

SPRINT 2: Classification of Arrhythmia by Using Deep Learning With 2-D ECG Spectral Image Representation

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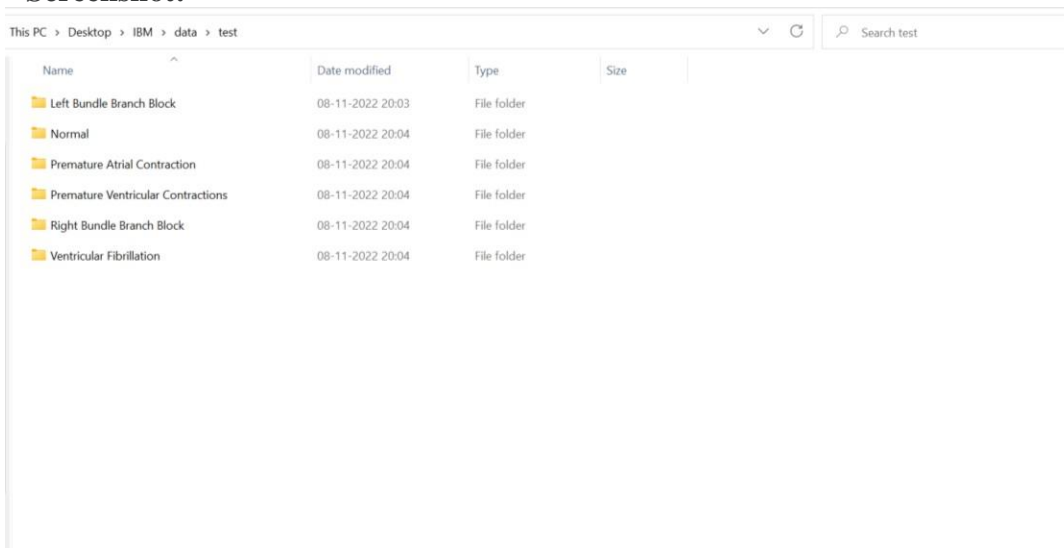
Code: Updated in GitHub in the Deliverables section in Sprint 2 folder.

Description of USN and Screenshots:

USN-4:

As a user, I want quality data to be collected for the purposes of training the model. Also, image processing methods must be employed to pre-process the dataset.

Screenshot:



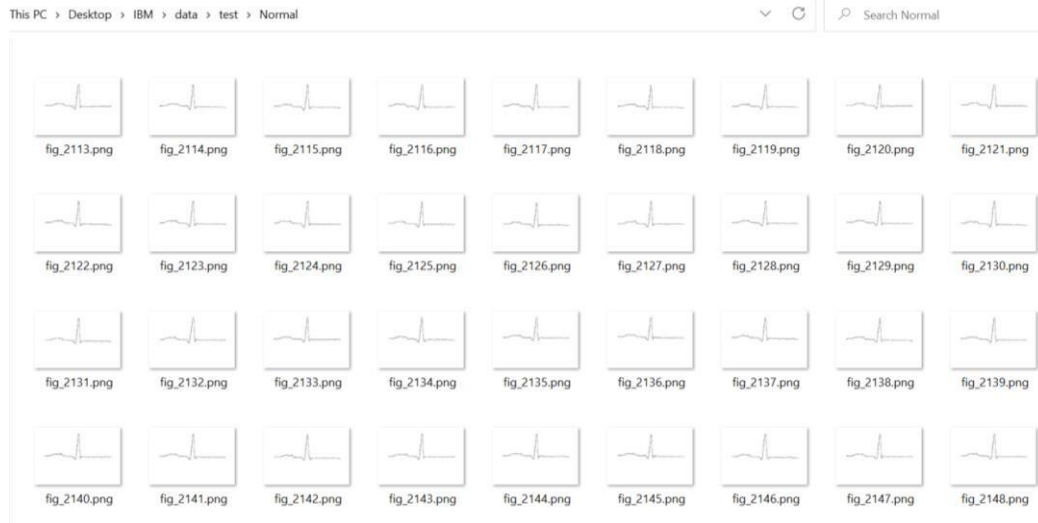


Image Split:

Left Bundle Branch Block – 504 images

Normal – 7436 images

Premature Atrial Contraction – 2054 images

Premature Ventricular Contractions – 2759 images

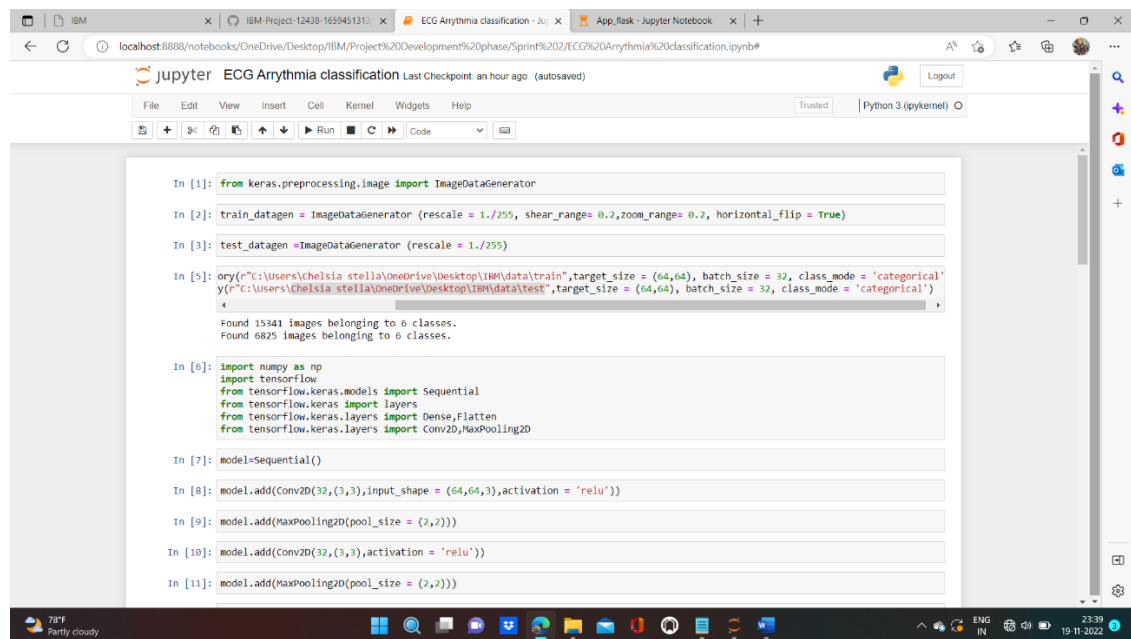
Right Bundle Branch Block – 2239 images

Ventricular Fibrillation – 439 images

For reducing skewness in the dataset, ImageDataGenerator class was used for both processing and handling with data imbalance

As a user, I want the ML model to be as accurate as possible.

