Heartbeat Classification using LSTM

Importing necessay libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow import expand_dims
from tensorflow.keras import Input, Model
from tensorflow.keras.layers import LSTM, Flatten, Dense, Conv1D, Activation
from tensorflow.keras.metrics import AUC
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import f1_score, accuracy_score, confusion_matrix
import seaborn as sns
```

```
df = pd.read_csv('/content/sample_data/mnist_train_small.csv')
print(df.shape)
```

```
(19999, 785)
```

```
# Assuming your CSV files are in a directory named 'data'
data_dir = 'data'
```

First we will tackle the binary classification (normal and abnormal) problem with PTB dataset. Later we will deal with multi-class (five categories) classification problem with MIT-BIH dataset.

Binary Classification of Normal and Abnormal Heartbeat from PTB data

Reading PTB files for binary classification

```
df_list = [pd.read_csv('/content/sample_data/mnist_train_small.csv') for i in ['abnormal
for i,df in enumerate(df_list):
    df.columns = list(range(len(df.columns)))
    df_list[i] = df.rename({187:'Label'}, axis=1)
```

```
# Abnormal
df_list[0].head()
```

	0	1	2	3	4	5	6	7	8	9	...	775	776	777	778	779	780	781	782	783	7
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
1	7	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
2	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
3	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
4	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	

5 rows × 785 columns

```
# Normal
df_list[1].head()
```

	0	1	2	3	4	5	6	7	8	9	...	775	776	777	778	779	780	781	782	783	7
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
1	7	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
2	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
3	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	
4	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	

5 rows × 785 columns

```
# Let's concat them
df = pd.concat(df_list, axis=0).reset_index(drop=True)
df
```

	0	1	2	3	4	5	6	7	8	9	...	775	776	777	778	779	780	781	782
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
1	7	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
2	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
3	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
4	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
39993	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39994	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39995	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39996	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39997	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0

39998 rows × 785 columns

```
y = df['Label']
y
```

	Label
0	236
1	97
2	0
3	123
4	196
...	...
39993	44
39994	0
39995	253
39996	255
39997	221

39998 rows × 1 columns

dtype: int64

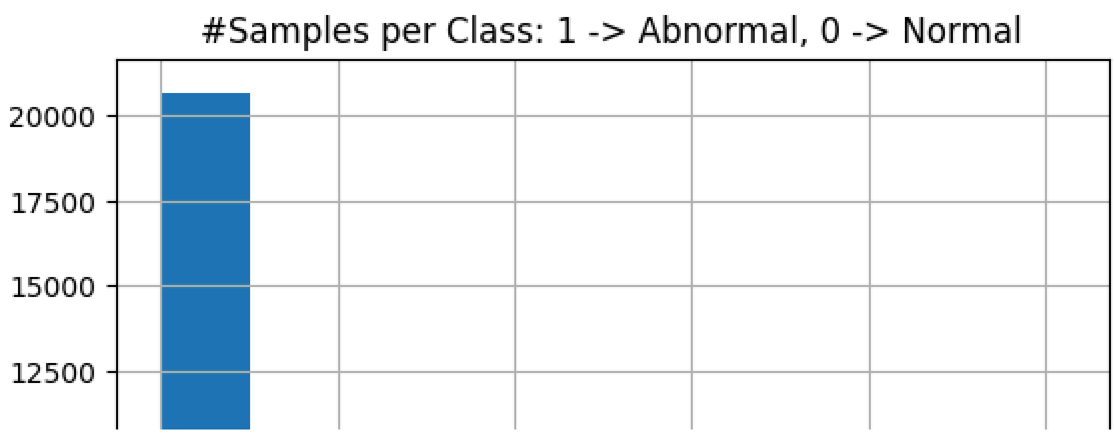
```
X = df.drop('Label', axis=1)
X
```

	0	1	2	3	4	5	6	7	8	9	...	775	776	777	778	779	780	781	782
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
1	7	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
2	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
3	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
4	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
39993	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39994	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39995	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39996	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
39997	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0

39998 rows × 784 columns

Visualization

```
y.hist()
plt.title('#Samples per Class: 1 -> Abnormal, 0 -> Normal')
plt.show()
```

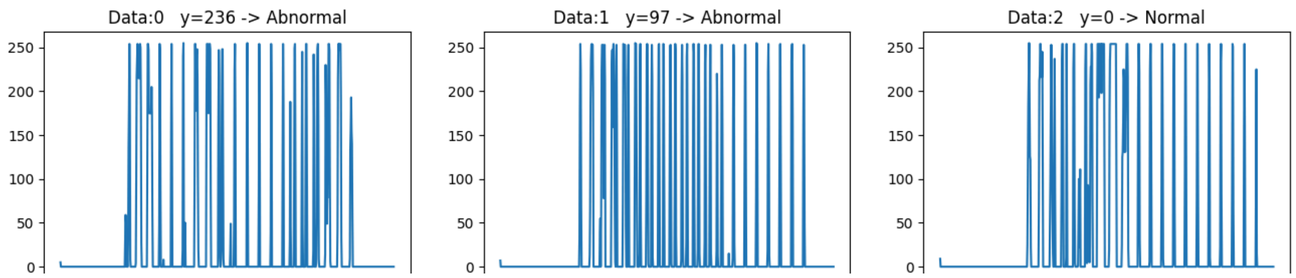


```
import matplotlib.pyplot as plt

n = 6
plt.figure(figsize=(16,7))
s = 0
for i in range(n):
    if i > 3:
        s = 100
    plt.subplot(200 + (n * 5) + i + 1)

    if s + i < len(X):
        X.iloc[s + i].plot()
        t = 'Normal'
        if y.iloc[s + i]:
            t = 'Abnormal'
        plt.title(f'Data:{s + i}   y={y.iloc[s + i]} -> {t}')
    else:
        print(f"Warning: Skipping index {s + i} as it's out of bounds.")

plt.show()
```




```
# Spectrogram visualization
i=0
print(y[i])
data = X.iloc[i]
NFFT = 64
Fs = 125
plt.figure(figsize=(10,7))
ax1 = plt.subplot(211)
```

```
data.plot()
plt.subplot(212)
Pxx, freqs, bins, im = plt.specgram(data, NFFT=NFFT,   Fs=Fs,noverlap=63) #, cmap=plt.cm
plt.show()
```

```
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/usr/local/lib/python3.10/dist-packages/matplotlib/axes/_axes.py:7939: Runtime
  Z = 10. * np.log10(spec)
```
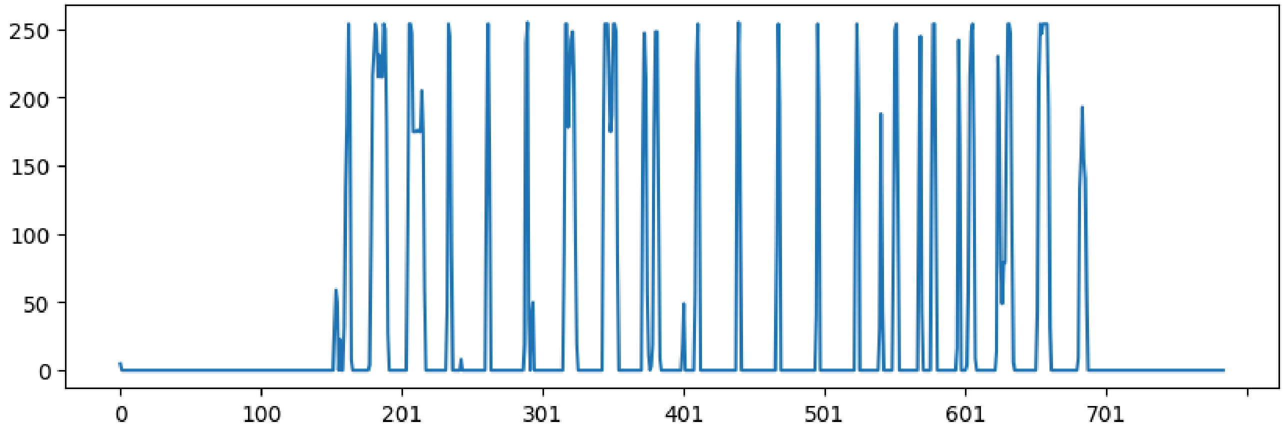




