



Deep Learning

Heartbeat Sound Classification

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In This Lecture

- Heartbeat sound
- Classifying heartbeat anomalies from audio
- Implement the convolutional neural networks using tensorflow



Outline

- ➔ ☐ **Problem Definition**
- ☐ Preprocessing Codes
- ☐ Answers



Motivation

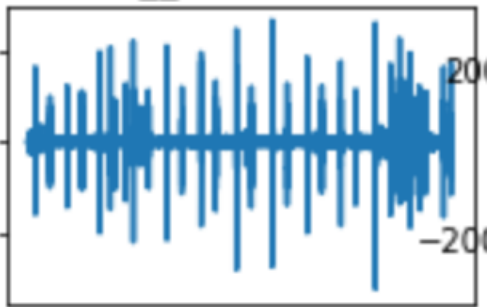
- According to the World Health Organization, cardiovascular diseases (CVDs) are the number one cause of death globally
- Detecting heart disease could have a significant impact on world health



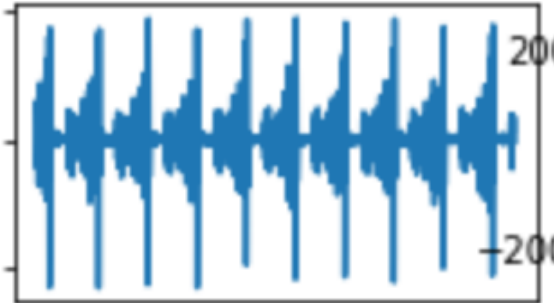
Goals

- Classify real heart audio (also known as “beat classification”) into one of three categories
 - One category is normal, and others are abnormal

Normal



Murmur



Artifact





Problem Definition

- **Given** heartbeat audio data
- **Classify** the data into the correct categories



Dataset (1)

- Heartbeat sound data collected from the general public via an iPhone app
- There are three categories
 - Normal
 - Murmur
 - Artifact



Dataset(2)

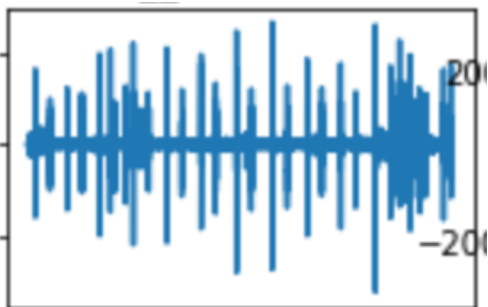
- There are 176 heartbeat examples
 - Normal: 58, Murmur: 65, Artifact: 53
- The audio files are of varying lengths, between 1 second and 9 seconds
 - In this practice, we set the length of the heartbeat sound data to 1551 by downsampling the data



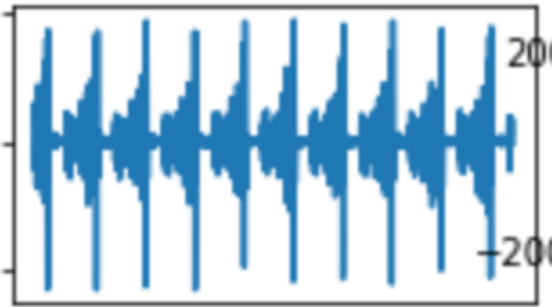
Category description

- Normal
 - Healthy heart sounds
- Murmur
 - There is a noise in a heart sound
- Artifact
 - There are a wide range of different sounds, including feedback squeals and echoes, speech, music and noise

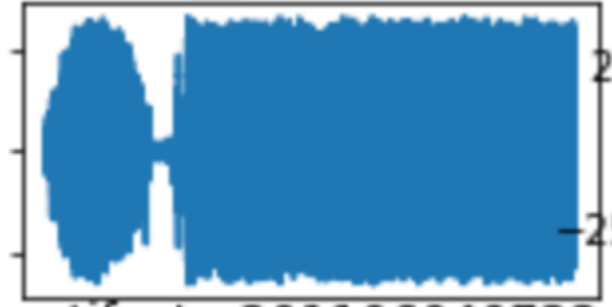
Normal



Murmur



Artifact





Data File description

- Time series data (set_a/.wav)
 - Wav file of heartbeat sound
 - File name is (category)_(generated date).wav
 - The categories in file name can be different from the labels in input.csv file
 - The labels are re-labeled by an expert
- Meta data (input.csv)
 - Labels information of wav files.