Screenshot:



```
In [1]: from keras.preprocessing.image import ImageDataGenerator

In [2]: train_datagen = ImageDataGenerator(rescale = 1./255, shear_range= 0.2, zoom_range= 0.2, horizontal_flip = True)

In [3]: test_datagen = ImageDataGenerator(rescale = 1./255)

In [5]: x_train = train_datagen.flow_from_directory(r"C:\Users\Chelsia\OneDrive\Desktop\IBM\data\train", target_size = (64,64), batch_size = 32, class_mode = 'categorical')
y_train = train_datagen.flow_from_directory(r"C:\Users\Chelsia\OneDrive\Desktop\IBM\data\test", target_size = (64,64), batch_size = 32, class_mode = 'categorical')

Found 15341 images belonging to 6 classes.
Found 6825 images belonging to 6 classes.

In [6]: import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten

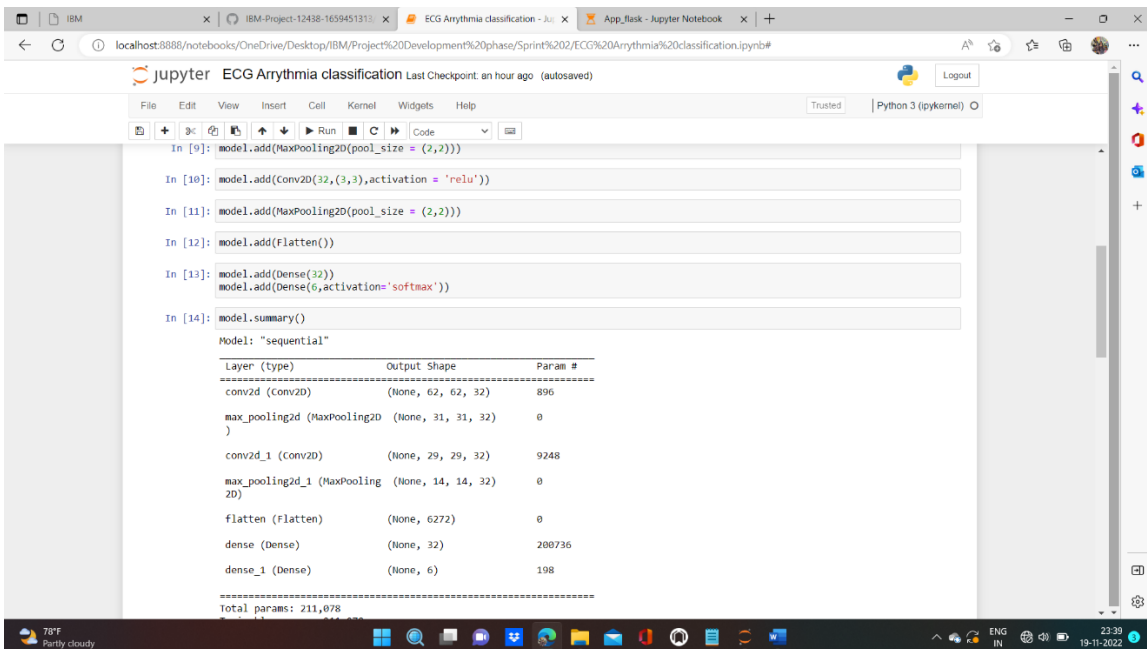
In [7]: model = Sequential()

In [8]: model.add(Conv2D(32, (3,3), input_shape = (64,64,3), activation = 'relu'))

In [9]: model.add(MaxPooling2D(pool_size = (2,2)))

In [10]: model.add(Conv2D(32, (3,3), activation = 'relu'))

In [11]: model.add(MaxPooling2D(pool_size = (2,2)))
```



```
In [9]: model.add(MaxPooling2D(pool_size = (2,2)))

In [10]: model.add(Conv2D(32, (3,3), activation = 'relu'))

In [11]: model.add(MaxPooling2D(pool_size = (2,2)))

In [12]: model.add(Flatten())

In [13]: model.add(Dense(32))
model.add(Dense(6, activation='softmax'))

In [14]: model.summary()

Model: "sequential"
Layer (type) Output Shape Param #
-----
conv2d (Conv2D) (None, 62, 62, 32) 896
max_pooling2d (MaxPooling2D) (None, 31, 31, 32) 0
conv2d_1 (Conv2D) (None, 29, 29, 32) 9248
max_pooling2d_1 (MaxPooling2D) (None, 14, 14, 32) 0
flatten (Flatten) (None, 6272) 0
dense (Dense) (None, 32) 200736
dense_1 (Dense) (None, 6) 198
Total params: 211,078
```

Model Architecture:

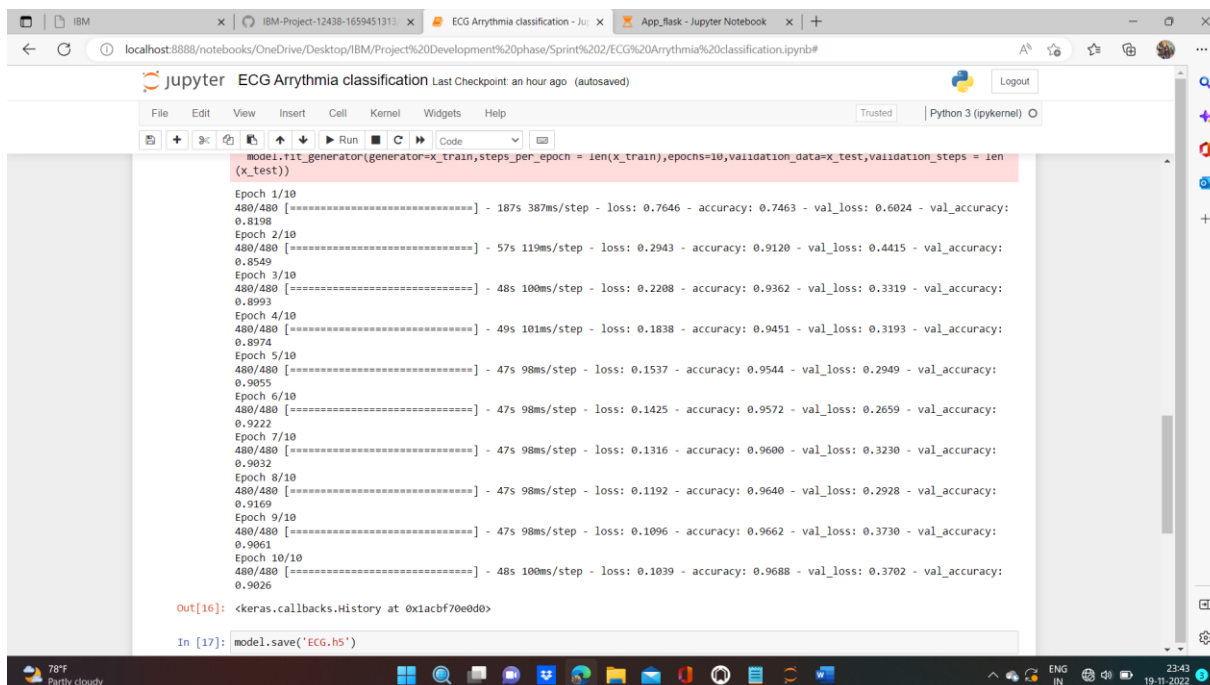
Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 32)	200736
dense_1 (Dense)	(None, 6)	198
=====		