```
Pxx.shape
```

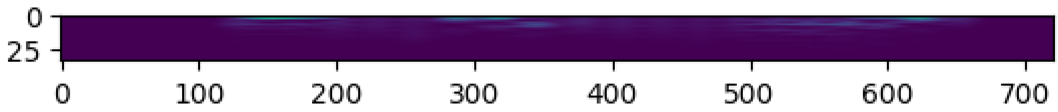
```
(33, 721)
```

```
Pxx
```

```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

```
plt.imshow(Pxx)
```

```
<matplotlib.image.AxesImage at 0x7d356fc73d90>
```




```
freqs, bins
```

```
(array([ 0.       ,  1.953125,  3.90625 ,  5.859375,  7.8125  ,  9.765625,
        11.71875 , 13.671875, 15.625   , 17.578125, 19.53125 , 21.484375,
        23.4375  , 25.390625, 27.34375 , 29.296875, 31.25    , 33.203125,
        35.15625 , 37.109375, 39.0625  , 41.015625, 42.96875 , 44.921875,
        46.875   , 48.828125, 50.78125 , 52.734375, 54.6875  , 56.640625,
        58.59375 , 60.546875, 62.5     ]),
 array([0.256, 0.264, 0.272, 0.28 , 0.288, 0.296, 0.304, 0.312, 0.32 ,
        0.328, 0.336, 0.344, 0.352, 0.36 , 0.368, 0.376, 0.384, 0.392,
        0.4  , 0.408, 0.416, 0.424, 0.432, 0.44 , 0.448, 0.456, 0.464,
        0.472, 0.48 , 0.488, 0.496, 0.504, 0.512, 0.52 , 0.528, 0.536,
        0.544, 0.552, 0.56 , 0.568, 0.576, 0.584, 0.592, 0.6  , 0.608,
        0.616, 0.624, 0.632, 0.64 , 0.648, 0.656, 0.664, 0.672, 0.68 ,
        0.688, 0.696, 0.704, 0.712, 0.72 , 0.728, 0.736, 0.744, 0.752,
        0.76 , 0.768, 0.776, 0.784, 0.792, 0.8  , 0.808, 0.816, 0.824,
        0.832, 0.84 , 0.848, 0.856, 0.864, 0.872, 0.88 , 0.888, 0.896,
        0.904, 0.912, 0.92 , 0.928, 0.936, 0.944, 0.952, 0.96 , 0.968,
        0.976, 0.984, 0.992, 1.   , 1.008, 1.016, 1.024, 1.032, 1.04 ,
        1.048, 1.056, 1.064, 1.072, 1.08 , 1.088, 1.096, 1.104, 1.112,
        1.12 , 1.128, 1.136, 1.144, 1.152, 1.16 , 1.168, 1.176, 1.184,
        1.192, 1.2  , 1.208, 1.216, 1.224, 1.232, 1.24 , 1.248, 1.256,
        1.264, 1.272, 1.28 , 1.288, 1.296, 1.304, 1.312, 1.32 , 1.328,
        1.336, 1.344, 1.352, 1.36 , 1.368, 1.376, 1.384, 1.392, 1.4  ,
        1.408, 1.416, 1.424, 1.432, 1.44 , 1.448, 1.456, 1.464, 1.472,
        1.48 , 1.488, 1.496, 1.504, 1.512, 1.52 , 1.528, 1.536, 1.544,
        1.552, 1.56 , 1.568, 1.576, 1.584, 1.592, 1.6  , 1.608, 1.616,
        1.624, 1.632, 1.64 , 1.648, 1.656, 1.664, 1.672, 1.68 , 1.688,
        1.696, 1.704, 1.712, 1.72 , 1.728, 1.736, 1.744, 1.752, 1.76 ,
        1.768, 1.776, 1.784, 1.792, 1.8  , 1.808, 1.816, 1.824, 1.832,
        1.84 , 1.848, 1.856, 1.864, 1.872, 1.88 , 1.888, 1.896, 1.904,
        1.912, 1.92 , 1.928, 1.936, 1.944, 1.952, 1.96 , 1.968, 1.976,
        1.984, 1.992, 2.   , 2.008, 2.016, 2.024, 2.032, 2.04 , 2.048,
        2.056, 2.064, 2.072, 2.08 , 2.088, 2.096, 2.104, 2.112, 2.12 ,
        2.128, 2.136, 2.144, 2.152, 2.16 , 2.168, 2.176, 2.184, 2.192,
        2.2  , 2.208, 2.216, 2.224, 2.232, 2.24 , 2.248, 2.256, 2.264,
        2.272, 2.28 , 2.288, 2.296, 2.304, 2.312, 2.32 , 2.328, 2.336,
        2.344, 2.352, 2.36 , 2.368, 2.376, 2.384, 2.392, 2.4  , 2.408,
        2.416, 2.424, 2.432, 2.44 , 2.448, 2.456, 2.464, 2.472, 2.48 ,
        2.488, 2.496, 2.504, 2.512, 2.52 , 2.528, 2.536, 2.544, 2.552,
        2.56 , 2.568, 2.576, 2.584, 2.592, 2.6  , 2.608, 2.616, 2.624,
        2.632, 2.64 , 2.648, 2.656, 2.664, 2.672, 2.68 , 2.688, 2.696,
        2.704, 2.712, 2.72 , 2.728, 2.736, 2.744, 2.752, 2.76 , 2.768,
        2.776, 2.784, 2.792, 2.8  , 2.808, 2.816, 2.824, 2.832, 2.84 ,
        2.848, 2.856, 2.864, 2.872, 2.88 , 2.888, 2.896, 2.904, 2.912,
        2.92 , 2.928, 2.936, 2.944, 2.952, 2.96 , 2.968, 2.976, 2.984,
        2.992, 3.   , 3.008, 3.016, 3.024, 3.032, 3.04 , 3.048, 3.056,
        3.064, 3.072, 3.08 , 3.088, 3.096, 3.104, 3.112, 3.12 , 3.128,
        3.136, 3.144, 3.152, 3.16 , 3.168, 3.176, 3.184, 3.192, 3.2  ,
        3.208, 3.216, 3.224, 3.232, 3.24 , 3.248, 3.256, 3.264, 3.272,
        3.28 , 3.288, 3.296, 3.304, 3.312, 3.32 , 3.328, 3.336, 3.344,
        3.352, 3.36 , 3.368, 3.376, 3.384, 3.392, 3.4  , 3.408, 3.416,
        3.424, 3.432, 3.44 , 3.448, 3.456, 3.464, 3.472, 3.48 , 3.488,
```

```
       3.496, 3.504, 3.512, 3.52 , 3.528, 3.536, 3.544, 3.552, 3.56 ,
       3.568, 3.576, 3.584, 3.592, 3.6  , 3.608, 3.616, 3.624, 3.632,
       3.64 , 3.648, 3.656, 3.664, 3.672, 3.68 , 3.688, 3.696, 3.704,
       3.712, 3.72 , 3.728, 3.736, 3.744, 3.752, 3.76 , 3.768, 3.776,
       3.784, 3.792, 3.8  , 3.808, 3.816, 3.824, 3.832, 3.84 , 3.848,
       3.856, 3.864, 3.872, 3.88 , 3.888, 3.896, 3.904, 3.912, 3.92 ,
       3.928, 3.936, 3.944, 3.952, 3.96 , 3.968, 3.976, 3.984, 3.992,
```

```
from scipy import signal
# Scipy spectrogram
# i=0
print(y[i])
data = X.iloc[i]
NFFT = 128
Fs = 125
f, t, Sxx = signal.spectrogram(data, nperseg=NFFT, nfft=NFFT, fs=Fs, noverlap=127) #, cma

plt.pcolormesh(t, f, Sxx, shading='gouraud')
plt.ylabel('Frequency [Hz]')
plt.xlabel('Time [sec]')
plt.show()
```

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```
Sxx
```

```
array([[1.41782407e-03, 0.00000000e+00, 0.00000000e+00, ...,
        8.51841972e+01, 6.14433031e+01, 3.88575922e+01],
       [5.33708680e-05, 0.00000000e+00, 0.00000000e+00, ...,
        1.48606352e+02, 1.37465242e+02, 1.30150445e+02],
       [4.16960574e-05, 0.00000000e+00, 0.00000000e+00, ...,
        4.03249276e+01, 5.16035385e+01, 6.19726775e+01],
       ...,
       [1.28973814e-14, 0.00000000e+00, 0.00000000e+00, ...,
        1.01829387e+00, 1.05329407e+00, 1.08521710e+00],
```

```
       [1.60436144e-15, 0.00000000e+00, 0.00000000e+00, ...,
        1.28091757e+00, 1.23762270e+00, 1.20071132e+00],
       [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
        7.08029816e-01, 6.66135702e-01, 6.30588160e-01]])
```

Get specgram pxx for all X's

```
def get_specgram(data):
    NFFT = 64
    Fs = 125
    pxx, freqs, bins, im = plt.specgram(data, NFFT=NFFT, Fs=Fs, noverlap=63) #, cmap=plt
    return pxx
```

```
from scipy import signal
def get_spectrogram(data):
    NFFT = 128
    Fs = 125
    f, t, Sxx = signal.spectrogram(data, nperseg=NFFT, nfft=NFFT, fs=Fs, noverlap=127) #
    return Sxx
```

