```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import tensorflow as tf

print(f"tensorflow version: {tf.__version__}")
```

```
tensorflow version: 2.14.0
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Loading Data

testpathzip = "/content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_test.csv.zip"

trainpathzip = "/content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_train.csv.zip"

```
!unzip "/content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_test.csv.zip"
```

```
Archive:  /content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_test.csv.zip
  inflating: mitbih_test.csv
```

```
!unzip "/content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_train.csv.zip"
```

```
Archive:  /content/drive/MyDrive/Datasets/ArrythmiaData/mitbih_train.csv.zip
  inflating: mitbih_train.csv
```

```
train_data = pd.read_csv('/content/mitbih_train.csv', header = None)
test_data = pd.read_csv('/content/mitbih_test.csv', header = None)
```

```
train_data.head()
```

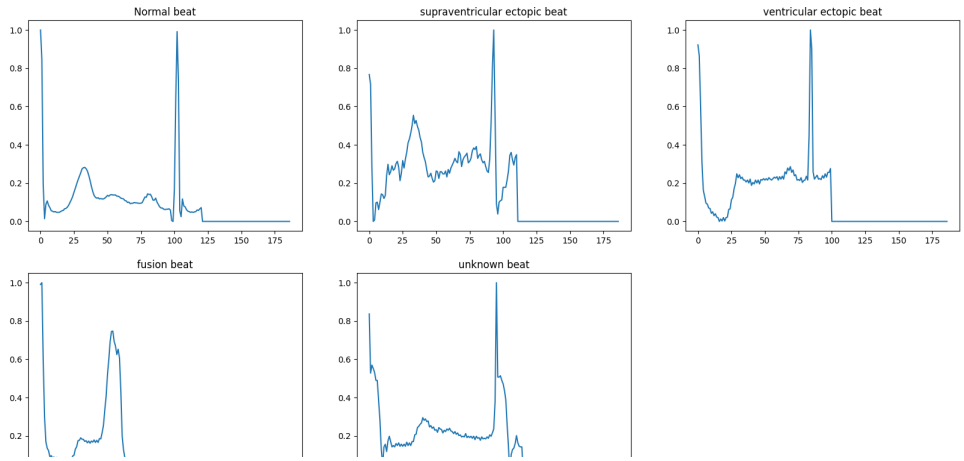
	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	186	187
0	0.977941	0.926471	0.681373	0.245098	0.154412	0.191176	0.151961	0.085784	0.058824	0.049020	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.960114	0.863248	0.461538	0.196581	0.094017	0.125356	0.099715	0.088319	0.074074	0.082621	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.000000	0.659459	0.186486	0.070270	0.070270	0.059459	0.056757	0.043243	0.054054	0.045946	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.925414	0.665746	0.541436	0.276243	0.196133	0.077348	0.071823	0.060773	0.066298	0.058011	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.967136	1.000000	0.830986	0.586854	0.356808	0.248826	0.145540	0.089202	0.117371	0.150235	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 188 columns

```
print ('infromation about train data')
train_data.info()
print ('\n infromation about test data')
test_data.info()
```

```
infromation about train data
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87554 entries, 0 to 87553
Columns: 188 entries, 0 to 187
dtypes: float64(188)
memory usage: 125.6 MB

