0	0.0
8	0.0	1.0	0.0
9	0.0	1.0	0.0

We define a class and few utility functions for training and evaluating models.

[6]:
```
class Classifier(pl.LightningModule):

    def __init__(self, model, learning_rate=0.001):
        super().__init__()
        self.save_hyperparameters(ignore=['model'])
        self.model = model
        self.learning_rate = learning_rate
        self.example_input_array = torch.zeros((1,) + self.model.input_shape)

    def configure_optimizers(self):
        return torch.optim.Adam(self.parameters(), lr=self.learning_rate)

    def forward(self, x):
        return self.model(x)

    def training_step(self, batch, batch_idx):
        return self._run_step(batch, 'train')

    def validation_step(self, batch, batch_idx):
        self._run_step(batch, 'val')

    def test_step(self, batch, batch_idx):
        self._run_step(batch, 'test')

    def predict_step(self, batch, batch_idx, dataloader_idx=0):
        x, y = batch
        return self.model(x)

    def _run_step(self, batch, subset):
        x, y = batch
        logits = self.model(x)
        loss = torch.nn.functional.cross_entropy(logits, y)
        acc = (torch.argmax(y, 1) == torch.argmax(logits, 1)).float().mean()
        self.log_dict({
            f'{subset}_loss': loss,
            f'{subset}_acc': acc,
        }, on_step=False, on_epoch=True, prog_bar=True)
        return loss
```

```python
def build_loader(*tensors, batch_size=100, shuffle=False, n_workers=0):
    dataset = torch.utils.data.TensorDataset(*map(torch.Tensor, tensors))
    return torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=batch_size,
        shuffle=shuffle,
        num_workers=n_workers,
    )


def train_model(name, model, x, y, i_train, i_val, learning_rate=0.001, batch_size=100, n_epochs=10):
    train_loader = build_loader(x[i_train], y[i_train], batch_size=batch_size, shuffle=True)
    val_loader = build_loader(x[i_val], y[i_val], batch_size=batch_size)
    classifier = Classifier(model, learning_rate)
    print(pl.utilities.model_summary.ModelSummary(classifier, max_depth=-1))

    with warnings.catch_warnings():
        warnings.simplefilter('ignore')
        trainer = pl.Trainer(
            default_root_dir=LOG_DIRECTORY,
            logger=pl.loggers.TensorBoardLogger(LOG_DIRECTORY, name),
            enable_model_summary=False,
            max_epochs=n_epochs,
        )
        trainer.fit(classifier, train_loader, val_loader)

    return classifier


def evaluate_model(model, x, y, i_train, i_val, i_test, batch_size=100):
    loader = build_loader(x, y, batch_size=batch_size)

    with warnings.catch_warnings():
        warnings.simplefilter('ignore')
        trainer = pl.Trainer(
            default_root_dir=LOG_DIRECTORY,
            logger=False,
            enable_progress_bar=False,
            enable_model_summary=False,
        )
        z = trainer.predict(model, loader)
    z = np.vstack([u.numpy() for u in z])
```

```
    references = np.argmax(y, axis=1)
    predictions = np.argmax(z, axis=1)
    matrices = {}
    for subset, indices in (('train', i_train), ('val', i_val), ('test',␣
↪i_test)):
        matrices[subset] = sklearn.metrics.confusion_matrix(
            references[indices],
            predictions[indices],
        )

    return matrices
```

We start TensorBoard to visualize performance metrics during training.

If you prefer to view TensorBoard in a separate window, you can open http://localhost:6006/ in your web browser.

[7]:
```
%reload_ext tensorboard
%tensorboard --logdir ../logs/ecg_rhythm_classification --port 6006
```

```
<IPython.core.display.HTML object>
```

We define a convolutional neural network.

[8]:
```
class CnnModel(torch.nn.Module):

    def __init__(self, input_shape, output_shape, kernel_size=5):
        super().__init__()
        self.input_shape = input_shape
        self.output_shape = output_shape
        self.layers = torch.nn.Sequential(
            torch.nn.Conv1d(self.input_shape[0], 8, kernel_size,␣
↪padding='same'),
            torch.nn.BatchNorm1d(8),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(8, 16, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(16),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(16, 32, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(32),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(32, 64, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(64),
```

```
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),

            torch.nn.Flatten(),
            torch.nn.Linear(64, self.output_shape[0]),
        )

    def forward(self, x):
        return self.layers(x)
```

Then, we train and evaluate this model.