```
%%time
X_sxx = X.apply(lambda row : get_spectrogram(row), axis=1)
```

```
plt.imshow(X_sxx[0])
```

```
Sxx
```

```
X_sxx[0]
```

```
X_sxx.shape
```

```
X_sxx = np.array(list(X_sxx))
```

```
X_sxx.shape
```

```
(12142, 65, 60)
```

```
X_sxx = np.moveaxis(X_sxx, 1, -1)
```

```
X_sxx.shape
```

```
(12142, 60, 65)
```

Train-Test Split

```
# Using only time domain data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
```

Model

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8499, 187), (3643, 187), (8499,), (3643,))
```

```
import tensorflow as tf
from tensorflow.keras.layers import Input, Conv1D, Activation, LSTM, Flatten, Dense, Resh
from tensorflow.keras.models import Model

inputs = Input(shape=(X_train.shape[1],))
expand = Reshape((X_train.shape[1], 1))(inputs)
conv1 = Conv1D(filters=128,kernel_size=5,strides=1)(expand)
conv1 = Activation("relu")(conv1)
conv2 = Conv1D(filters=256,kernel_size=5,strides=2)(conv1)
conv2 = Activation("relu")(conv2)
lstm = LSTM(100,return_sequences=True)(conv2)
lstm = LSTM(100,return_sequences=True)(lstm)
flatten = Flatten()(lstm)
outputs = Dense(1, activation='sigmoid')(flatten)
model = Model(inputs=inputs, outputs=outputs)
model.summary()
```

Model: "functional"

Layer (type)	Output Shape
input_layer (InputLayer)	(None, 187)
reshape (Reshape)	(None, 187, 1)
conv1d (Conv1D)	(None, 183, 128)
activation (Activation)	(None, 183, 128)
conv1d_1 (Conv1D)	(None, 90, 256)
activation_1 (Activation)	(None, 90, 256)
lstm (LSTM)	(None, 90, 100)
lstm_1 (LSTM)	(None, 90, 100)
flatten (Flatten)	(None, 9000)
dense (Dense)	(None, 1)

```
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy',AUC(name='auc')])
```

```
callbacks_list = [EarlyStopping(monitor='val_loss',
                                patience=20,
                                restore_best_weights=True)]
```

```
model_history = model.fit(X_train,
                          y_train,
                          validation_split=0.2,
                          batch_size=128,
                          epochs=100,
                          callbacks=callbacks_list)
```

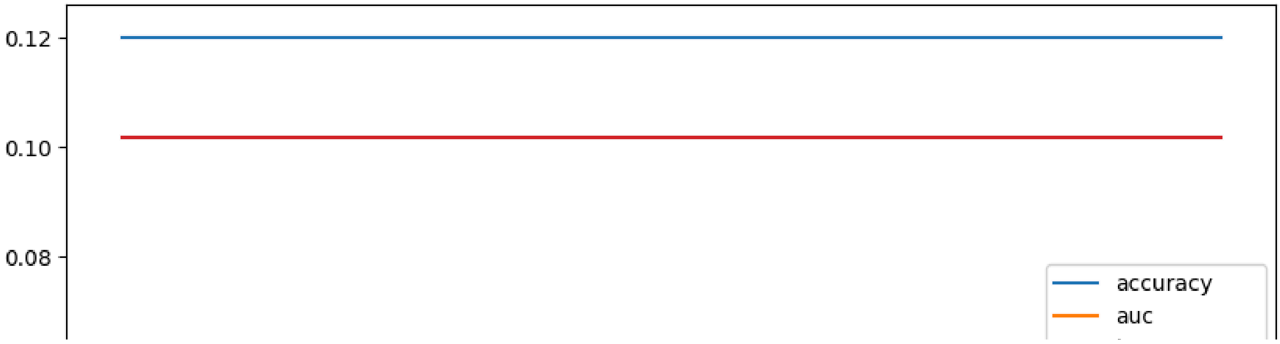
```
Epoch 1/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 57s 1s/step - accuracy: 0.1169 - auc: 0.0000e+0
Epoch 2/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 75s 919ms/step - accuracy: 0.1208 - auc: 0.0000
Epoch 3/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 81s 921ms/step - accuracy: 0.1194 - auc: 0.0000
Epoch 4/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 83s 948ms/step - accuracy: 0.1209 - auc: 0.0000
Epoch 5/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 81s 925ms/step - accuracy: 0.1211 - auc: 0.0000
Epoch 6/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 49s 909ms/step - accuracy: 0.1171 - auc: 0.0000
Epoch 7/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 80s 873ms/step - accuracy: 0.1167 - auc: 0.0000
Epoch 8/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 83s 896ms/step - accuracy: 0.1215 - auc: 0.0000
Epoch 9/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 84s 930ms/step - accuracy: 0.1183 - auc: 0.0000
Epoch 10/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 81s 905ms/step - accuracy: 0.1252 - auc: 0.0000
Epoch 11/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 83s 910ms/step - accuracy: 0.1282 - auc: 0.0000
Epoch 12/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 81s 905ms/step - accuracy: 0.1146 - auc: 0.0000
Epoch 13/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 84s 936ms/step - accuracy: 0.1258 - auc: 0.0000
Epoch 14/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 80s 909ms/step - accuracy: 0.1211 - auc: 0.0000
Epoch 15/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 82s 907ms/step - accuracy: 0.1132 - auc: 0.0000
Epoch 16/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 49s 905ms/step - accuracy: 0.1182 - auc: 0.0000
Epoch 17/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 82s 907ms/step - accuracy: 0.1166 - auc: 0.0000
Epoch 18/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 52s 953ms/step - accuracy: 0.1151 - auc: 0.0000
Epoch 19/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 79s 909ms/step - accuracy: 0.1190 - auc: 0.0000
Epoch 20/100
54/54 ━━━━━━━━━━━━━━━━━━━━ 82s 907ms/step - accuracy: 0.1173 - auc: 0.0000
```

```
model_history.history.keys()
```

```
dict_keys(['accuracy', 'auc', 'loss', 'val_accuracy', 'val_auc', 'val_loss'])
```

```
plt.figure(figsize=[10,6])
for key in model_history.history.keys():
```

```
    plt.plot(model_history.history[key], label=key)

plt.legend()
plt.show()
```



Model Evaluation

```
results = model.evaluate(X_test, y_test, verbose=1)
```

```
114/114 ━━━━━━━━━━━━━━━━━━━━ 9s 80ms/step - accuracy: 0.1167 - auc: 0.0000
```

```
print("         Loss: {:.2f}".format(results[0]))
print("Test Accuracy: {:.2f}%".format(results[1] * 100))
print("     Test AUC: {:.4f}".format(results[2]))
```

```
         Loss: nan
Test Accuracy: 11.31%
     Test AUC: 0.0000
```

```
pred = model.predict(X_test)
pred
```

```
114/114 ━━━━━━━━━━━━━━━━━━━━ 13s 115ms/step
array([[nan],
       [nan],
       [nan],
       ...,
       [nan],
       [nan],
       [nan]], dtype=float32)
```

```
pred_05 = (pred > 0.5)
pred_05
```

```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

```
sum(pred_05), len(pred_05)-sum(pred_05)
```

```
(array([0]), array([3643]))
```

```
y_test.value_counts()
```

Label	count
0.0	412
3.0	241
4.0	178
2.0	175
1.0	171

dtype: int64

```
import numpy as np
import pandas as pd
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.impute import SimpleImputer

# Assuming y_test is a pandas Series or a numpy array
# If y_test is a numpy array, convert it to a pandas Series for easier handling
if isinstance(y_test, np.ndarray):
    y_test = pd.Series(y_test)

# Check for and handle missing values in y_test
if y_test.isnull().any():
    # Option 1: Remove rows with missing values
    # y_test = y_test.dropna()  # This will drop rows with NaN values in y_test
    # X_test = X_test.loc[y_test.index]  # Drop corresponding rows in X_test

    # Option 2: Impute missing values (e.g., with the mean)
    imputer = SimpleImputer(strategy='most_frequent')  # Use most frequent value for impu
    # Convert y_test to a NumPy array before reshaping
    y_test_np = y_test.to_numpy().reshape(-1, 1)
    y_test = imputer.fit_transform(y_test_np)
    y_test = pd.Series(y_test.flatten())

# Now you can calculate the precision, recall, fscore, and support
precision, recall, fscore, support = score(y_test, pred_05)
print('      Class : [     0         1     ]')
```

```
print('  precision : {}'.format(precision))
print('     recall : {}'.format(recall))
print('     fscore : {}'.format(fscore))
print('    support : {}'.format(support))
```

```
      Class : [     0         1     ]
  precision : [0.79000823 0.         0.         0.         0.        ]
     recall : [1. 0. 0. 0. 0.]
     fscore : [0.8826867 0.        0.        0.        0.       ]
    support : [2878  171  175  241  178]
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:153
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