 infromation about test data
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21892 entries, 0 to 21891
Columns: 188 entries, 0 to 187
dtypes: float64(188)
memory usage: 31.4 MB
```

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

plt.subplot(2,3,1)
plt.plot (range (0,187), (train_data.loc [train_data[187] ==0]).sample(1).iloc [:,:-1].values[0] )
plt.title ('Normal beat')

plt.subplot(2,3,2)
plt.plot ( (train_data.loc [train_data[187] ==1]).sample(1).iloc [:,:-1].values[0])
plt.title ('supraventricular ectopic beat')

plt.subplot(2,3,3)
plt.plot ( (train_data.loc [train_data[187] ==2]).sample(1).iloc [:,:-1].values[0])
plt.title ('ventricular ectopic beat')

plt.subplot(2,3,4)
plt.plot ( (train_data.loc [train_data[187] ==3]).sample(1).iloc [:,:-1].values[0])
plt.title ('fusion beat')

plt.subplot(2,3,5)
plt.plot ( (train_data.loc [train_data[187] ==4]).sample(1).iloc [:,:-1].values[0])
plt.title ('unknown beat')

plt.show()
```




```
class_names = ['normal beat', 'unknownbeat', 'ventricular ectopic beat', 'supraventricular ectopic beat', 'fusion beat']
plt.figure(figsize=(10,10))
plt.pie(train_data [187].value_counts().values, labels = class_names, autopct='%1.1f%%')
plt.show()
```

```
class_names, len(class_names)
```

```
(['normal beat',
  'unknownbeat',
  'ventricular ectopic beat',
  'supraventricular ectopic beat',
  'fusion beat'],
 5)
```

```
train_data[187].unique() #
```

```
array([0., 1., 2., 3., 4.])
```

```
array = tf.one_hot(train_data[187].unique(), depth=5)
array #
```

```
<tf.Tensor: shape=(5, 5), dtype=float32, numpy=
array([[1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.]], dtype=float32)>
```

```
X = train_data.drop([187], axis = 1)
y = train_data[187]
```

ventricular ectopic beat

```
X
```

	0	1	2	3	4	5	6	7	8	9	...	177	178	179	180	181	182	183	184	185	186
0	0.977941	0.926471	0.681373	0.245098	0.154412	0.191176	0.151961	0.085784	0.058824	0.049020	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.960114	0.863248	0.461538	0.196581	0.094017	0.125356	0.099715	0.088319	0.074074	0.082621	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.000000	0.659459	0.186486	0.070270	0.070270	0.059459	0.056757	0.043243	0.054054	0.045946	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.925414	0.665746	0.541436	0.276243	0.196133	0.077348	0.071823	0.060773	0.066298	0.058011	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.967136	1.000000	0.830986	0.586854	0.356808	0.248826	0.145540	0.089202	0.117371	0.150235	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
87549	0.807018	0.494737	0.536842	0.529825	0.491228	0.484211	0.456140	0.396491	0.284211	0.136842	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
87550	0.718333	0.605000	0.486667	0.361667	0.231667	0.120000	0.051667	0.001667	0.000000	0.013333	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
87551	0.906122	0.624490	0.595918	0.575510	0.530612	0.481633	0.444898	0.387755	0.322449	0.191837	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
87552	0.858228	0.645570	0.845570	0.248101	0.167089	0.131646	0.121519	0.121519	0.118987	0.103797	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
87553	0.901506	0.845886	0.800695	0.748552	0.687138	0.599073	0.512167	0.427578	0.395133	0.402086	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

87554 rows × 187 columns

```
y
```

```
0        0.0
1        0.0
2        0.0
3        0.0
4        0.0
        ...
87549    4.0
87550    4.0
87551    4.0
87552    4.0
87553    4.0
Name: 187, Length: 87554, dtype: float64
```

```
X.shape, y.shape
```

```
((87554, 187), (87554,))
```

```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size = 0.2, random_state = 34)
```

```
X_train.shape, y_train.shape, X_val.shape, y_val.shape
```

```
((70043, 187), (70043,), (17511, 187), (17511,))
```

