Real Time Anomaly Detection in Heart Activity

Amro Ghoneim Ismail El Sharkawy Zeyad Ali

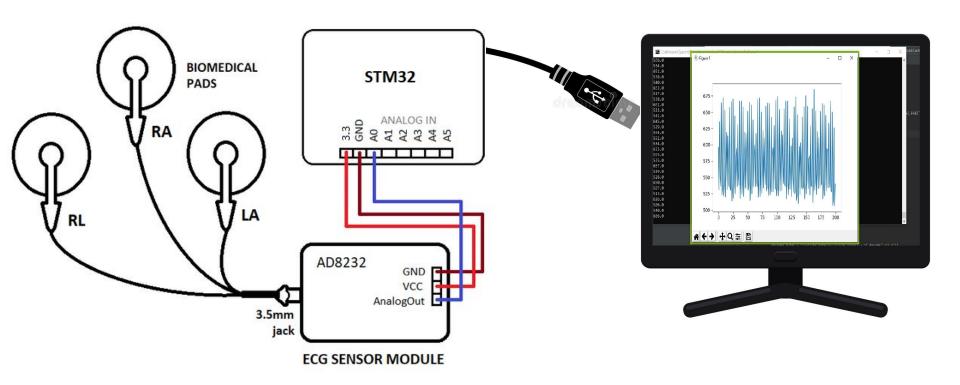
Our Project

The aim of our project is detect anomalies in heartbeats constructed from an electrocardiogram (ECG) monitor, which is the recording of the electrical pulse/activity of one's heart within the MCU. The recording of the heart beat will be displayed and the system will detect if there is an anomaly in the heart beat.

Design

- The heart pulses will be detected using the AD8232 module.
- The readings detected from the AD8232 will be sent to the STM32 microcontroller on one of its ADC input pins.
- Needed Preprocessing tasks will be applied to the incoming readings
- The readings will then be given to the machine learning model deployed on the MCU for real time inference
- The readings/output will then be transmitted via UART and/or displayed on MCU(LEDs)

Design



Implementation: Keil (Old)

The embedded code on the STM32 received the ADC input from the AD8232 and transmitted it through the UART. (Sampling rate unchanged)

```
while (1)
    // Test: Set GPIO pin high
  //HAL GPIO WritePin(GPIOB, GPIO PIN 3, GPIO PIN SET);
  // Get ADC value
 HAL ADC Start (&hadcl);
  HAL ADC PollForConversion(&hadcl, HAL MAX DELAY);
  raw = HAL ADC GetValue(&hadcl);
  // Test: Set GPIO pin low
  //HAL GPIO WritePin(GPIOA, GPIO PIN 10, GPIO PIN RESET);
  // Convert to string and print
  sprintf(reading, "%hu\r\n", raw);
  HAL UART Transmit(&huart2, (uint8 t*)reading, sizeof(reading)-5, HAL MAX DELAY);
 // Pretend we have to do something else for a while
 HAL Delay(1);
```

Sampling

- Clock Configuration
 - Set the timer clock to 8MHz
- Timer
 - Enable TIM2 for counter
- ADC interrupt
 - Fire an interrupt every 8ms

125Hz sampling rate

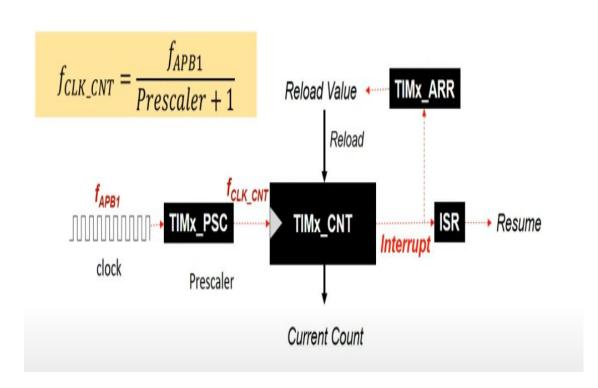
• $f_{apb} = 8MHz$

Prescaler= 7, clock counter
would count up to 1MHz (slow)