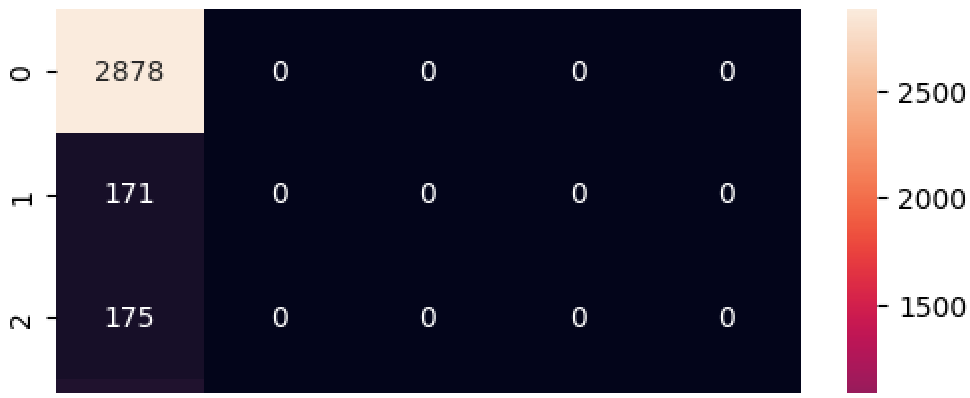
```
!pip install scikit-learn
import numpy as np
from sklearn.metrics import average_precision_score, accuracy_score, f1_score, confusion_

# Assuming 'pred' is your original array with NaNs
# Replace NaNs with a suitable value, e.g., 0
pred_no_nan = np.nan_to_num(pred, nan=0.0)  # Replace NaN with 0.0

acc = accuracy_score(y_test, pred_05)
ap = average_precision_score(y_test, pred_no_nan)  # Use the modified array
f1 = f1_score(y_test, pred_05, average=None, labels=[0,1])
cm = confusion_matrix(y_test, pred_05)
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.
```

```
print("        Accuracy: {:.2f}%".format(acc*100))
print("  Avg. precision: {0:0.4f}".format(ap))
print("                :[0,          1]")
print("        F1 Score:{}".format(f1))
print("Confusion Matrix:\n{}".format(cm))
```

```
        Accuracy: 79.00%
  Avg. precision: 0.7900
                :[0,          1]
        F1 Score:[0.8826867 0.        ]
Confusion Matrix:
[[2878    0    0    0    0]
 [ 171    0    0    0    0]
 [ 175    0    0    0    0]
 [ 241    0    0    0    0]
 [ 178    0    0    0    0]]
```

```
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt="d")
plt.show()
```




```python
import numpy as np
import pandas as pd
from sklearn.metrics import precision_recall_curve
from sklearn.preprocessing import label_binarize

# Assuming you have 'y_test' and 'pred_no_nan' from your previous code

# Get the unique classes in y_test
classes = np.unique(y_test)

# Binarize the labels for each class
y_test_binarized = label_binarize(y_test, classes=classes)

# Calculate precision-recall curve for each class
for i, c in enumerate(classes):
    # If pred_no_nan has only one column, use it directly
    # Otherwise, select the appropriate column based on the class index
    if pred_no_nan.ndim > 1 and pred_no_nan.shape[1] > i:
        target_predictions = pred_no_nan[:, i]
    else:
        target_predictions = pred_no_nan.ravel()  # Use ravel to flatten if single colum

    precision, recall, thresholds = precision_recall_curve(
        y_test_binarized[:, i], target_predictions
    )

    # Now you can use 'precision', 'recall', and 'thresholds' for class 'c'
    print(f"Precision-Recall Curve for Class {c}:")
    print(f"Precision: {precision}")
    print(f"Recall: {recall}")
    print(f"Thresholds: {thresholds}")

    # You can further plot the curves or calculate other metrics for each class
```

```
Precision-Recall Curve for Class 0.0:
Precision: [0.79000823 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 1.0:
Precision: [0.04693934 1.        ]
```

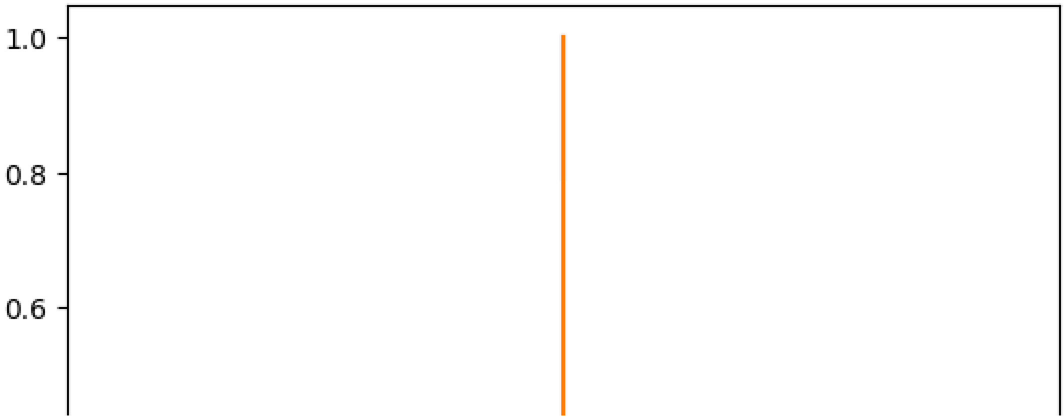
```
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 2.0:
Precision: [0.04803733 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 3.0:
Precision: [0.06615427 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 4.0:
Precision: [0.04886083 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
```

```
import numpy as np
import pandas as pd
from sklearn.metrics import precision_recall_curve
from sklearn.preprocessing import label_binarize

# Assuming you have 'y_test' and 'pred_no_nan' from your previous code

# Get the unique classes in y_test
classes = np.unique(y_test)

# Binarize the labels for each class
y_test_binarized = label_binarize(y_test, classes=classes)

# Calculate precision-recall curve for each class
precision = dict()
recall = dict()
thresholds = dict()
for i, c in enumerate(classes):
    # If pred_no_nan has only one column, use it directly
    # Otherwise, select the appropriate column based on the class index
    # If pred_no_nan has only one column, use it directly
    # Otherwise, select the appropriate column based on the class index
    if pred_no_nan.ndim > 1 and pred_no_nan.shape[1] > 1:  # Check for multi-column pred
        target_predictions = pred_no_nan[:, i]
    else:
        target_predictions = pred_no_nan.ravel()  # Use ravel to flatten if single colum

    precision[i], recall[i], thresholds[i] = precision_recall_curve(
        y_test_binarized[:, i], target_predictions
    )

    # Now you can use 'precision[i]', 'recall[i]', and 'thresholds[i]' for class 'c'
    print(f"Precision-Recall Curve for Class {c}:")
    print(f"Precision: {precision[i]}")
    print(f"Recall: {recall[i]}")
    print(f"Thresholds: {thresholds[i]}")

    # You can further plot the curves or calculate other metrics for each class

# To calculate differences in thresholds, access the specific class's thresholds:
# Check the shape and size of thresholds before accessing elements
if thresholds[0].shape[0] > 1:  # Access thresholds for class 0, for example
    # If there are multiple thresholds, calculate differences
    diff1 = thresholds[0][1] - thresholds[0][0]
    diff2 = thresholds[0][2] - thresholds[0][1]
    diff3 = thresholds[0][3] - thresholds[0][2]
    print(diff1, diff2, diff3)  # Print the differences
```

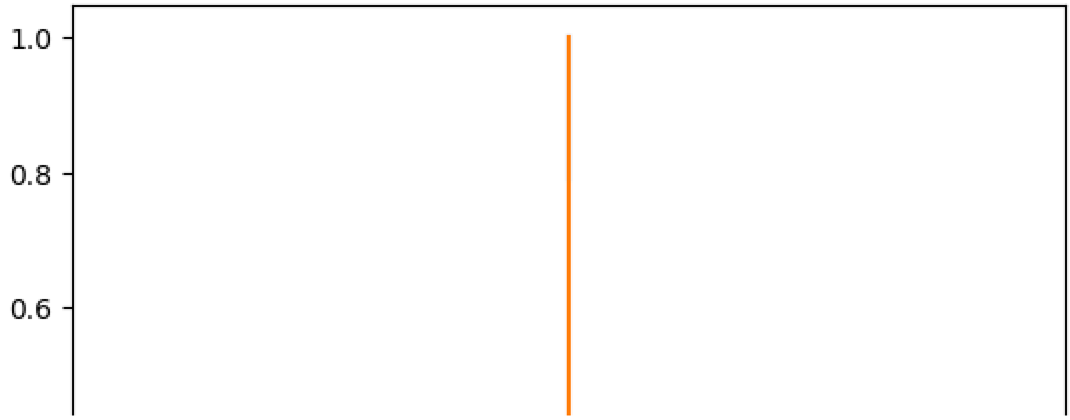
```
else:
    # If there is only one threshold, print a message
    print("Thresholds array has only one element. Cannot calculate differences.")
```

```
Precision-Recall Curve for Class 0.0:
Precision: [0.79000823 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 1.0:
Precision: [0.04693934 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 2.0:
Precision: [0.04803733 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 3.0:
Precision: [0.06615427 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Precision-Recall Curve for Class 4.0:
Precision: [0.04886083 1.        ]
Recall: [1. 0.]
Thresholds: [0.]
Thresholds array has only one element. Cannot calculate differences.
```

```
import matplotlib.pyplot as plt

# Assuming you want to plot for class 0, for example
class_index = 0

plt.plot([0] + list(thresholds[class_index]), precision[class_index])
plt.plot([0] + list(thresholds[class_index]), recall[class_index])
plt.show()
```



```
# Accessing data for class 0, for example
plt.plot([0] + list(thresholds[0]), precision[0])
plt.plot([0] + list(thresholds[0]), recall[0])
plt.show()
```