Total params: 211,078

Trainable params: 211,078

Non-trainable params: 0



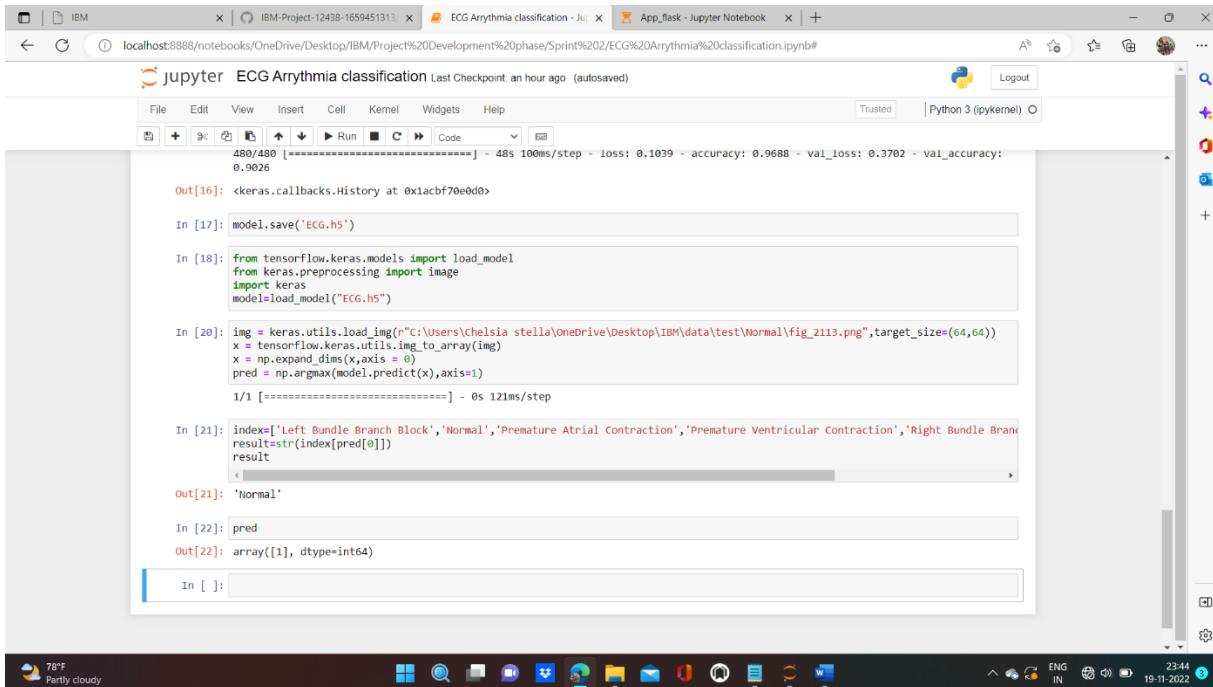
The screenshot shows a Jupyter Notebook interface with a single code cell. The code cell contains a `model.fit_generator` call and its output. The output displays training progress over 10 epochs, including time per step, loss, accuracy, validation loss, and validation accuracy. The final output shows the model's history and the save command.

```
model.fit_generator(generator=x_train, steps_per_epoch=len(x_train), epochs=10, validation_data=(x_test, y_test), validation_steps=len(x_test))

Epoch 1/10
480/480 [=====] - 187s 387ms/step - loss: 0.7646 - accuracy: 0.7463 - val_loss: 0.6024 - val_accuracy: 0.8198
Epoch 2/10
480/480 [=====] - 57s 119ms/step - loss: 0.2943 - accuracy: 0.9120 - val_loss: 0.4415 - val_accuracy: 0.8549
Epoch 3/10
480/480 [=====] - 48s 100ms/step - loss: 0.2208 - accuracy: 0.9362 - val_loss: 0.3319 - val_accuracy: 0.8993
Epoch 4/10
480/480 [=====] - 49s 101ms/step - loss: 0.1838 - accuracy: 0.9451 - val_loss: 0.3193 - val_accuracy: 0.8974
Epoch 5/10
480/480 [=====] - 47s 98ms/step - loss: 0.1537 - accuracy: 0.9544 - val_loss: 0.2949 - val_accuracy: 0.9055
Epoch 6/10
480/480 [=====] - 47s 98ms/step - loss: 0.1425 - accuracy: 0.9572 - val_loss: 0.2659 - val_accuracy: 0.9222
Epoch 7/10
480/480 [=====] - 47s 98ms/step - loss: 0.1316 - accuracy: 0.9600 - val_loss: 0.3230 - val_accuracy: 0.9032
Epoch 8/10
480/480 [=====] - 47s 98ms/step - loss: 0.1192 - accuracy: 0.9640 - val_loss: 0.2928 - val_accuracy: 0.9169
Epoch 9/10
480/480 [=====] - 47s 98ms/step - loss: 0.1096 - accuracy: 0.9662 - val_loss: 0.3730 - val_accuracy: 0.9061
Epoch 10/10
480/480 [=====] - 48s 100ms/step - loss: 0.1039 - accuracy: 0.9688 - val_loss: 0.3702 - val_accuracy: 0.9026

Out[16]: <keras.callbacks.History at 0x1acbf70e0d0>

In [17]: model.save('ECG.h5')
```