 TIM_ARR set to value we want to count to: 7999

$$f_{Interrupt} = \frac{f_{CLK_CNT}}{TIM_ARR + 1}$$

$$f_{interrupt} = 1MHz/8000 = 125 S/S$$



The embedded code on the STM32 received the ADC input by firing an ADC interrupt every 8 milliseconds (125SPS). The ADC value was read and stored each time an interrupt occurred.

```
void HAL ADC ConvCpltCallback(ADC HandleTypeDef *hadc)
/* Prevent unused argument(s) compilation warning */
UNUSED (hadc);
/* NOTE : This function should not be modified. When the callback is needed,
          function HAL ADC ConvCpltCallback must be implemented in the user file.
HAL ADC PollForConversion(&hadcl, HAL MAX DELAY);
adcval = HAL ADC GetValue(&hadcl); //getting the ADC value
//adcval= ((float)adcval/4096.0) * 2048.0;
if(count<187){ //only add the first 187 samples to the buffer in data
      in data[count] = adcval;
      if (in data[count] < min) //get the minimum value
       min=in data[count];
      if (in data[count]>max) //get the maximum value
       max=in data[count];
      count++;
sprintf(reading, "%hu", adcval); // copy the adc value to a reading buffer to display the readings if needed.
HAL UART Transmit(&huart2, (uint8 t*) reading, sizeof(reading), HAL MAX DELAY); //transmit reading
HAL UART Transmit(&huart2, (uint8 t*)newline, sizeof(newline), HAL MAX DELAY); //newline
```

After we read the ADC value and add it to the in_data buffer and then proceed to get the minimum and the maximum values for later normalization.

```
void HAL ADC ConvCpltCallback(ADC HandleTypeDef *hadc)
/* Prevent unused argument(s) compilation warning */
UNUSED (hadc) ;
/* NOTE: This function should not be modified. When the callback is needed.
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if(count<187){ //only add the first 187 samples to the buffer in data
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      if (in data[count] < min) //get the minimum value
       min=in data[count];
      if(in data[count]>max) //gt the maximum value
        max=in data[count];
      count++:
sprintf(reaumy, and, adcval); // copy the adc value to a reading buffer to display the readings if needed.
HAL UART Transmit(&huart2, (uint8 t*) reading, sizeof(reading), HAL MAX DELAY); //transmit reading
HAL UART Transmit(&huart2, (uint8 t*)newline, sizeof(newline), HAL MAX DELAY); //newline
```

In the while loop the ADC interrupt is stopped when 187 samples are collected and then these samples are normalized.

```
while (1)
  if(count>=187){ //if Counter exceeded 187 samples
    HAL ADC Stop IT(&hadcl); //stop ADC interrupts so no more values are read
     for (int j=0; j<187; j++) {
       norm in data[j] = (in data[j]-min)/(max-min); //normailize the signals in in data buffer
      test = MX & COBE AT Process (norm in data); //use the AI Process to get the prediction
      if(!isnan(test))
      {sprintf(inference, "%f\r\n", test); //copy the probability to inference array
      //HAL UART Transmit(&huart2, (uint8 t*)inference, sizeof(inference), HAL MAX DELAY);
      if((inference[2]=='9') || (inference[0]=='1')) //check if the probability is >=0.9
        HAL UART Transmit(&huart2, (uint8 t*)normal, sizeof(normal), HAL MAX DELAY); //transmit normal
      else
       HAL UART Transmit(&huart2, (uint8 t*)abnormal, sizeof(abnormal), HAL MAX DELAY); //transmit abnormal
      count =0; //reset counter
      min=9999999; //reset minimum
     max=-1; //reset maximum
      HAL ADC Start IT(&hadcl); //start ADC interrupt again.
```

Implementation: Python Application

Using python's library Pyserial, the port of interest "COM3" was specified alongside the corresponding baudrate.

UART output is read line by line and formatted using the decode("utf-8") function after being parsed to output desired format.

Data is then gathered and stored in a csv file for later review.

For better visualization of errors and changes, data is then graphed in real time as shown in slide 8.

```
plot window = 200
y_var = np.array(np.zeros([plot_window]))
plt.ion()
fig, ax = plt.subplots()
line, = ax.plot(y var)
if ser.isOpen():
        while 1:
            ser bytes = ser.readline()
            decoded bytes = float(ser bytes[0:len(ser bytes) - 2].decode("utf-8"))
            print(decoded bytes)
                writer = csv.writer(f, delimiter=",")
                writer.writerow([time.time(), decoded_bytes])
                y_var = np.append(y_var, decoded_bytes)
                y_var = y_var[1:plot_window + 1]
                line.set ydata(y var)
                ax.relim()
                ax.autoscale view()
                fig.canvas.draw()
                fig.canvas.flush events()
        print("error")
                                                                                  Looks like you're using NumPy
```

ser = serial.Serial(port='COM3', baudrate=9600, bytesize=serial.EIGHTBITS, parity=serial.PARITY NONE, timeout=2)

ser.flushInput()