Balancing the data (2 classes)

```
# df
```

```
y.value_counts()
```

Label	count
0.0	1400
3.0	800
2.0	600
4.0	600
1.0	598

dtype: int64

```
g = df.groupby('Label')
balanced_df = g.apply(lambda x: x.sample(g.size().min()).reset_index(drop=True))
```

```
<ipython-input-66-a575cc3f406e>:2: DeprecationWarning: DataFrameGroupBy.apply
  balanced_df = g.apply(lambda x: x.sample(g.size().min()).reset_index(drop=Tr
```

```
y = balanced_df['Label']
y
```

		Label
Label		
0.0	**0**	0.0
	1	0.0
	2	0.0
	3	0.0
	4	0.0
...	**...**	...
4.0	**593**	4.0
	594	4.0
	595	4.0
	596	4.0
	597	4.0

2990 rows × 1 columns

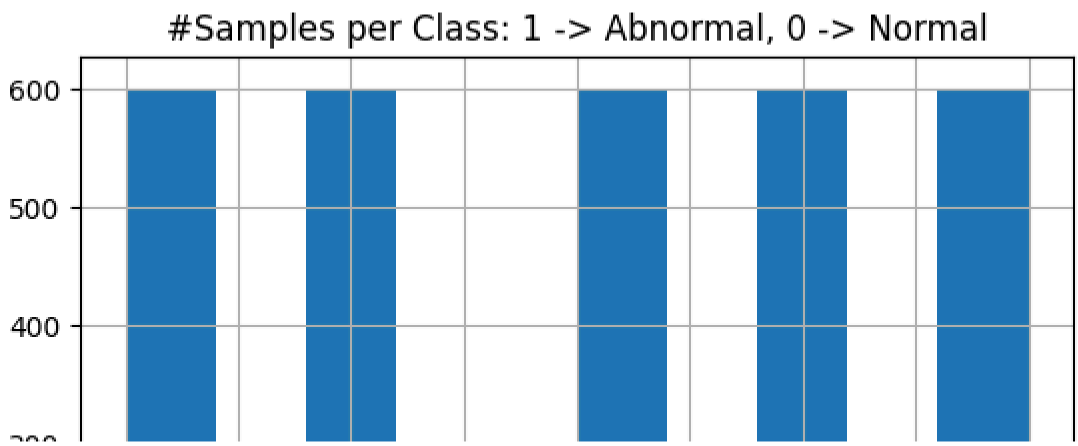
dtype: float64

```
X = balanced_df.drop('Label', axis=1)
X
```

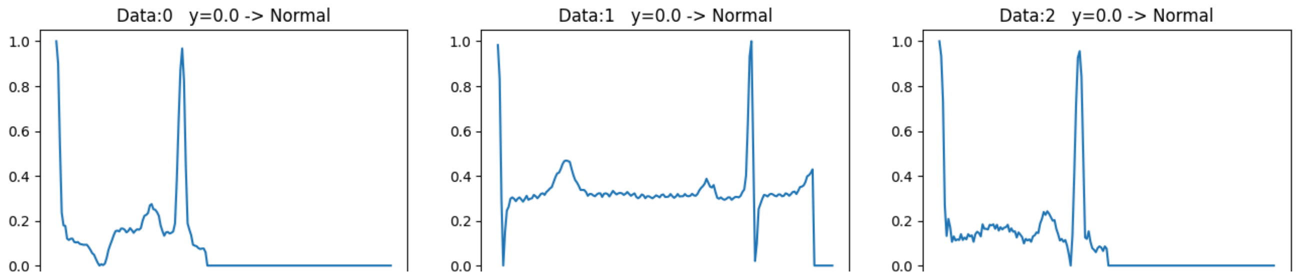
		0	1	2	3	4	5	6	7	8	9	.
Label												
0.0	**0**	1.000	0.901	0.538	0.236	0.1790	0.1770	0.1200	0.1140	0.1200	0.1200	
	1	0.983	0.832	0.297	0.000	0.1510	0.2450	0.2620	0.2980	0.3040	0.2980	
	2	1.000	0.935	0.732	0.268	0.1320	0.2080	0.1710	0.1060	0.1300	0.1120	
	3	1.000	0.634	0.328	0.373	0.3130	0.3130	0.2990	0.3280	0.3060	0.3280	
	4	1.000	0.985	0.542	0.121	0.0458	0.0771	0.0812	0.0875	0.0812	0.0688	
...	**...**	...	...	...	...	...	...	...	...	...	...	
4.0	**593**	0.827	0.503	0.509	0.512	0.4670	0.4640	0.3990	0.2890	0.1430	0.0000	
	594	1.000	0.939	0.882	0.800	0.6950	0.5840	0.4650	0.3720	0.2850	0.2100	
	595	0.897	0.522	0.558	0.594	0.6030	0.5940	0.5800	0.5180	0.3440	0.1790	
	596	0.471	0.440	0.396	0.361	0.3270	0.2860	0.2480	0.1820	0.1330	0.0332	
	597	0.679	0.612	0.504	0.325	0.1940	0.2130	0.1680	0.0821	0.0634	0.0709	

2990 rows × 187 columns

```
y.hist()
plt.title('#Samples per Class: 1 -> Abnormal, 0 -> Normal')
plt.show()
```



```
n = 6
plt.figure(figsize=(16,7))
s=0 # Changed s to 0 to start from the beginning of the DataFrame
for i in range(n):
    if i>3:
        # Consider adjusting this logic if needed for a different subset of data
        s = 1000 # Changed s to a value within the bounds of the DataFrame
    plt.subplot(200+(n*5)+i+1)
    X.iloc[s+i].plot()
    t = 'Normal'
    if y.iloc[s+i]:
        t = 'Abnormal'
    plt.title(f'Data:{s+i}   y={y.iloc[s+i]} -> {t}')

plt.show()
```




```
# Using only time domain data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
```

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((2093, 187), (897, 187), (2093,), (897,))
```

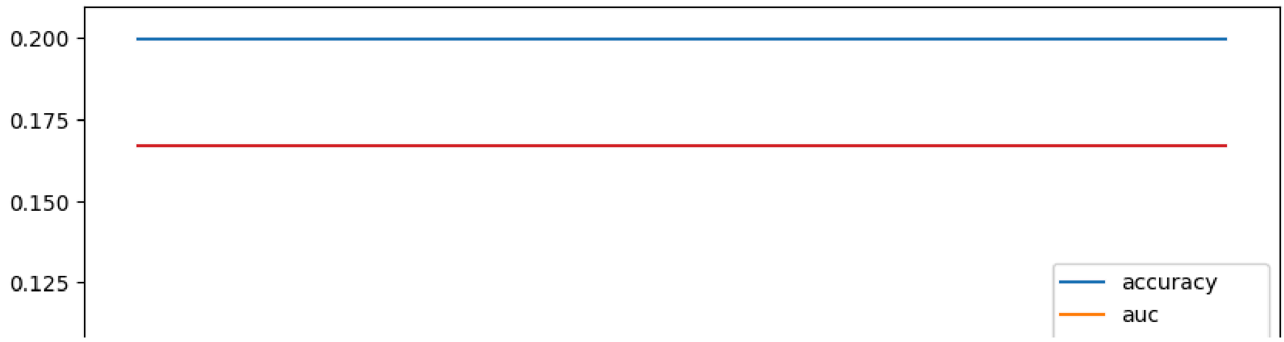
```
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy',AUC(name='auc')])
```

```
callbacks_list = [EarlyStopping(monitor='val_loss',
                                patience=20,
                                restore_best_weights=True)]
```

```
model_history = model.fit(X_train,
                          y_train,
                          validation_split=0.2,
                          batch_size=128,
                          epochs=100,
                          callbacks=callbacks_list)
```

```
Epoch 1/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 17s 980ms/step - accuracy: 0.1939 - auc: 0.0000
Epoch 2/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 13s 925ms/step - accuracy: 0.1870 - auc: 0.0000
Epoch 3/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 928ms/step - accuracy: 0.1900 - auc: 0.0000
Epoch 4/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 896ms/step - accuracy: 0.2167 - auc: 0.0000
Epoch 5/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 13s 926ms/step - accuracy: 0.1976 - auc: 0.0000
Epoch 6/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 898ms/step - accuracy: 0.1950 - auc: 0.0000
Epoch 7/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 21s 971ms/step - accuracy: 0.2006 - auc: 0.0000
Epoch 8/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 916ms/step - accuracy: 0.1895 - auc: 0.0000
Epoch 9/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 889ms/step - accuracy: 0.2035 - auc: 0.0000
Epoch 10/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 13s 924ms/step - accuracy: 0.2131 - auc: 0.0000
Epoch 11/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 19s 812ms/step - accuracy: 0.1930 - auc: 0.0000
Epoch 12/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 22s 927ms/step - accuracy: 0.2060 - auc: 0.0000
Epoch 13/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 14s 1s/step - accuracy: 0.1984 - auc: 0.0000e+0
Epoch 14/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 18s 897ms/step - accuracy: 0.1921 - auc: 0.0000
Epoch 15/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 889ms/step - accuracy: 0.1875 - auc: 0.0000
Epoch 16/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 21s 897ms/step - accuracy: 0.1915 - auc: 0.0000
Epoch 17/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 13s 934ms/step - accuracy: 0.2103 - auc: 0.0000
Epoch 18/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 887ms/step - accuracy: 0.2082 - auc: 0.0000
Epoch 19/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 20s 882ms/step - accuracy: 0.2002 - auc: 0.0000
Epoch 20/100
14/14 ━━━━━━━━━━━━━━━━━━━━ 21s 895ms/step - accuracy: 0.1995 - auc: 0.0000
```