Selection of an Algorithm

- The dataset has time-series structure
- We use Convolutional Neural Networks



Model Structure

- Implement 4 cnn layers and 1 fully-connected layer
- Use dropout in the fourth hidden layer
- Optimizer: Adam
- Loss function: cross entropy



Outline

☒ Problem Definition

 ☐ **Preprocessing Codes**

☐ Answers



Import libraries

- Import the libraries such as tensorflow, numpy, and so on

```
import numpy as np
import pandas as pd
import tensorflow as tf

from scipy.io import wavfile
from scipy.signal import decimate

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
```

```
INPUT_LIB = './data/heartbeat/'
SAMPLE_RATE = 44100
CLASSES = ['artifact', 'normal', 'murmur']
CODE_BOOK = {x:i for i,x in enumerate(CLASSES)}
NB_CLASSES = len(CLASSES)
```



Loading the Dataset (1)

- Using the pandas library, we prepare the input data
- Define functions to load the files

```
def load_wav_file(name, path):  
    _, b = wavfile.read(path + name)  
    assert _ == SAMPLE_RATE  
    return b
```

```
def repeat_to_length(arr, length):  
    """Repeats the numpy 1D array to given length, and makes datatype float"""  
    result = np.empty((length, ), dtype = 'float32')  
    l = len(arr)  
    pos = 0  
    while pos + l <= length:  
        result[pos:pos+l] = arr  
        pos += l  
    if pos < length:  
        result[pos:length] = arr[:length-pos]  
    return result
```



Loading the Dataset (2)

- Using the pandas library, we prepare the input data
- Read the csv file
- Read the wav files and convert those into 1-D array

```
df = pd.read_csv(INPUT_LIB + 'input.csv')
df['time_series'] = df['file_name'].apply(load_wav_file,
                                          path=INPUT_LIB + 'set_a/')
df['len_series'] = df['time_series'].apply(len)
MAX_LEN = max(df['len_series'])
df['time_series'] = df['time_series'].apply(repeat_to_length,
                                          length=MAX_LEN)
```




Loading the Dataset (3)

- You can check the contents:
 - Type `df.head()`

```
df.head()
```

	index	file_name	labels	time_series	len_series
0	0	artifact__201012172012.wav	0	[1.0, -3.0, -1.0, -7.0, -9.0, -2.0, -6.0, -5.0...	396900
1	1	artifact__201105040918.wav	0	[-2.0, 3.0, -4.0, 4.0, -3.0, 2.0, -1.0, 0.0, 0...	396900
2	2	artifact__201105041959.wav	0	[6.0, -4.0, -9.0, -1.0, -4.0, 1.0, -5.0, 2.0, ...	396900
3	3	artifact__201105051017.wav	0	[-85.0, -198.0, -214.0, -173.0, -177.0, -206.0...	396900
4	4	artifact__201105060108.wav	0	[53.0, -35.0, 47.0, 170.0, 340.0, 436.0, 535.0...	396900



Dividing the Dataset

- We prepare the training and test data
- Use 25% of the total data as test data

```
x_data = np.stack(df['time_series'].values, axis=0)  
y_data = pd.get_dummies(df['labels']).values
```

```
x_train, x_test, y_train, y_test, train_filenames, test_filenames = \  
    train_test_split(x_data, y_data, df['file_name'].values, test_size=0.25)
```



Downsampling the Dataset

- Down-sample the data with what is in effect a very aggressive low pass filter.
- This is not needed for computational time, but it seems to improve generalization on this dataset.
 - The reason this works is probably that what you hear in the stethoscope is almost exclusively low frequency sounds, especially murmurs.

```
x_train = decimate(x_train, 8, axis=1)
x_train = decimate(x_train, 8, axis=1)
x_train = decimate(x_train, 4, axis=1)
x_test = decimate(x_test, 8, axis=1)
x_test = decimate(x_test, 8, axis=1)
x_test = decimate(x_test, 4, axis=1)
```