[9]:
```
input_shape = signals.shape[1:]
output_shape = encoded_rhythms.shape[1:]
n_epochs = 50
batch_size = 100

cnn = train_model(
    name='cnn',
    model=CnnModel(input_shape, output_shape),
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    learning_rate=0.0001,
    batch_size=batch_size,
    n_epochs=n_epochs,
)

cnn_matrices = evaluate_model(
    model=cnn,
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    i_test=i_test,
    batch_size=batch_size,
)
```

```
   | Name             | Type                | Params | Mode  | In sizes      | Out
sizes
--------------------------------------------------------------------------------
-------------
0  | model            | CnnModel            | 14.2 K | train | [1, 1, 1280] | [1,
5]
1  | model.layers     | Sequential          | 14.2 K | train | [1, 1, 1280] | [1,
5]
2  | model.layers.0   | Conv1d              | 48     | train | [1, 1, 1280] | [1,
```

```
8, 1280]
3  | model.layers.1  | BatchNorm1d       | 16     | train | [1, 8, 1280] | [1,
8, 1280]
4  | model.layers.2  | ReLU              | 0      | train | [1, 8, 1280] | [1,
8, 1280]
5  | model.layers.3  | MaxPool1d         | 0      | train | [1, 8, 1280] | [1,
8, 640]
6  | model.layers.4  | Conv1d            | 656    | train | [1, 8, 640]  | [1,
16, 640]
7  | model.layers.5  | BatchNorm1d       | 32     | train | [1, 16, 640] | [1,
16, 640]
8  | model.layers.6  | ReLU              | 0      | train | [1, 16, 640] | [1,
16, 640]
9  | model.layers.7  | MaxPool1d         | 0      | train | [1, 16, 640] | [1,
16, 320]
10 | model.layers.8  | Conv1d            | 2.6 K  | train | [1, 16, 320] | [1,
32, 320]
11 | model.layers.9  | BatchNorm1d       | 64     | train | [1, 32, 320] | [1,
32, 320]
12 | model.layers.10 | ReLU              | 0      | train | [1, 32, 320] | [1,
32, 320]
13 | model.layers.11 | MaxPool1d         | 0      | train | [1, 32, 320] | [1,
32, 160]
14 | model.layers.12 | Conv1d            | 10.3 K | train | [1, 32, 160] | [1,
64, 160]
15 | model.layers.13 | BatchNorm1d       | 128    | train | [1, 64, 160] | [1,
64, 160]
16 | model.layers.14 | ReLU              | 0      | train | [1, 64, 160] | [1,
64, 160]
17 | model.layers.15 | AdaptiveAvgPool1d | 0      | train | [1, 64, 160] | [1,
64, 1]
18 | model.layers.16 | Flatten           | 0      | train | [1, 64, 1]   | [1,
64]
19 | model.layers.17 | Linear            | 325    | train | [1, 64]      | [1,
5]
--------------------------------------------------------------------------------
-------------
14.2 K    Trainable params
0         Non-trainable params
14.2 K    Total params
0.057     Total estimated model params size (MB)
20        Modules in train mode
0         Modules in eval mode

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]
```

```
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
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Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
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Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
```
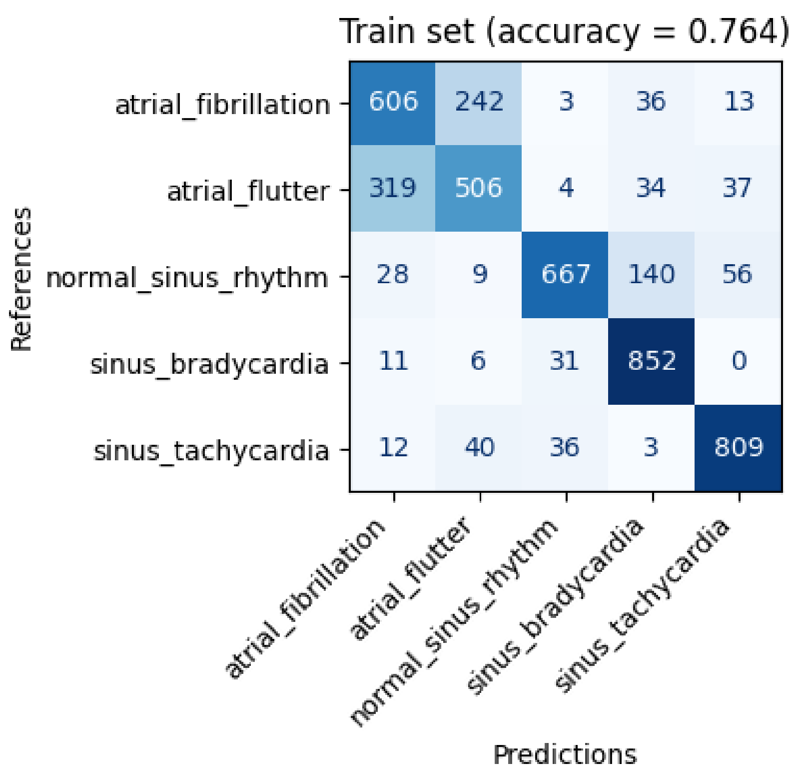
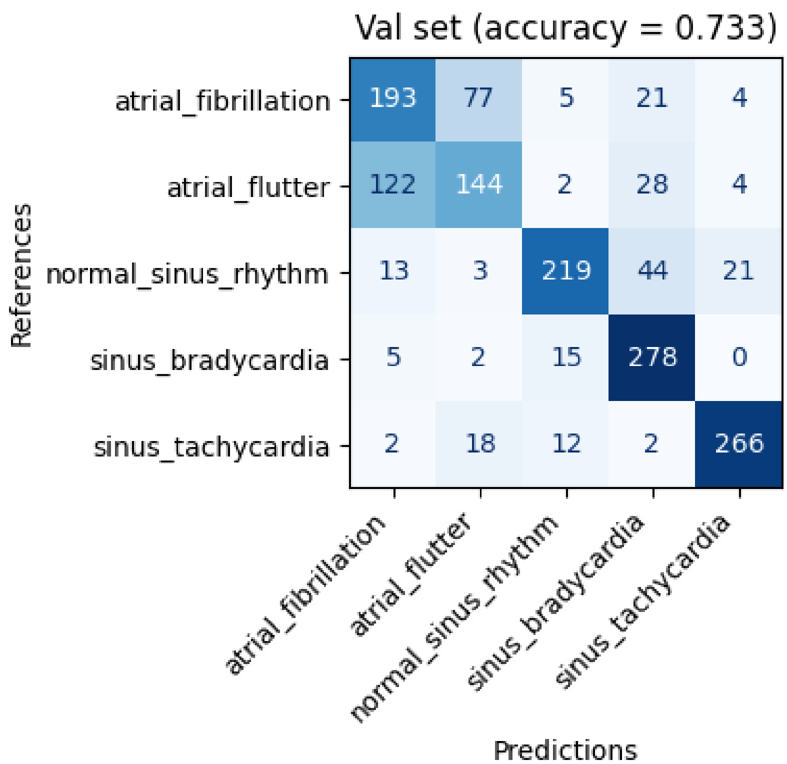

```
Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]
```