```
plt.figure(figsize=[10,6])
for key in model_history.history.keys():
    plt.plot(model_history.history[key], label=key)

plt.legend()
plt.show()
```



```
results = model.evaluate(X_test, y_test, verbose=1)
```

```
29/29 ━━━━━━━━━━━━━━━━━━━━ 2s 79ms/step - accuracy: 0.2242 - auc: 0.0000e+
```

```
print("         Loss: {:.2f}".format(results[0]))
print("Test Accuracy: {:.2f}%".format(results[1] * 100))
print("     Test AUC: {:.4f}".format(results[2]))
```

```
         Loss: nan
Test Accuracy: 21.63%
     Test AUC: 0.0000
```

```
pred = model.predict(X_test)
pred
```

```
29/29 ━━━━━━━━━━━━━━━━━━━━ 3s 88ms/step
array([[nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
```

```
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
       [nan],
```

```
pred_05 = (pred > 0.5)
pred_05
```

```
array([[False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
       [False],
```

```
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
             [False],
```

```
from sklearn.metrics import precision_recall_fscore_support as score
precision, recall, fscore, support = score(y_test, pred_05)
print('      Class : [     0        1     ]')
print('  precision : {}'.format(precision))
print('     recall : {}'.format(recall))
print('     fscore : {}'.format(fscore))
print('    support : {}'.format(support))
```

```
      Class : [     0         1     ]
  precision : [0.21627648 0.         0.         0.         0.        ]
     recall : [1. 0. 0. 0. 0.]
     fscore : [0.35563703 0.         0.         0.         0.        ]
    support : [194 175 178 168 182]
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:153
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

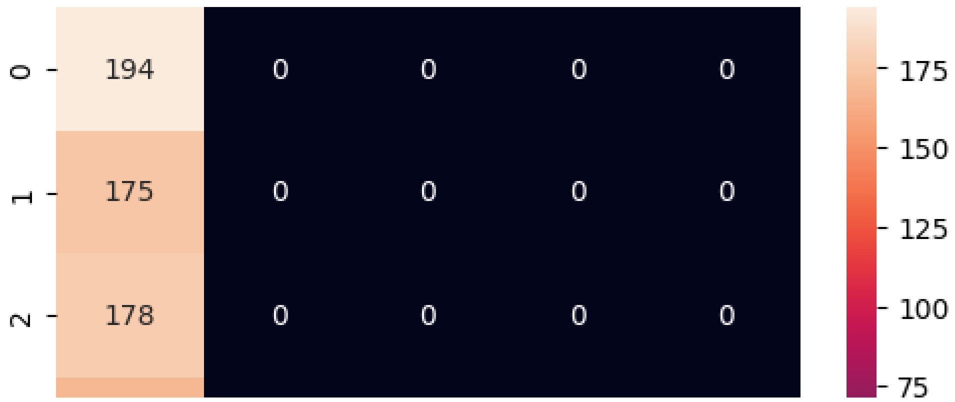
```
!pip install numpy

import numpy as np
from sklearn.metrics import average_precision_score, accuracy_score, f1_score, confusion_

# Replace NaN values in 'pred' with a suitable value, e.g., 0.
pred = np.nan_to_num(pred, nan=0.0) # Replace NaNs in 'pred' with 0

acc = accuracy_score(y_test, pred_05)
ap = average_precision_score(y_test, pred)
f1 = f1_score(y_test, pred_05, average=None, labels=[0,1])
cm = confusion_matrix(y_test, pred_05)
```

```
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-package
```

```
print("        Accuracy: {:.2f}%".format(acc*100))
print("  Avg. precision: {0:0.4f}".format(ap))
print("                :[0,           1]")
print("        F1 Score:{}".format(f1))
print("Confusion Matrix:\n{}".format(cm))
```

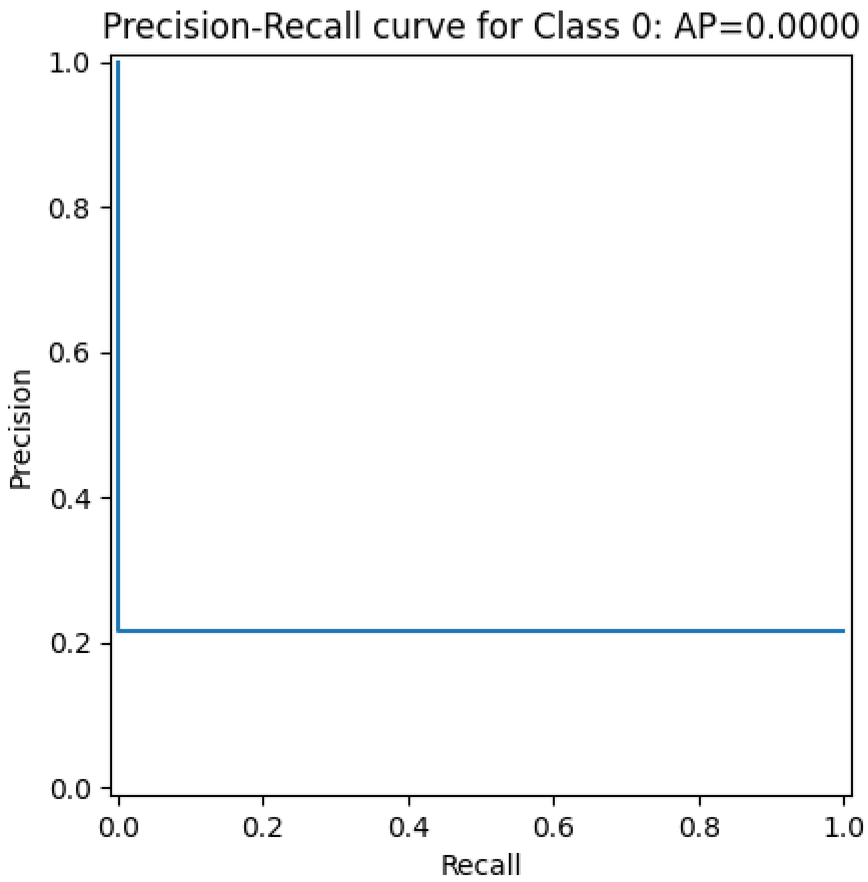
```
        Accuracy: 21.63%
  Avg. precision: 0.2163
                :[0,            1]
        F1 Score:[0.35563703 0.         ]
Confusion Matrix:
[[194   0   0   0   0]
 [175   0   0   0   0]
 [178   0   0   0   0]
 [168   0   0   0   0]
 [182   0   0   0   0]]
```

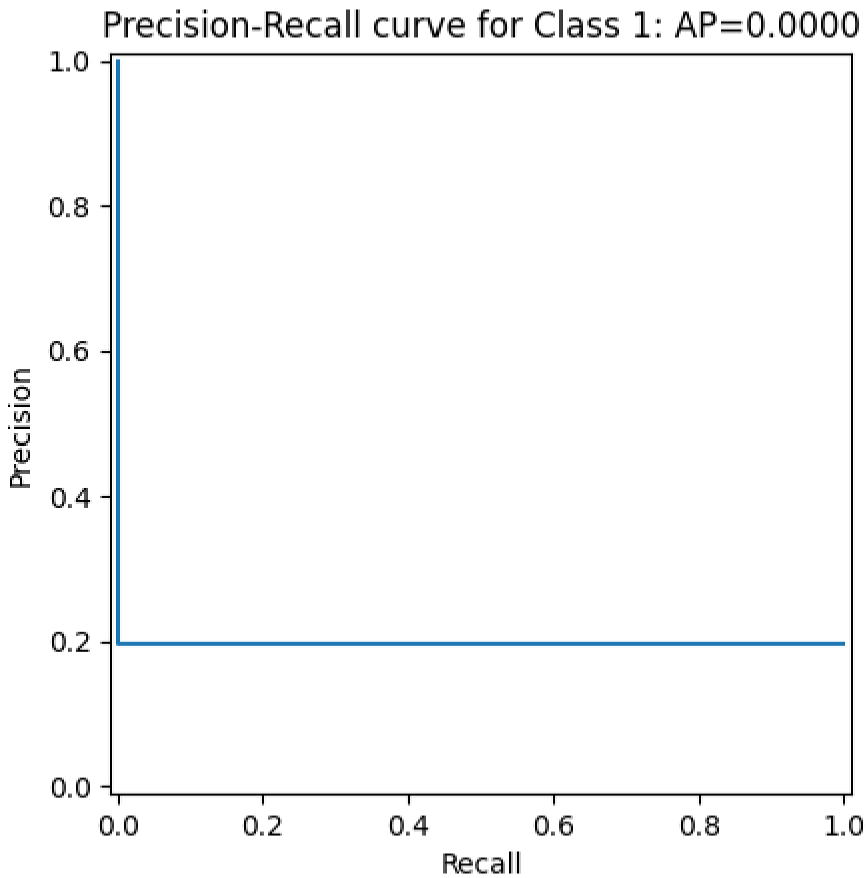
```
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt="d")
plt.show()
```