About the Data set

- Number of Samples: 109446
- Number of Categories: 5
- Sampling Frequency: 125Hz
- Data Source: Physionet's MIT-BIH Arrhythmia Dataset
 - Preprocessing steps described in this paper to create the data set
- Classes: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]
 - N is the normal class and the rest are different anomalies

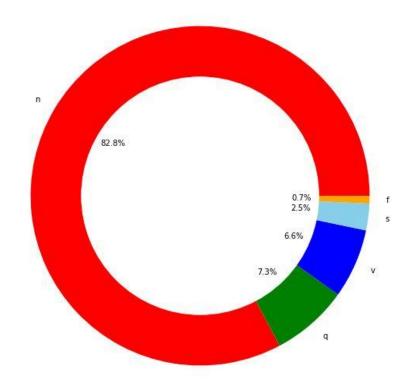
Data set Class Distribution

Initial Class distribution of the data set shows highly imbalanced data!

This will affect model performance for detecting anomalies

```
9 72471
4 6431
2 5788
1 2223
3 641
```

Name: 187, dtype: int64



Data set resampling

Resampled the data set to have a balanced class distribution

Each class now has 20,000 samples each

4 20000

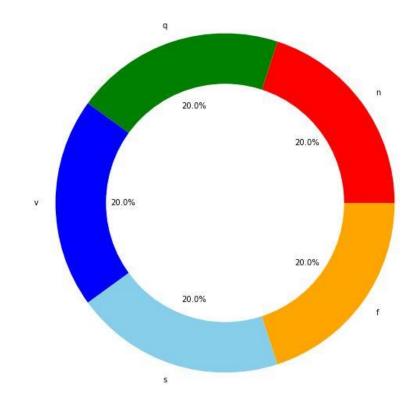
3 20000

2 20000

1 20000

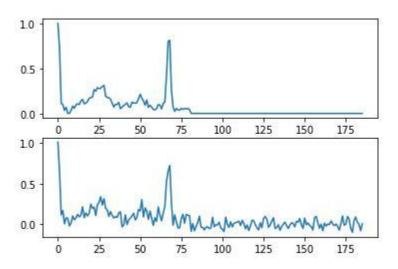
9 20000

Name: 187, dtype: int64



Other preprocessing techniques

Added some noise to the data to make it more generalized



Keras

Open-source neural-network library written in Python

Can run on top of Tensorflow, Theano and other machine learning frameworks

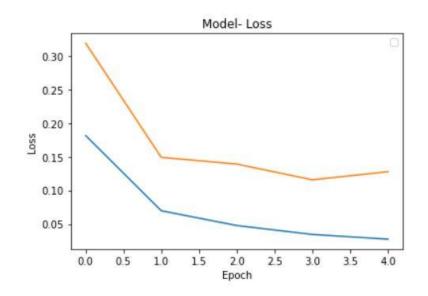
User Friendly, Modular and Extensible

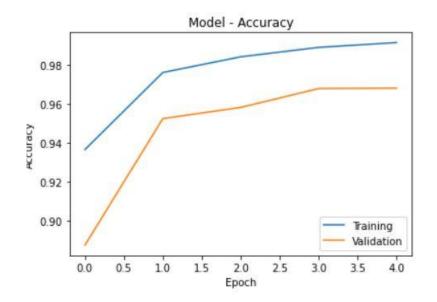
Model Architecture - initial

```
data input=(X train.shape[1],1)
inputs cnn=Input(shape=(im shape), name='data input')
conv1 1=Convolution1D(64, (6), activation='relu', input shape=im shape)(inputs cnn)
conv1 1=BatchNormalization()(conv1 1)
pool1=MaxPool1D(pool size=(3), strides=(2), padding="same")(conv1 1)
conv2 1=Convolution1D(64, (3), activation='relu', input shape=im shape)(pool1)
conv2 1=BatchNormalization()(conv2 1)
pool2=MaxPool1D(pool size=(2), strides=(2), padding="same")(conv2 1)
conv3 1=Convolution1D(64, (3), activation='relu', input shape=im shape)(pool2)
conv3 1=BatchNormalization()(conv3 1)
pool3=MaxPool1D(pool size=(2), strides=(2), padding="same")(conv3 1)
flatten=Flatten()(pool3)
dense end1 = Dense(64, activation='relu')(flatten)
dense end2 = Dense(32, activation='relu')(dense end1)
main output = Dense(5, activation='softmax', name='main output')(dense end2)
```