Preparing the Dataset

- Scale each observation to unit variance
- To use CNNs, we increase a dimension of data

```
x_train = x_train / np.std(x_train, axis=1).reshape(-1,1)  
x_test = x_test / np.std(x_test, axis=1).reshape(-1,1)
```

```
x_train = x_train[:, :, np.newaxis]  
x_test = x_test[:, :, np.newaxis]
```

```
print(f"X train shape: {x_train.shape}")  
print(f"X test shape: {x_test.shape}")
```

```
X train shape: (132, 1551, 1)  
X test shape: (44, 1551, 1)
```




Helpful Modules

- You may need these modules:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Conv1D
from tensorflow.keras.layers import MaxPool1D
from tensorflow.keras.layers import Flatten
from tensorflow.keras.callbacks import EarlyStopping
```



Outline

- ☒ Problem Definition
- ☒ Preprocessing Codes
-  ☐ **Answers**



Define the model

■ Implement the model for classification

```
def create_cnn(pkeep=0.1):  
    model = Sequential()  
  
    model.add(Conv1D(filters=2, kernel_size=9,  
                     padding='same', activation='relu',  
                     input_shape=x_train.shape[1:]))  
    model.add(MaxPool1D(pool_size=4, strides=4, padding='same'))  
  
    model.add(Conv1D(filters=2, kernel_size=9,  
                     padding='same', activation='relu'))  
    model.add(MaxPool1D(pool_size=4, strides=4, padding='same'))  
  
    model.add(Conv1D(filters=4, kernel_size=9,  
                     activation='relu', padding='same'))  
    model.add(MaxPool1D(pool_size=4, strides=4, padding='same'))  
  
    model.add(Conv1D(filters=6, kernel_size=9,  
                     padding='same', activation='relu'))  
    model.add(MaxPool1D(pool_size=4, strides=6, padding='same'))  
  
    model.add(Flatten())  
    model.add(Dropout(1-pkeep))  
    model.add(Dense(units=3, activation = 'softmax'))  
    # print(model.summary())  
    return model
```



Set hyperparameters

- Create the model with `create_cnn()`
- Define cost and optimizer variables
 - Cross entropy as a loss function
 - Adam as an optimizer

```
pkeep = 0.5  
batch_size = 8  
epochs = 100
```

```
model = create_cnn(pkeep)  
opt = tf.keras.optimizers.Adam(learning_rate=0.001)  
  
model.compile(loss='categorical_crossentropy', optimizer = opt,  
              metrics = ['accuracy'])
```




Train the Model

- Implement the training part
 - `hists`: records the training loss and so on.