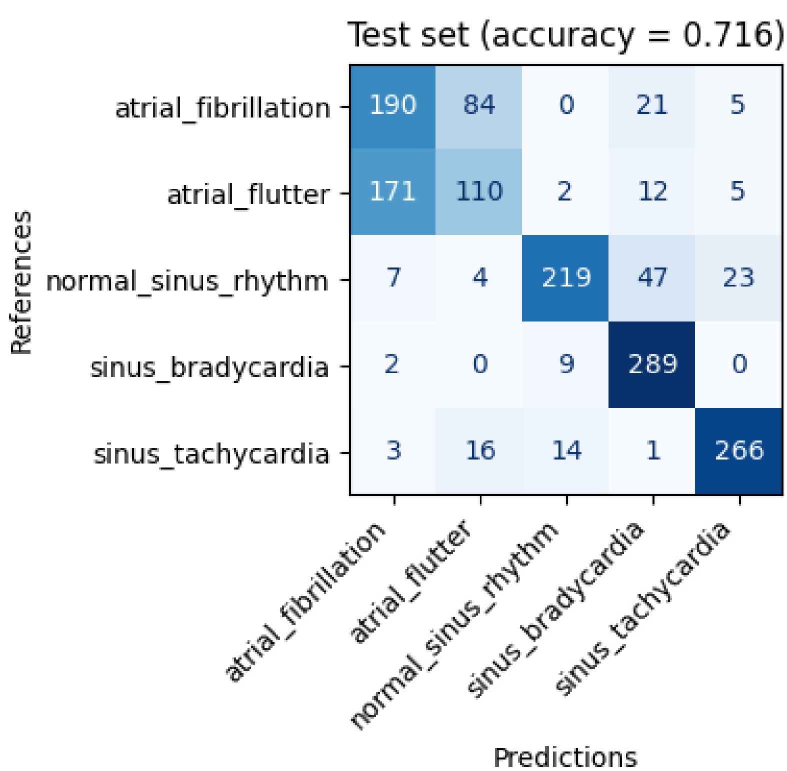
After the evaluation is finished, we can plot the confusion matrices for the training, validatoin, and test sets.

[10]:
```python
def plot_confusion_matrix(c, labels=None, title=None):
    c = np.asarray(c)

    fig = plt.figure(figsize=(5, 4), constrained_layout=True)
    image = plt.imshow(c, cmap='Blues', interpolation='nearest')

    threshold = (c.min() + c.max()) / 2
    for i, j in itertools.product(range(c.shape[0]), repeat=2):
        if c[i, j] < threshold:
            color = image.cmap(image.cmap.N)
        else:
            color = image.cmap(0)
        text = format(c[i, j], '.2g')
        if c.dtype.kind != 'f':
            integer_text = format(c[i, j], 'd')
            if len(integer_text) < len(text):
                text = integer_text
        plt.text(j, i, text, color=color, ha='center', va='center')
```

```
    if labels is not None:
        plt.xticks(np.arange(c.shape[-1]), labels, rotation=45, ha='right')
        plt.yticks(np.arange(c.shape[-1]), labels)
    plt.xlabel('Predictions')
    plt.ylabel('References')
    if title is not None:
        plt.title(title)



def plot_confusion_matrices(matrices, labels):
    for subset in ('train', 'val', 'test'):
        c = matrices[subset]
        accuracy = np.trace(c) / c.sum()
        title = f'{subset.capitalize()} set (accuracy = {accuracy:.3f})'
        plot_confusion_matrix(c, labels=labels, title=title)


plot_confusion_matrices(cnn_matrices, np.unique(rhythms))
```




Val set (accuracy = 0.733)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
193 77 5 21 4
122 144 2 28 4
13 3 219 44 21
5 2 15 278 0
2 18 12 2 266


Test set (accuracy = 0.716)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
190 84 0 21 5
171 110 2 12 5
7 4 219 47 23
2 0 9 289 0
3 16 14 1 266

Question 2

Comment the metrics shown in TensorBoard and the confusion matrices. Does the model overfit? Are there some rhythms that are difficult to classify?