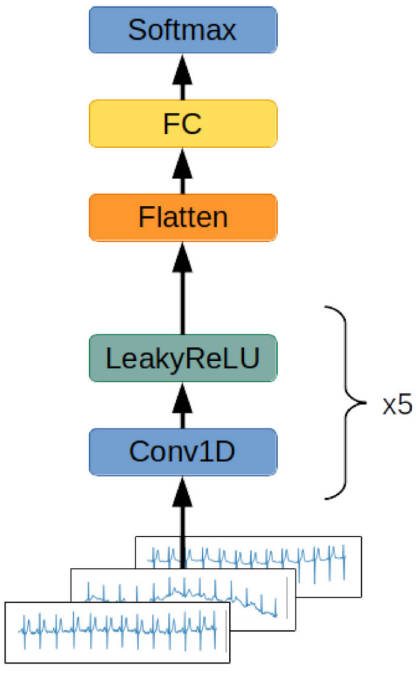
```
X_train.max(), X_train.min()
```

```
(0      1.0
 1      1.0
 2      1.0
 3      1.0
 4      1.0
       ...
 182    1.0
 183    1.0
 184    1.0
 185    1.0
 186    1.0
 Length: 187, dtype: float64,
 0      0.0
 1      0.0
 2      0.0
 3      0.0
 4      0.0
       ...
 182    0.0
 183    0.0
 184    0.0
 185    0.0
 186    0.0
 Length: 187, dtype: float64)
```

```
y_train = tf.one_hot(y_train, depth = len(class_names))
y_val = tf.one_hot(y_val, depth = len(class_names))
```

```
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Flatten, LeakyReLU, Conv1D
```

▾ Model Architecture :




```
X_train.shape
```

```
(70043, 187)
```

```
X_train = np.expand_dims(X_train, axis = 2)
X_train.shape
```

```
(70043, 187, 1)
```

```
y_train.shape
```

```
TensorShape([70043, 5])
```

```
X_val = np.expand_dims(X_val, axis = 2)
X_val.shape
```

```
(17511, 187, 1)
```

```
y_val.shape
```

```
TensorShape([17511, 5])
```

```
X_train[0].shape
```

```
(187, 1)
```

```
# model creation based on given architecture and assumed hyperparameters
model = Sequential([
    Conv1D(filters = 16, kernel_size = 3, strides = 1, padding = 'valid', input_shape = (187, 1)),
    LeakyReLU(alpha = 0.2),

    Conv1D(filters = 32, kernel_size = 3, strides = 1, padding = 'valid'),
    LeakyReLU(alpha = 0.2),

    Conv1D(filters = 64, kernel_size = 3, strides = 1, padding = 'valid'),
    LeakyReLU(alpha = 0.2),

    Conv1D(filters = 128, kernel_size = 3, strides = 1, padding = 'valid'),
    LeakyReLU(alpha = 0.2),

    Conv1D(filters = 256, kernel_size = 3, strides = 1, padding = 'valid'),
    LeakyReLU(alpha = 0.2),

    Flatten(),
    Dense(units = len(class_names), activation = 'softmax')
])
```

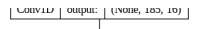
```
model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 1e-3),
              loss = tf.keras.losses.CategoricalCrossentropy(),
              metrics = ['accuracy'])
```

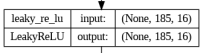
```
model.summary()
```

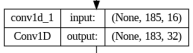
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 185, 16)           64

 leaky_re_lu (LeakyReLU)     (None, 185, 16)           0

 conv1d_1 (Conv1D)           (None, 183, 32)           1568

 leaky_re_lu_1 (LeakyReLU)   (None, 183, 32)           0

 conv1d_2 (Conv1D)           (None, 181, 64)           6208

 leaky_re_lu_2 (LeakyReLU)   (None, 181, 64)           0

 conv1d_3 (Conv1D)           (None, 179, 128)          24704

 leaky_re_lu_3 (LeakyReLU)   (None, 179, 128)          0

 conv1d_4 (Conv1D)           (None, 177, 256)          98560

 leaky_re_lu_4 (LeakyReLU)   (None, 177, 256)          0

 flatten (Flatten)           (None, 45312)             0

 dense (Dense)               (None, 5)                 226565

=================================================================
Total params: 357669 (1.36 MB)
Trainable params: 357669 (1.36 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