```
hists = model.fit(x_train, y_train,  
                  batch_size=batch_size, epochs=epochs, validation_split=0.2,  
                  callbacks=[EarlyStopping(monitor="val_loss", patience=10,  
                                           restore_best_weights=True)])
```

Epoch 1/100

14/14 [=====] - 1s 62ms/step - loss: 1.7454 - accuracy: 0.247
6 - val_loss: 1.3021 - val_accuracy: 0.2222

Epoch 2/100

14/14 [=====] - 0s 12ms/step - loss: 1.3233 - accuracy: 0.266
7 - val_loss: 1.2088 - val_accuracy: 0.1852

Epoch 3/100

14/14 [=====] - 0s 10ms/step - loss: 1.2164 - accuracy: 0.304
8 - val_loss: 1.1765 - val_accuracy: 0.2963

Epoch 4/100

14/14 [=====] - 0s 12ms/step - loss: 1.1569 - accuracy: 0.342
9 - val_loss: 1.1583 - val_accuracy: 0.3704

Epoch 5/100

14/14 [=====] - 0s 11ms/step - loss: 1.1129 - accuracy: 0.400
0 - val_loss: 1.1536 - val_accuracy: 0.4074



Plot Training Result

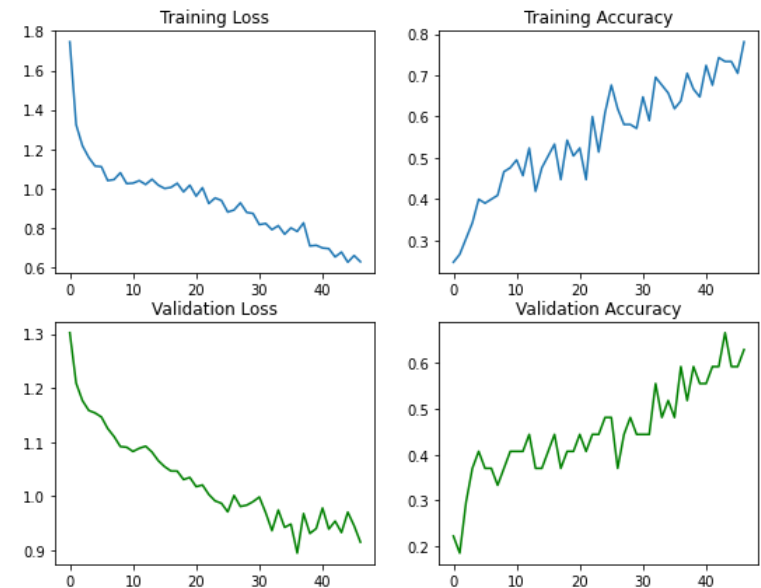
■ Get results form `hists`

```
loss = hists.history['loss']  
val_loss = hists.history['val_loss']
```

```
acc = hists.history['accuracy']  
val_acc = hists.history['val_accuracy']
```

■ Plot the results

```
plt.figure(figsize=(9, 7))  
  
plt.subplot(221)  
plt.title("Training Loss")  
plt.plot(loss)  
  
plt.subplot(222)  
plt.title("Training Accuracy")  
plt.plot(acc)  
  
plt.subplot(223)  
plt.title("Validation Loss")  
plt.plot(val_loss, color='green')  
  
plt.subplot(224)  
plt.title("Validation Accuracy")  
plt.plot(val_acc, color='green')  
  
plt.show()
```





Test the Model

■ Implement the test part

```
preds = tf.argmax(model.predict(x_test), 1)
labels = tf.argmax(y_test, 1)
```