Answer The model does not overfit (0.71 for test set against 0.76 for validation). Furthermore, by inspecting the confusion matrices, we can observe that there is a cluster with atrial fibrillation and atrial flutter. In fact, these two rhythms are difficult to classify and are often confused with one another in the model.

Question 3

Define two custom models to classify cardiac rhythms from ECG signals.

You can directly define the layers of the custom models in the following classes.

[ ]:
```
class CustomModel1(torch.nn.Module):

    def __init__(self, input_shape, output_shape):
        super().__init__()
        self.input_shape = input_shape
        self.output_shape = output_shape

        kernel_size = 5
        # Implement you own model here.
        # define two twins CNNs
        self.cnn1 = torch.nn.Sequential(
            torch.nn.Conv1d(self.input_shape[0], 8, kernel_size,␣
 ↪padding='same'),
            torch.nn.BatchNorm1d(8),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(8, 16, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(16),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(16, 32, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(32),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(32, 64, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(64),
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),
        )
```

```
        self.cnn2 = torch.nn.Sequential(
            torch.nn.Conv1d(self.input_shape[0], 8, kernel_size,␣
 ↪padding='same'),
            torch.nn.BatchNorm1d(8),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(8, 16, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(16),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(16, 32, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(32),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(32, 64, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(64),
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),
        )

        self.classif = torch.nn.Sequential(
            torch.nn.Flatten(),
            torch.nn.Linear(2*64, self.output_shape[0]),
        )

    def forward(self, x):
        tmp = torch.concat([self.cnn1(x), self.cnn2(x)], dim=1)
        return self.classif(tmp)


class CustomModel2(torch.nn.Module):

    def __init__(self, input_shape, output_shape):
        super().__init__()
        self.input_shape = input_shape
        self.output_shape = output_shape

        # Implement you own model here.
        kernel_size = 3
        self.layers = torch.nn.Sequential(
            torch.nn.Conv1d(self.input_shape[0], 8, kernel_size,␣
 ↪padding='same'),
            torch.nn.BatchNorm1d(8),
            torch.nn.ReLU(),
```

```
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(8, 16, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(16),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(16, 32, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(32),
            torch.nn.ReLU(),
            torch.nn.MaxPool1d(2),

            torch.nn.Conv1d(32, 64, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(64),
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),

            torch.nn.Conv1d(64, 32, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(32),
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),

            torch.nn.Conv1d(32, 16, kernel_size, padding='same'),
            torch.nn.BatchNorm1d(16),
            torch.nn.ReLU(),
            torch.nn.AdaptiveAvgPool1d(1),

            torch.nn.Flatten(),
            torch.nn.Linear(16, self.output_shape[0]),
        )

    def forward(self, x):
        return self.layers(x)
```

You can train and evaluate the first custom model.