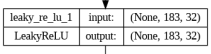
```
from keras.utils import plot_model
```

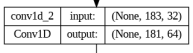
```
plot_model(model, show_shapes = True)
```

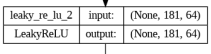


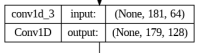


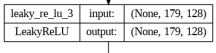


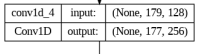


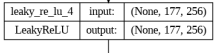


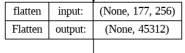


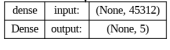













```
# training model
history = model.fit(X_train,
                    y_train,
                    epochs = 8,
                    batch_size = 128,
                    validation_data = [X_val, y_val]
                    )
```

```
Epoch 1/8
548/548 [==============================] - 19s 14ms/step - loss: 0.2555 - accuracy: 0.9303 - val_loss: 0.1623 - val_accuracy: 0.9539
Epoch 2/8
548/548 [==============================] - 7s 13ms/step - loss: 0.1361 - accuracy: 0.9623 - val_loss: 0.1350 - val_accuracy: 0.9668
Epoch 3/8
548/548 [==============================] - 7s 13ms/step - loss: 0.1085 - accuracy: 0.9702 - val_loss: 0.1096 - val_accuracy: 0.9700
Epoch 4/8
548/548 [==============================] - 7s 12ms/step - loss: 0.0933 - accuracy: 0.9740 - val_loss: 0.1015 - val_accuracy: 0.9712
Epoch 5/8
548/548 [==============================] - 8s 14ms/step - loss: 0.0829 - accuracy: 0.9763 - val_loss: 0.0903 - val_accuracy: 0.9737
Epoch 6/8
548/548 [==============================] - 7s 13ms/step - loss: 0.0759 - accuracy: 0.9785 - val_loss: 0.0856 - val_accuracy: 0.9764
Epoch 7/8
548/548 [==============================] - 7s 13ms/step - loss: 0.0703 - accuracy: 0.9797 - val_loss: 0.0869 - val_accuracy: 0.9765
```

```
Epoch 8/8
548/548 [==============================] - 7s 13ms/step - loss: 0.0648 - accuracy: 0.9814 - val_loss: 0.0909 - val_accuracy: 0.9765
```

```
X_test = test_data.drop([187], axis = 1)
y_test = test_data[187]
```

```
X_test = np.expand_dims(X_test, axis = 2)
X_test.shape
```

```
(21892, 187, 1)
```

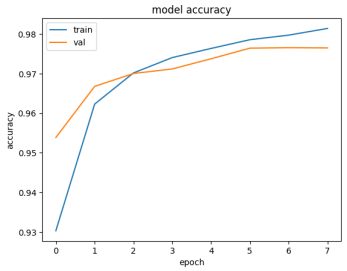
```
y_test = tf.one_hot(y_test, depth=5)
y_test.shape      # we forgot to do this that is why 88% accuracy now see :)
```

```
TensorShape([21892, 5])
```

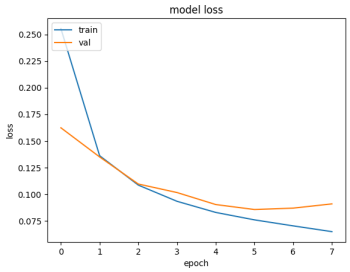
```
model.evaluate(X_test, y_test)
```

```
685/685 [==============================] - 4s 5ms/step - loss: 0.0987 - accuracy: 0.9754
[0.09870412945747375, 0.9754248261451721]
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```