```
accuracy_op = tf.keras.metrics.Accuracy()
test_acc = accuracy_op(preds, labels).numpy()
```

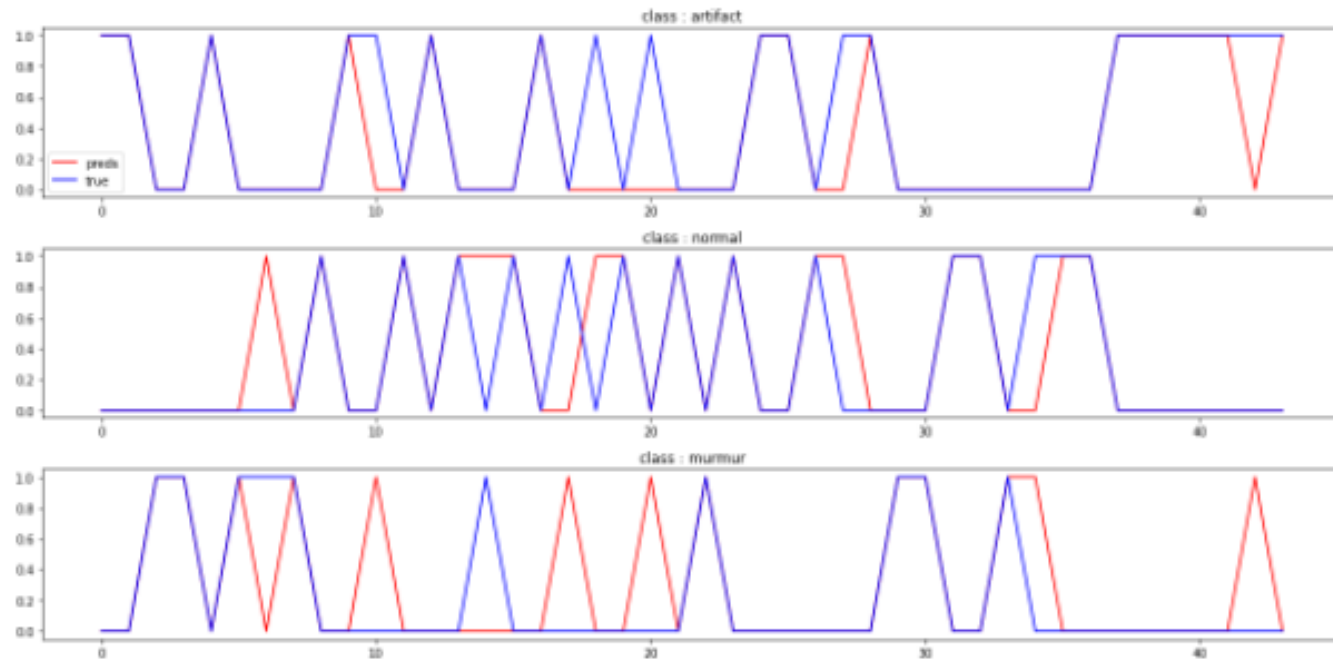
```
result = pd.get_dummies(preds).values
plt.figure(figsize=(16, 8))
print(f"Accuracy = {test_acc:.2f}")
for i in range(3):
    plt.subplot(3, 1, i+1)
    plt.plot(result[:,i], c='r')
    plt.plot(y_test[:,i], c='b')
    plt.title(f"class : {CLASSES[i]}")
    if i == 0:
        plt.legend(['preds', 'true'])
```



Test the Model

■ Implement the test part

Accuracy = 0.80





Prediction

■ Draw a plot for the mis-predicted data after test

```
mis_preds = [ i for i in range(len(labels)) if (preds[i].numpy() != labels[i].numpy())]
```