[15]:
```
custom1 = train_model(
    name='custom1',
    model=CustomModel1(input_shape, output_shape),
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    learning_rate=0.0001,
    batch_size=batch_size,
    n_epochs=n_epochs,
)
```

```python
custom1_matrices = evaluate_model(
    model=custom1,
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    i_test=i_test,
    batch_size=batch_size,
)

plot_confusion_matrices(custom1_matrices, np.unique(rhythms))
```

```
   | Name              | Type               | Params | Mode  | In sizes      | Out
sizes
--------------------------------------------------------------------------------
-------------
0  | model             | CustomModel1       | 28.3 K | train | [1, 1, 1280] | [1,
5]
1  | model.cnn1        | Sequential         | 13.8 K | train | [1, 1, 1280] | [1,
64, 1]
2  | model.cnn1.0      | Conv1d             | 48     | train | [1, 1, 1280] | [1,
8, 1280]
3  | model.cnn1.1      | BatchNorm1d        | 16     | train | [1, 8, 1280] | [1,
8, 1280]
4  | model.cnn1.2      | ReLU               | 0      | train | [1, 8, 1280] | [1,
8, 1280]
5  | model.cnn1.3      | MaxPool1d          | 0      | train | [1, 8, 1280] | [1,
8, 640]
6  | model.cnn1.4      | Conv1d             | 656    | train | [1, 8, 640]  | [1,
16, 640]
7  | model.cnn1.5      | BatchNorm1d        | 32     | train | [1, 16, 640] | [1,
16, 640]
8  | model.cnn1.6      | ReLU               | 0      | train | [1, 16, 640] | [1,
16, 640]
9  | model.cnn1.7      | MaxPool1d          | 0      | train | [1, 16, 640] | [1,
16, 320]
10 | model.cnn1.8      | Conv1d             | 2.6 K  | train | [1, 16, 320] | [1,
32, 320]
11 | model.cnn1.9      | BatchNorm1d        | 64     | train | [1, 32, 320] | [1,
32, 320]
12 | model.cnn1.10     | ReLU               | 0      | train | [1, 32, 320] | [1,
32, 320]
13 | model.cnn1.11     | MaxPool1d          | 0      | train | [1, 32, 320] | [1,
32, 160]
14 | model.cnn1.12     | Conv1d             | 10.3 K | train | [1, 32, 160] | [1,
64, 160]
15 | model.cnn1.13     | BatchNorm1d        | 128    | train | [1, 64, 160] | [1,
```

```
64, 160]
16 | model.cnn1.14   | ReLU              | 0      | train | [1, 64, 160] | [1,
64, 160]
17 | model.cnn1.15   | AdaptiveAvgPool1d | 0      | train | [1, 64, 160] | [1,
64, 1]
18 | model.cnn2      | Sequential        | 13.8 K | train | [1, 1, 1280] | [1,