```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```




```
# plot confusion Matrix and heat map of the same
# also show precision and recall
# your welcome for the project
# check step before model.evaluate
```

```
y_probs = model.predict(X_test)
y_probs[:20]
```

```
685/685 [==============================] - 2s 3ms/step
array([[9.9991560e-01, 8.3513005e-05, 5.7005312e-09, 8.8578895e-07,
        4.0846707e-08],
       [9.9973720e-01, 2.1368421e-04, 4.1517753e-05, 7.4380396e-06,
        1.3721280e-07],
       [9.9514800e-01, 2.0604040e-03, 2.4613518e-08, 3.3470375e-09,
        2.7916336e-03],
       [9.9340492e-01, 2.0377628e-04, 5.4989541e-03, 2.2270911e-05,
        8.7006344e-04],
       [9.2485076e-01, 2.5178399e-03, 6.7745537e-02, 2.0414031e-04,
        4.6818401e-03],
       [9.9999845e-01, 4.4744746e-07, 8.4541789e-08, 9.8211945e-07,
        8.2862095e-10],
       [9.9997270e-01, 1.7853532e-05, 1.6005573e-07, 9.2655682e-06,
        1.6060785e-09],
       [9.9944955e-01, 3.3400778e-04, 1.7321554e-04, 2.1243555e-07,
        4.2969470e-05],
       [9.9999714e-01, 2.8171223e-06, 4.9600999e-08, 1.1715916e-10,
        9.3769481e-10],
       [9.9978417e-01, 2.1246362e-04, 3.3574254e-06, 1.4653704e-08,
        7.2573062e-13],
       [9.9997485e-01, 1.8270977e-05, 5.5836841e-08, 6.9037146e-06,
        2.2050072e-08],
       [9.9999893e-01, 4.9375802e-07, 4.1269348e-07, 1.6807698e-07,
        3.1290623e-10],
       [9.9184239e-01, 1.3681231e-03, 3.7707850e-05, 6.7509073e-03,
        9.0356588e-07],
       [9.9791747e-01, 2.0204810e-03, 5.6419231e-05, 3.4337990e-08,
        5.5659993e-06],
       [9.9989474e-01, 3.9593371e-05, 1.5317015e-05, 8.2442577e-09,
        5.0344934e-05],
       [9.5768434e-01, 8.5590072e-03, 3.3633403e-02, 1.2179671e-04,
        1.3883288e-06],
       [9.9988401e-01, 1.1303997e-04, 1.7521492e-07, 2.8156192e-06,
        3.2939773e-10],
       [9.9926418e-01, 3.4146029e-05, 2.4250444e-06, 6.9915794e-04,
        7.4950079e-10],
       [9.9968851e-01, 3.0857595e-04, 1.1659780e-07, 2.8999004e-06,
        1.9764335e-09],
       [9.9734855e-01, 1.9787231e-03, 5.7467929e-04, 7.3613111e-05,
        2.4329775e-05]], dtype=float32)
```

```
y_pred = tf.argmax(y_probs, axis = 1)
y_pred[:10]
```

```
<tf.Tensor: shape=(), dtype=int64, numpy=0>
```

```
y_pred
```

```
<tf.Tensor: shape=(21892,), dtype=int64, numpy=array([0, 0, 0, ..., 4, 4, 4])>
```

```
import seaborn as sns
```

```
from sklearn.metrics import confusion_matrix, classification_report
```

```
cm = confusion_matrix(y_pred=y_pred, y_true=tf.argmax(y_test, axis = 1))
```

```
cm
```

```
array([[18000,    21,    50,    30,    17],
       [  205,   342,     7,     2,     0],
       [   77,     4,  1322,    40,     5],
       [   34,     0,     9,   119,     0],
       [   31,     0,     6,     0,  1571]])
```

```
print(classification_report(y_pred=y_pred, y_true=tf.argmax(y_test, axis = 1)))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99     18118
           1       0.93      0.62      0.74       556
           2       0.95      0.91      0.93      1448
           3       0.62      0.73      0.67       162
           4       0.99      0.98      0.98      1608

    accuracy                           0.98     21892
   macro avg       0.89      0.85      0.86     21892
weighted avg       0.98      0.98      0.97     21892
```