The screenshot shows a Jupyter Notebook titled "ECG Arrhythmia classification" running on a local host. The notebook contains several code cells. The first cell shows the model's history, indicating a loss of 0.1039 and an accuracy of 0.9688. The second cell saves the model as "ECG.h5". The third cell imports necessary libraries (tensorflow.keras.models, keras.preprocessing.image, and keras). The fourth cell loads an image from a local path, preprocesses it, and predicts the class. The output shows the predicted class as "Normal". The fifth cell prints the prediction result, which is an array [1].

```
Out[16]: <keras.callbacks.History at 0x1acbf70e0d0>

In [17]: model.save('ECG.h5')

In [18]: from tensorflow.keras.models import load_model
         from keras.preprocessing import image
         import keras
         model=load_model("ECG.h5")

In [20]: img = keras.utils.load_img(r"C:\Users\Chelsia stella\OneDrive\Desktop\IBM\data\test\Normal\fig_2113.png",target_size=(64,64))
         x = tensorflow.keras.utils.img_to_array(img)
         x = np.expand_dims(x,axis = 0)
         pred = np.argmax(model.predict(x),axis=1)

         1/1 [=====] - 0s 121ms/step

In [21]: index=['Left Bundle Branch Block','Normal','Premature Atrial Contraction','Premature Ventricular Contraction','Right Bundle Branch Block']
         result=str(index[pred[0]])
         result

Out[21]: 'Normal'

In [22]: pred

Out[22]: array([1], dtype=int64)

In [ ]:
```

As a user, I can view my home page in the dashboard. I will get the full idea of ECG Arrhythmia classification using CNN where the details of the webpage will be given and info about different CVDs are provided. The homepage must properly define the Arrhythmia, its causes and effects and understand how the application helps in solving the problem.

Home Info Predict

Classification of Arrhythmia by using Deep Learning with 2D ECG Spectral Image Representation

A heartbeat is an event that occurs when the heart contracts and relaxes rhythmically. Electrocardiogram (ECG) is a tool used for observing the electrical activity of the heart. Each heartbeat has a P wave, QRS complex, and T wave that represent repolarization and depolarization of the atria and ventricles of the heart. The heart rate for a healthy person ranges from 60 to 100 beats per minute. The heartbeat depends on one's instant activity that it may beat slower or faster. The heart beats faster when exercising, and it beats slower than active conditions during resting or sleeping. Arrhythmia is any abnormality in the cardiac cycle that can be considered as an irregular heart rate or irregular waveform. A heart that has an arrhythmic heartbeat cannot pump enough blood throughout the body as well as it should. This condition may damage many organs and pose a threat to daily life. Since cardiac arrhythmias are a major threat to human health, their early and accurate detection is essential in medical practice. Manual analysis of the ECG signal recordings is not efficient to correctly detect abnormalities in the heart rhythm. Analysis of long-duration ECG signals by physicians is a burdensome and time-consuming task that may yield inaccurate results. Developing automatic cardiac arrhythmia detection algorithms reduce the physician's workload, decreases arrhythmia detection time, and also improves diagnostic efficiency and accuracy. Many studies in the literature presented some forms of computer-aided systems by using different feature extraction and classification techniques to accurately detect abnormalities in the ECG signals.

A classification model to identify CVDs at their early stage could effectively reduce the mortality rate by providing a timely treatment [3]. One of the common sources of CVDs is cardiac arrhythmia, where heartbeats are known to deviate from their regular beating pattern. These deviations could be classified into various subclasses and represent different types of cardiac arrhythmia. An accurate classification of these types could help in diagnosing and treatment of heart disease patients.