64, 1]
19 | model.cnn2.0    | Conv1d            | 48     | train | [1, 1, 1280] | [1,
8, 1280]
20 | model.cnn2.1    | BatchNorm1d       | 16     | train | [1, 8, 1280] | [1,
8, 1280]
21 | model.cnn2.2    | ReLU              | 0      | train | [1, 8, 1280] | [1,
8, 1280]
22 | model.cnn2.3    | MaxPool1d         | 0      | train | [1, 8, 1280] | [1,
8, 640]
23 | model.cnn2.4    | Conv1d            | 656    | train | [1, 8, 640]  | [1,
16, 640]
24 | model.cnn2.5    | BatchNorm1d       | 32     | train | [1, 16, 640] | [1,
16, 640]
25 | model.cnn2.6    | ReLU              | 0      | train | [1, 16, 640] | [1,
16, 640]
26 | model.cnn2.7    | MaxPool1d         | 0      | train | [1, 16, 640] | [1,
16, 320]
27 | model.cnn2.8    | Conv1d            | 2.6 K  | train | [1, 16, 320] | [1,
32, 320]
28 | model.cnn2.9    | BatchNorm1d       | 64     | train | [1, 32, 320] | [1,
32, 320]
29 | model.cnn2.10   | ReLU              | 0      | train | [1, 32, 320] | [1,
32, 320]
30 | model.cnn2.11   | MaxPool1d         | 0      | train | [1, 32, 320] | [1,
32, 160]
31 | model.cnn2.12   | Conv1d            | 10.3 K | train | [1, 32, 160] | [1,
64, 160]
32 | model.cnn2.13   | BatchNorm1d       | 128    | train | [1, 64, 160] | [1,
64, 160]
33 | model.cnn2.14   | ReLU              | 0      | train | [1, 64, 160] | [1,
64, 160]
34 | model.cnn2.15   | AdaptiveAvgPool1d | 0      | train | [1, 64, 160] | [1,
64, 1]
35 | model.classif   | Sequential        | 645    | train | [1, 128, 1]  | [1,
5]
36 | model.classif.0 | Flatten           | 0      | train | [1, 128, 1]  | [1,
128]
37 | model.classif.1 | Linear            | 645    | train | [1, 128]     | [1,
5]
--------------------------------------------------------------------------------
-------------
28.3 K    Trainable params
```

```
0         Non-trainable params
28.3 K    Total params
0.113     Total estimated model params size (MB)
38        Modules in train mode
0         Modules in eval mode

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

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Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]
```
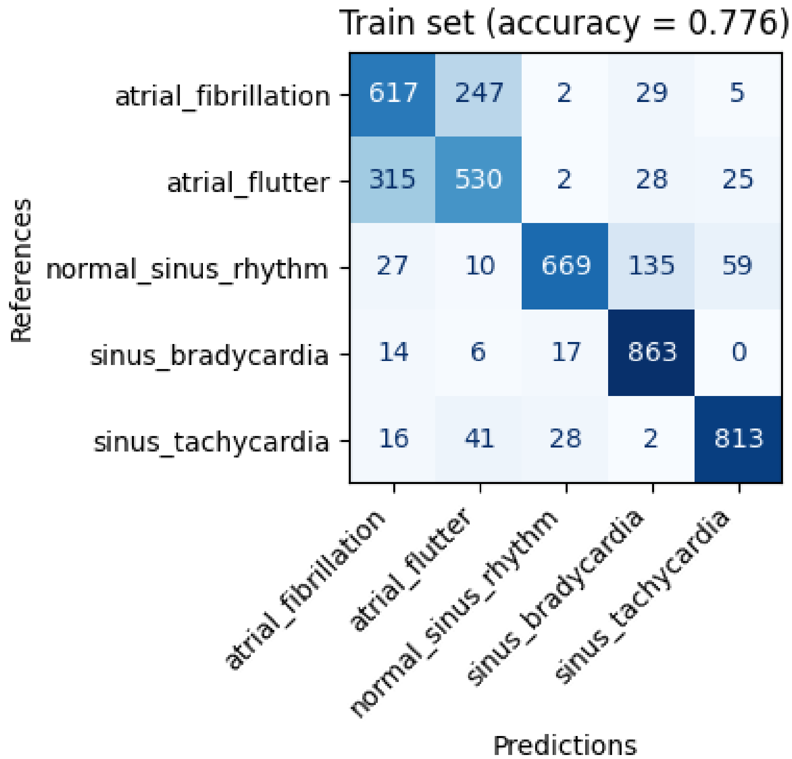
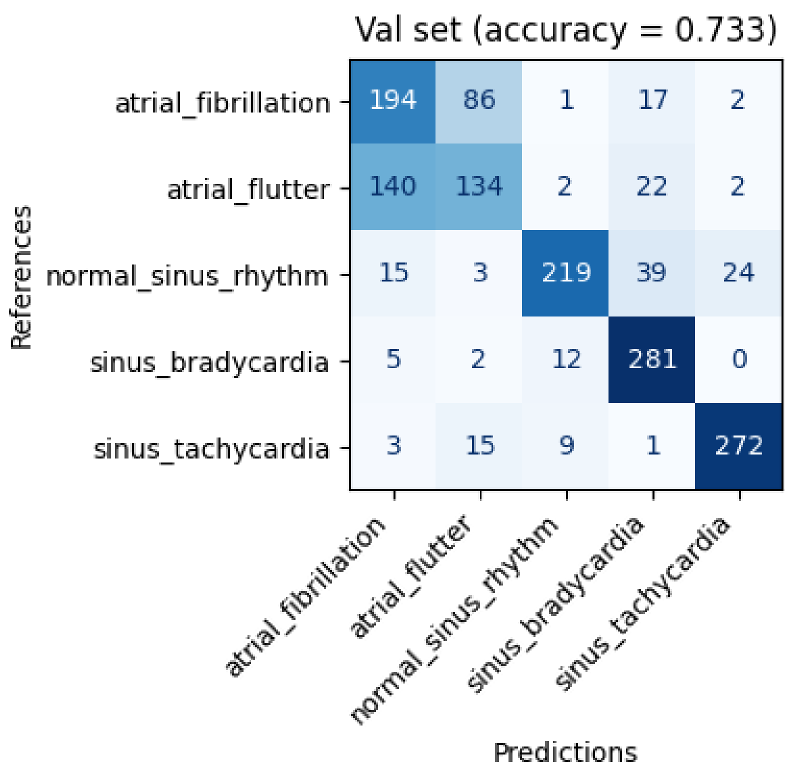
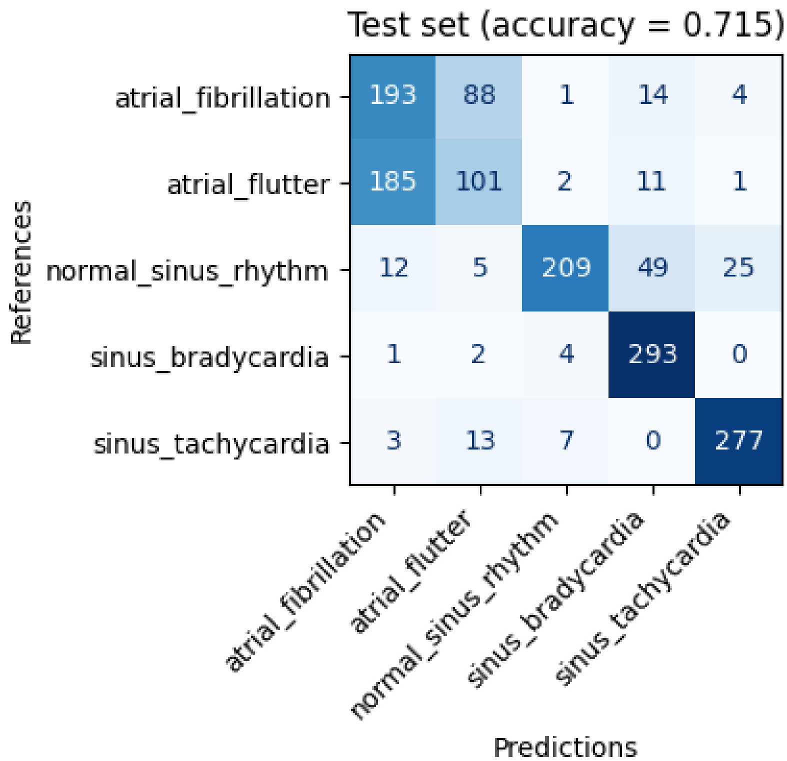

```
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
```