```
num = len(mis_preds)
```

```
print(f"the number of mis-prediction: {num}")
```

```
the number of mis-prediction: 9
```

```
row = 4
```

```
col = int(np.ceil(num/row))
```

```
fig = plt.figure(figsize=(20, 12))
```

```
for i in range(num):
    plt.subplot(row, col, i+1)
    plt.plot(x_test[mis_preds[i]]) # mis_preds: [0, 10, 15]
    plt.title(f"{i+1}. File: {test_filenames[mis_preds[i]]}\n"
              f"Pred: {CLASSES[preds[mis_preds[i]]]}, "
              f"True: {CLASSES[labels[mis_preds[i]]]}")
```

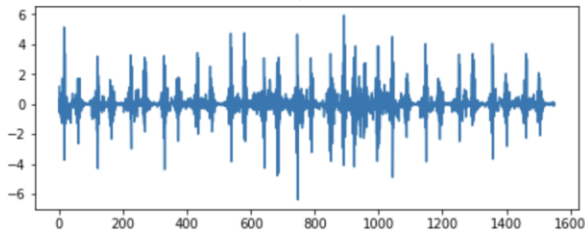
```
fig.tight_layout()
```



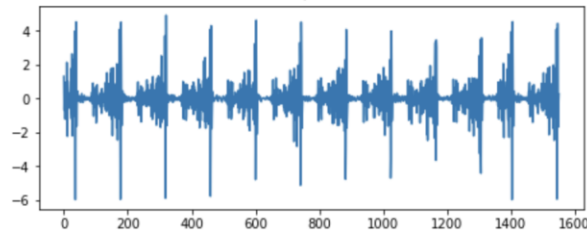
Prediction

- Draw a plot for the mis-predicted data after test

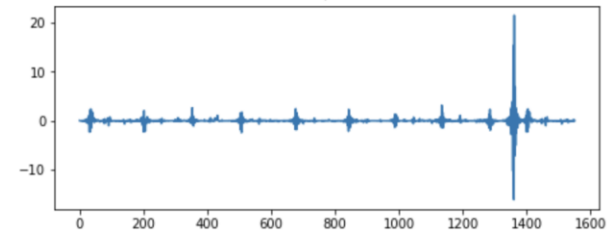
1. File: extrahls_201103200218.wav
Pred: normal, True: murmur



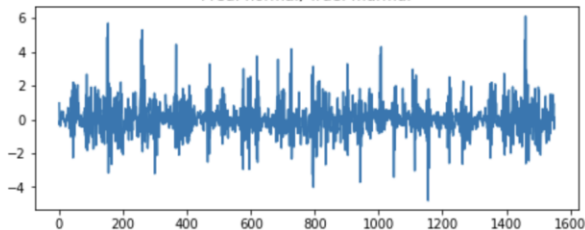
2. File: artifact_201105041959.wav
Pred: normal, True: murmur



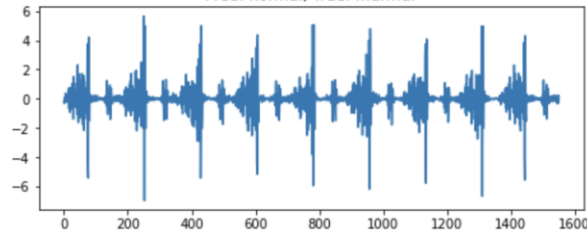
3. File: murmur_201106141148.wav
Pred: artifact, True: normal



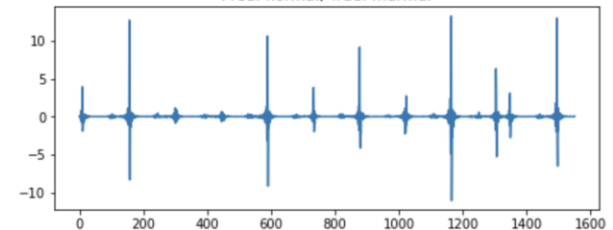
4. File: normal_201102081321.wav
Pred: normal, True: murmur



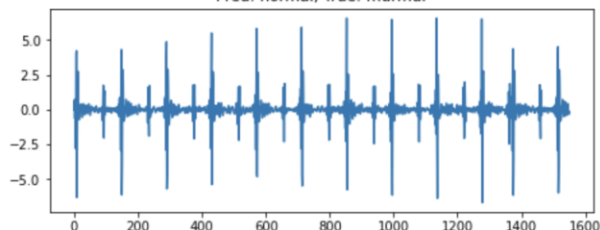
5. File: Aunlabelledtest_201108222222.wav
Pred: normal, True: murmur



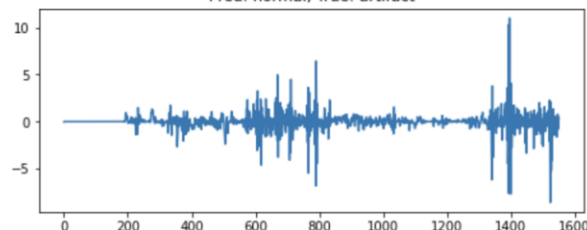
6. File: artifact_201105060108.wav
Pred: normal, True: murmur



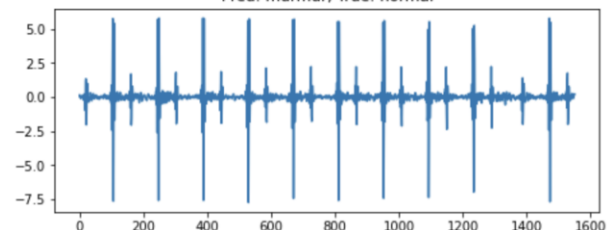
7. File: Aunlabelledtest_2011040239.wav
Pred: normal, True: murmur



8. File: extrahls_201104140118.wav
Pred: normal, True: artifact



9. File: normal_201103140132.wav
Pred: murmur, True: normal





What You Need to Know

- Time series classification
- Convolutional neural networks



Questions?