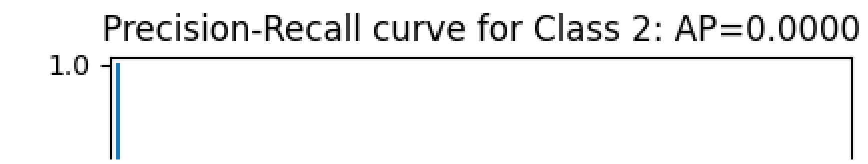



```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import PrecisionRecallDisplay
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt

# Assuming 'y_test' is your true labels and 'pred' your predictions

# If 'pred' contains probabilities for a single class, use it directly:
# No need to slice pred[:, i] in this case

# Binarize the labels if necessary
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))
# If y_test is already binary, this step is redundant but won't cause harm
```

```
# For multi-class scenario, iterate through classes:
n_classes = y_test_bin.shape[1]
for i in range(n_classes):
    # Use pred directly instead of pred[:, i] as it's already 1-dimensional
    precision, recall, thresholds = precision_recall_curve(y_test_bin[:, i], pred.ravel(
    disp = PrecisionRecallDisplay(precision=precision, recall=recall)
    disp.plot()
    plt.title(f'Precision-Recall curve for Class {i}: AP={0:0.4f}'.format(ap))
    plt.show()
```


Precision-Recall curve for Class 0: AP=0.0000
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall curve for Class 1: AP=0.0000
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall curve for Class 2: AP=0.0000
1.0

Save Model

```
model.save('ECG_PTB.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `
```

Multi-class Classification into five classes from MIT-BIH dataset

to be continued...

```
df_list = [pd.read_csv('/content/mit-bih_train.csv') for i in ['train','test']]
for i,df in enumerate(df_list):
    df.columns = list(range(len(df.columns)))
    df_list[i] = df.rename({187:'Label'}, axis=1)
```

```
import pandas as pd
import os

# Get the current directory
current_directory = os.getcwd()

# Define file paths relative to the current directory
file_paths = [os.path.join(current_directory, 'mitbih_'+i+'.csv') for i in ['train','tes

# Read the files into a list of DataFrames
df_list = [pd.read_csv('/content/mit-bih_train.csv') for file_path in file_paths]

for i,df in enumerate(df_list):
    df.columns = list(range(len(df.columns)))
    df_list[i] = df.rename({187:'Label'}, axis=1)


# Train
df_list[0]
```

	0	1	2	3	4	5	6	7	8	9	...	1
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...	0
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...	0
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...	0
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...	0
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
6066	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6067	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6068	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6069	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6070	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na

6071 rows × 188 columns

```
# Test
df_list[1]
```

	0	1	2	3	4	5	6	7	8	9	...	1
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...	0
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...	0
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...	0
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...	0
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
6066	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6067	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6068	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6069	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na
6070	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Na

6071 rows × 188 columns

```
# Let's concat them
df = pd.concat(df_list, axis=0).reset_index(drop=True)
df
```

	0	1	2	3	4	5	6	7	8	9	...
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...
...	...	...	...	...	...	...	...	...	...	...	...
12137	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12138	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12139	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12140	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12141	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...

12142 rows × 188 columns

```
# df = pd.read_csv('../input/heartbeat/mitbih_train.csv')
# df.columns = list(range(len(df.columns)))
# df = df.rename({187:'Label'}, axis=1)
```

```
y = df['Label']
y
```

	Label
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
12137	NaN
12138	NaN
12139	NaN
12140	NaN
12141	NaN

12142 rows × 1 columns

dtype: float64

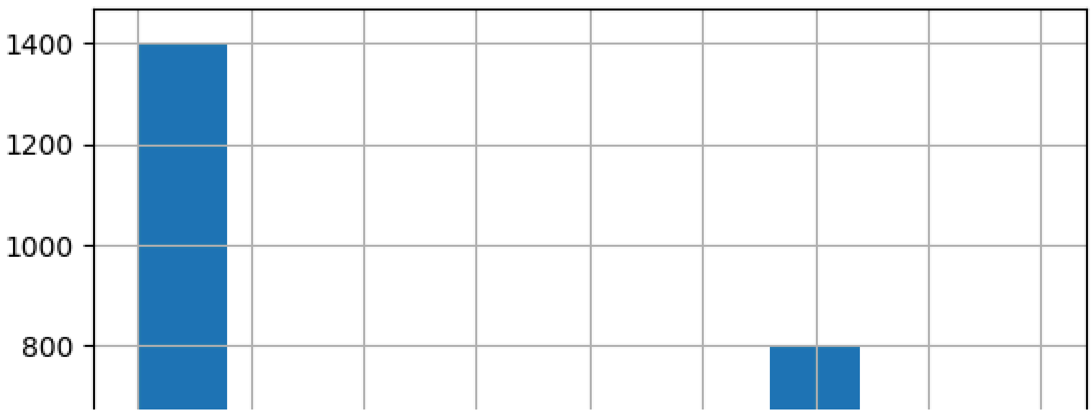
```
y.value_counts()
```

Label	count
0.0	1400
3.0	800
2.0	600
4.0	600
1.0	598

dtype: int64

```
y.hist()
```

```
<Axes: >
```

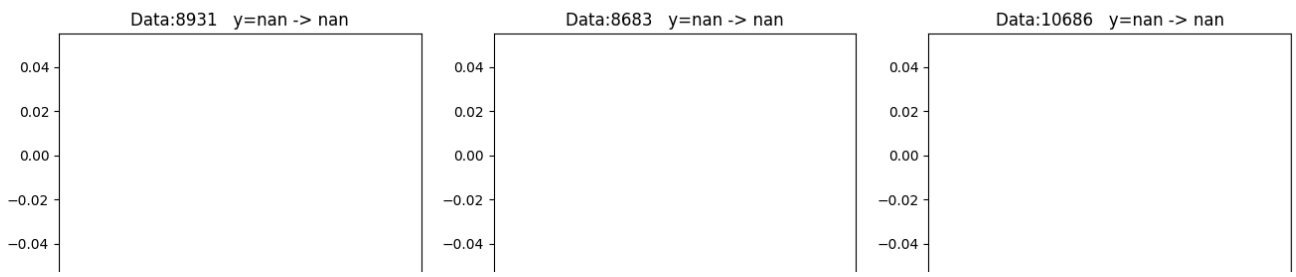



```
X = df.drop('Label', axis=1)
X
```

	0	1	2	3	4	5	6	7	8	9	...
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...
...	...	...	...	...	...	...	...	...	...	...	...
12137	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12138	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12139	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12140	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
12141	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...

12142 rows × 187 columns

```
import random
import matplotlib.pyplot as plt

n = 6
plt.figure(figsize=(16, 7))

for i in range(n):
    # Ensure the random index is within the bounds of the DataFrame
    s = random.randint(0, len(X) - 1)
    plt.subplot(200 + (n * 5) + i + 1)
    X.iloc[s].plot()  # Use s as the index directly
    plt.title(f'Data:{s}   y={y.iloc[s]} -> {y.iloc[s]}')

plt.show()
```



Label Encoding y's

```
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical  # Import to_categorical directly
```

```
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical  # Import to_categorical directly

encoder = LabelEncoder()
encoder.fit(y)
encoded_y = encoder.transform(y)
# convert integers to dummy variables (i.e. one hot encoded)
# Use to_categorical directly from tensorflow.keras.utils
dummy_y = to_categorical(encoded_y)
```

```
dummy_y
```

```
array([[1., 0., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0.],
       ...,
       [0., 0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 0., 1.]])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, dummy_y, test_size=0.3, random_sta
```

Model

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8499, 187), (3643, 187), (8499, 6), (3643, 6))
```

```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy',AUC(name='auc')])
```

```
callbacks_list = [EarlyStopping(monitor='val_loss',
                                patience=20,
                                restore_best_weights=True)]
```

Balancing the data (5 classes)

```
from sklearn.utils import resample
```

```
df_0 = df[df['Label']==0]
df_1 = df[df['Label']==1]
df_2 = df[df['Label']==2]
```

```
df_3 = df[df['Label']==3]
df_4 = df[df['Label']==4]


def sampling_k_elements(group, k=8039):
    if len(group) <= k:
        return group
    return group.sample(k)

balanced_df = df.groupby('Label').apply(sampling_k_elements).reset_index(drop=True)
```