Train set (accuracy = 0.776)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
617 247 2 29 5
315 530 2 28 25
27 10 669 135 59
14 6 17 863 0
16 41 28 2 813


Val set (accuracy = 0.733)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
194 86 1 17 2
140 134 2 22 2
15 3 219 39 24
5 2 12 281 0
3 15 9 1 272



And then the second custom model.

[16]:
```
custom2 = train_model(
    name='custom2',
    model=CustomModel2(input_shape, output_shape),
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    learning_rate=0.0001,
    batch_size=batch_size,
    n_epochs=n_epochs,
)

custom2_matrices = evaluate_model(
    model=custom2,
    x=signals,
    y=encoded_rhythms,
    i_train=i_train,
    i_val=i_val,
    i_test=i_test,
    batch_size=batch_size,
```

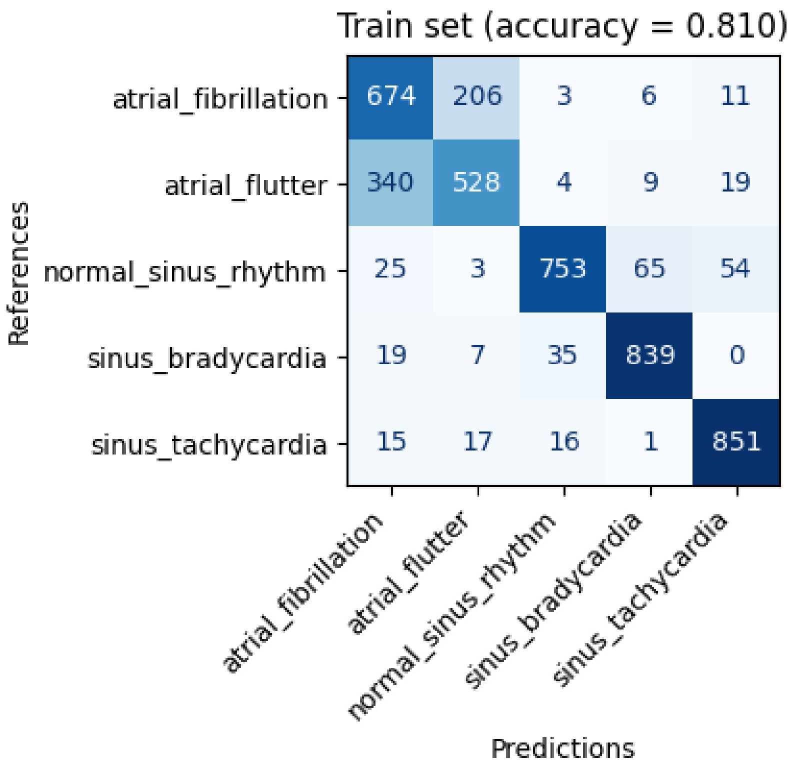
```
)

plot_confusion_matrices(custom2_matrices, np.unique(rhythms))
```

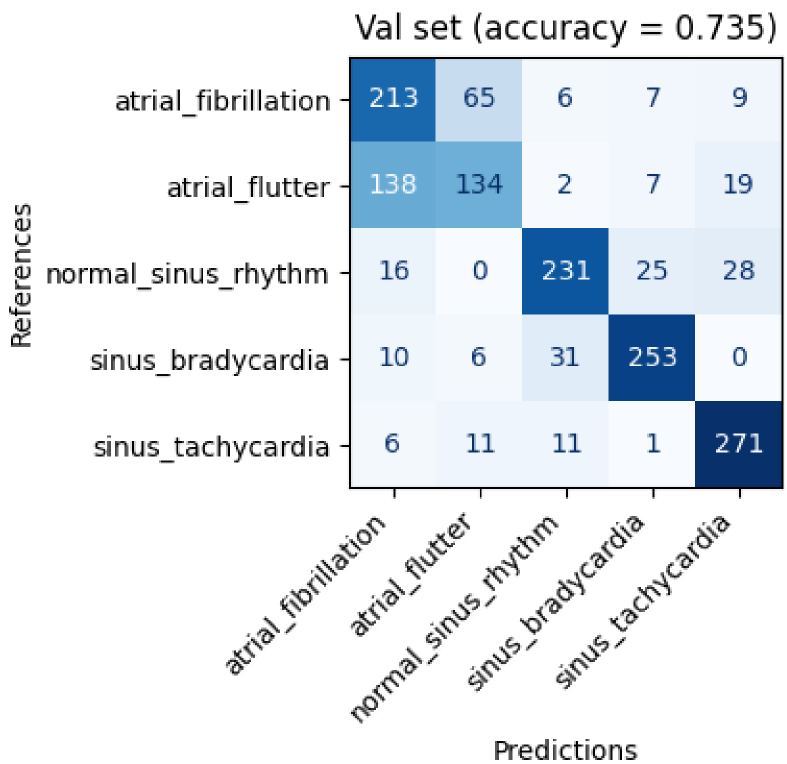
```
   | Name            | Type              | Params | Mode  | In sizes      | Out
sizes
--------------------------------------------------------------------------------
-------------
0  | model           | CustomModel2      | 16.4 K | train | [1, 1, 1280] | [1,
5]
1  | model.layers    | Sequential        | 16.4 K | train | [1, 1, 1280] | [1,
5]
2  | model.layers.0  | Conv1d            | 32     | train | [1, 1, 1280] | [1,
8, 1280]
3  | model.layers.1  | BatchNorm1d       | 16     | train | [1, 8, 1280] | [1,
8, 1280]
4  | model.layers.2  | ReLU              | 0      | train | [1, 8, 1280] | [1,
8, 1280]
5  | model.layers.3  | MaxPool1d         | 0      | train | [1, 8, 1280] | [1,
8, 640]
6  | model.layers.4  | Conv1d            | 400    | train | [1, 8, 640]  | [1,
16, 640]
7  | model.layers.5  | BatchNorm1d       | 32     | train | [1, 16, 640] | [1,
16, 640]
8  | model.layers.6  | ReLU              | 0      | train | [1, 16, 640] | [1,
16, 640]
9  | model.layers.7  | MaxPool1d         | 0      | train | [1, 16, 640] | [1,
16, 320]
10 | model.layers.8  | Conv1d            | 1.6 K  | train | [1, 16, 320] | [1,
32, 320]
11 | model.layers.9  | BatchNorm1d       | 64     | train | [1, 32, 320] | [1,
32, 320]
12 | model.layers.10 | ReLU              | 0      | train | [1, 32, 320] | [1,
32, 320]
13 | model.layers.11 | MaxPool1d         | 0      | train | [1, 32, 320] | [1,
32, 160]
14 | model.layers.12 | Conv1d            | 6.2 K  | train | [1, 32, 160] | [1,
64, 160]
15 | model.layers.13 | BatchNorm1d       | 128    | train | [1, 64, 160] | [1,
64, 160]
16 | model.layers.14 | ReLU              | 0      | train | [1, 64, 160] | [1,
64, 160]
17 | model.layers.15 | AdaptiveAvgPool1d | 0      | train | [1, 64, 160] | [1,
64, 1]
18 | model.layers.16 | Conv1d            | 6.2 K  | train | [1, 64, 1]   | [1,
32, 1]
19 | model.layers.17 | BatchNorm1d       | 64     | train | [1, 32, 1]   | [1,
32, 1]
```

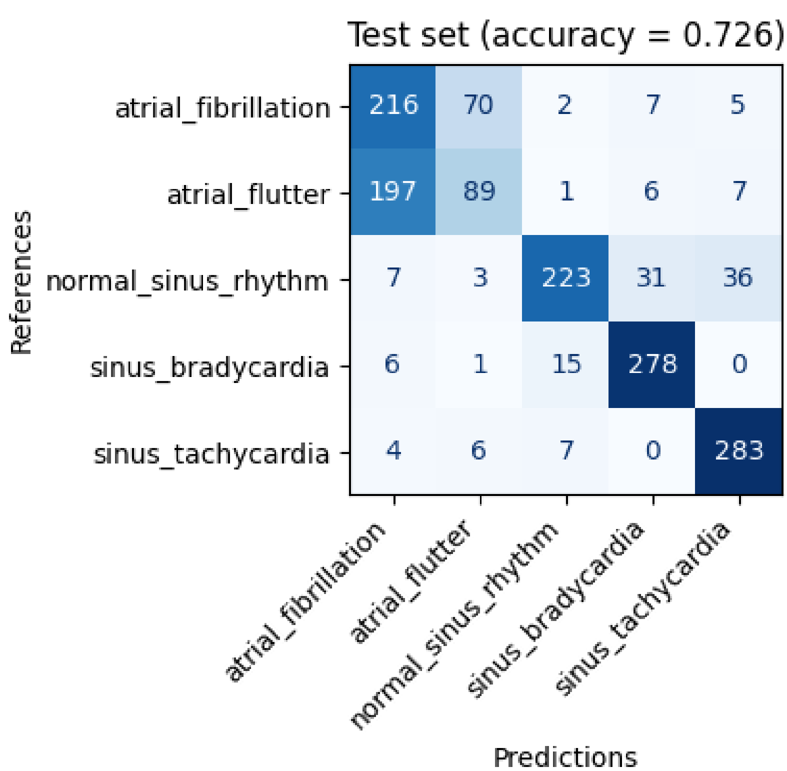
```
20 | model.layers.18 | ReLU              | 0     | train | [1, 32, 1]   | [1,
32, 1]
21 | model.layers.19 | AdaptiveAvgPool1d | 0     | train | [1, 32, 1]   | [1,
32, 1]
22 | model.layers.20 | Conv1d            | 1.6 K | train | [1, 32, 1]   | [1,
16, 1]
23 | model.layers.21 | BatchNorm1d       | 32    | train | [1, 16, 1]   | [1,
16, 1]
24 | model.layers.22 | ReLU              | 0     | train | [1, 16, 1]   | [1,
16, 1]
25 | model.layers.23 | AdaptiveAvgPool1d | 0     | train | [1, 16, 1]   | [1,
16, 1]
26 | model.layers.24 | Flatten           | 0     | train | [1, 16, 1]   | [1,
16]
27 | model.layers.25 | Linear            | 85    | train | [1, 16]      | [1,
5]
--------------------------------------------------------------------------------
-------------
16.4 K    Trainable params
0         Non-trainable params
16.4 K    Total params
0.065     Total estimated model params size (MB)
28        Modules in train mode
0         Modules in eval mode

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]
```

```
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
```

```
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
```




Val set (accuracy = 0.735)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
213 65 6 7 9
138 134 2 7 19
16 0 231 25 28
10 6 31 253 0
6 11 11 1 271


Test set (accuracy = 0.726)
References
Predictions
atrial_fibrillation
atrial_flutter
normal_sinus_rhythm
sinus_bradycardia
sinus_tachycardia
216 70 2 7 5
197 89 1 6 7
7 3 223 31 36
6 1 15 278 0
4 6 7 0 283

Question 4

How do the two custom models perform? Do they overfit? Do they outpeform the first model?

Answer Both of our custom models slightly outperform the first model in terms of accuracy, but seem to struggle with `atrial_flutter` and `atrial_fibrillation` signals just like the proposed model.