```
<ipython-input-113-79cef26650fd>:6: DeprecationWarning: DataFrameGroupBy.apply
  balanced_df = df.groupby('Label').apply(sampling_k_elements).reset_index(drc
```

```
balanced_df
```

	0	1	2	3	4	5	6	7	8	9	...	17
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...	0
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...	0
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...	0
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...	0
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
3993	0.616	0.455	0.428	0.4190	0.4020	0.3720	0.3550	0.3050	0.2260	0.1200	...	0
3994	0.706	0.621	0.512	0.4100	0.2760	0.1580	0.0782	0.0353	0.0000	0.0184	...	0
3995	0.876	0.823	0.758	0.6950	0.6050	0.4970	0.3750	0.2340	0.1290	0.0868	...	0
3996	0.772	0.514	0.514	0.5380	0.5140	0.5030	0.4620	0.4030	0.2660	0.1660	...	0
3997	0.994	1.000	0.700	0.4170	0.1810	0.1060	0.1140	0.1170	0.1080	0.1080	...	0

3998 rows × 188 columns

```
y = balanced_df['Label']
y
```

	Label
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3993	4.0
3994	4.0
3995	4.0
3996	4.0
3997	4.0

3998 rows × 1 columns

dtype: float64

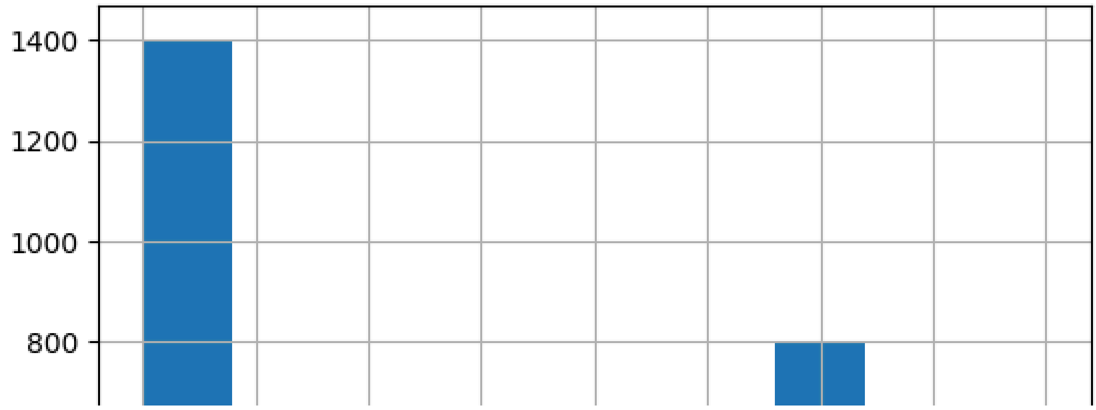
```
y.value_counts()
```

	count
Label	
0.0	1400
3.0	800
2.0	600
4.0	600
1.0	598

dtype: int64

```
y.hist()
```

<Axes: >



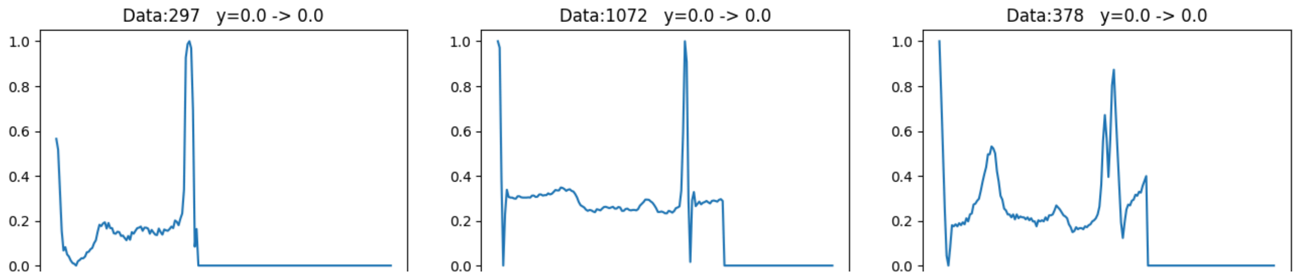

```
X = balanced_df.drop('Label', axis=1)
X
```

	0	1	2	3	4	5	6	7	8	9	...	1
0	0.960	0.863	0.462	0.1970	0.0940	0.1250	0.0997	0.0883	0.0741	0.0826	...	0
1	1.000	0.659	0.186	0.0703	0.0703	0.0595	0.0568	0.0432	0.0541	0.0459	...	0
2	0.925	0.666	0.541	0.2760	0.1960	0.0773	0.0718	0.0608	0.0663	0.0580	...	0
3	0.967	1.000	0.831	0.5870	0.3570	0.2490	0.1460	0.0892	0.1170	0.1500	...	0
4	0.927	1.000	0.627	0.1930	0.0950	0.0725	0.0432	0.0535	0.0933	0.1900	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
3993	0.616	0.455	0.428	0.4190	0.4020	0.3720	0.3550	0.3050	0.2260	0.1200	...	0
3994	0.706	0.621	0.512	0.4100	0.2760	0.1580	0.0782	0.0353	0.0000	0.0184	...	0
3995	0.876	0.823	0.758	0.6950	0.6050	0.4970	0.3750	0.2340	0.1290	0.0868	...	0
3996	0.772	0.514	0.514	0.5380	0.5140	0.5030	0.4620	0.4030	0.2660	0.1660	...	0
3997	0.994	1.000	0.700	0.4170	0.1810	0.1060	0.1140	0.1170	0.1080	0.1080	...	0

3998 rows × 187 columns

```
import random
import matplotlib.pyplot as plt

n = 6
```

```
plt.figure(figsize=(16,7))

for i in range(n):
    # Ensure the random index is within the bounds of the DataFrame
    s = random.randint(0, len(X) - n)  # Subtract n to prevent going out of bounds
    plt.subplot(200+(n*5)+i+1)
    X.iloc[s+i].plot()
    # t = 'Normal'
    # if y.iloc[s+i]:
    #     t = 'Abnormal'
    plt.title(f'Data:{s+i}   y={y.iloc[s+i]} -> {y.iloc[s+i]}')

plt.show()
```



Label Encoding y's

```
from sklearn.preprocessing import LabelEncoder
# from keras.utils import np_utils # np_utils is no longer part of keras.utils. Use tens
from tensorflow.keras.utils import to_categorical # Import to_categorical directly from

# Assuming 'y' is your target variable and you want to one-hot encode it:
# encoded_y = np_utils.to_categorical(y) # Replace this with the following:
encoded_y = to_categorical(y)
```

```
from sklearn.preprocessing import LabelEncoder
# from keras.utils import np_utils  # np_utils is deprecated, use to_categorical directly
from tensorflow.keras.utils import to_categorical # Import to_categorical

encoder = LabelEncoder()
encoder.fit(y)
encoded_y = encoder.transform(y)
# convert integers to dummy variables (i.e. one hot encoded)
dummy_y = to_categorical(encoded_y) # Use to_categorical directly
```

```
dummy_y
```

```
array([[1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
```

```
       [1., 0., 0., 0., 0.],
       ...,
       [0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 1.]])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, dummy_y, test_size=0.3, random_sta
```

Model

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((2798, 187), (1200, 187), (2798, 5), (1200, 5))
```

```
from tensorflow.keras.layers import Input, LSTM, Dense, Flatten, Activation, Conv1D, Resh
from tensorflow.keras.models import Model
from tensorflow.keras.backend import expand_dims

# ... (rest of your imports and code)

inputs = Input(shape=(X_train.shape[1],))
# Use Reshape instead of expand_dims
# expand = expand_dims(inputs, axis=2)  # Incorrect
expand = Reshape((X_train.shape[1], 1))(inputs) # Correct

# Adding Conv1D
conv1 = Conv1D(filters=128,kernel_size=5,strides=1)(expand)
conv1 = Activation("relu")(conv1)
conv2 = Conv1D(filters=256,kernel_size=5,strides=2)(conv1)
conv2 = Activation("relu")(conv2)
lstm = LSTM(100,return_sequences=True)(conv2)
lstm = LSTM(100,return_sequences=True)(lstm)
flatten = Flatten()(lstm)
outputs = Dense(5, activation='softmax')(flatten)
model = Model(inputs=inputs, outputs=outputs)
model.summary()
```

Model: "functional_1"

Layer (type)	Output Shape
input_layer_2 (InputLayer)	(None, 187)

```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy',AUC(name='auc')])
```

```
callbacks_list = [EarlyStopping(monitor='val_loss',
                                patience=20,
                                restore_best_weights=True)]
```

```
model_history = model.fit(X_train,
                          y_train,
                          validation_split=0.2,
                          batch_size=128,
                          epochs=100,
                          callbacks=callbacks_list)
```

```
Epoch 1/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 20s 896ms/step - accuracy: 0.3262 - auc: 0.6536
Epoch 2/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 16s 887ms/step - accuracy: 0.5553 - auc: 0.8492
Epoch 3/100
18/18 ━━━━━━━━━━━━━━━━━━━━ 16s 892ms/step - accuracy: 0.6421 - auc: 0.8829
```