Results - initial

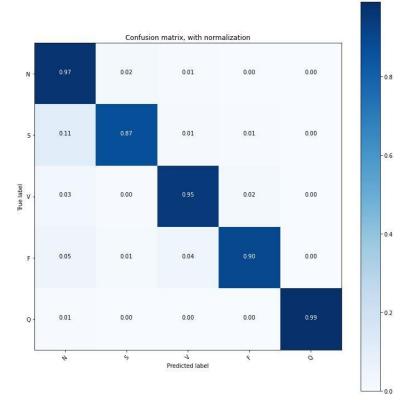
The graphs below show the training accuracy and validation loss over 5 epochs





Results - initial

 The confusion matrix shows that the model performs on the test set with slight decrease in results for the two classes S and F



STM32Cube.Al

- Interoperable with popular deep learning training tools (Keras)
- Compatible with many IDEs and compilers (Keil)
- Sensor and RTOS agnostic
- Allows multiple Artificial Neural Networks to be run on a single STM32 MCU
- Full support for ultra-low-power STM32 MCUs
- Allows for model compression (x4 & x8)

STM32Cube.Al

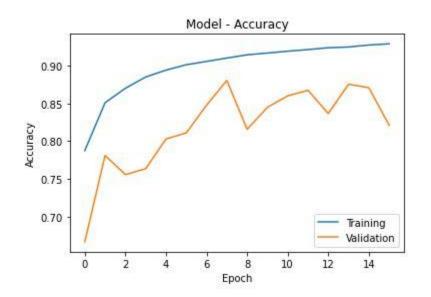
- Initial model too big for nucleo board provided, even after
 x8 compression
- New model implementation
 - a. consumes around 6.7KB of flash after x8 compression with somewhat degraded yet comparable results

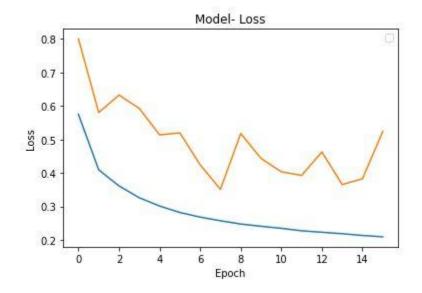
Model Architecture - final

```
def network_1(X_train,y_train,X_test,y_test):
    data_input=(X_train.shape[1],1)
    inputs_dense = Input(shape = (data_input), name = 'data_input')
    dense_1 = Dense(50, activation='relu', input_shape=data_input)(inputs_dense)
    dense_2 = Dense(50, activation='relu')(dense_1)
    flat = Flatten()(dense_2)
    dense_out = Dense(5, activation='softmax', name='main_output')(flat)
    model = Model(inputs= inputs_dense, outputs=dense_out)
    model.compile(optimizer='adam', loss='categorical_crossentropy',metrics = ['accuracy'])
```

Results - final

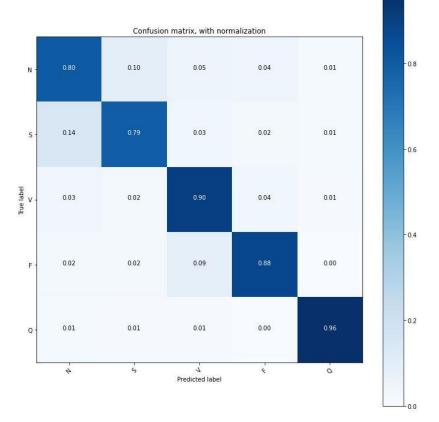
The graphs below show the training **accuracy** and **validation loss** over **20** epochs with overall accuracy of around 92%





Results - final

The confusion matrix
 shows that the new model
 is somewhat close to the
 initial model's results



STM32Cube.Al APIs

- STM32Cube.Al provides an application template for its APIs for easier deployment
 - MX_X_CUBE_AI_Init() function used to create and initialize the Neural Network

```
void MX_X_CUBE_AI_Init(void)

{
    /* USER CODE BEGIN 0 */
    /* Activation/working buffer is allocated as a static memory chunk
    * (bss section) */
    AI_ALIGNED(4)
    static ai_u8 activations[AI_NETWORK_DATA_ACTIVATIONS_SIZE];

aiInit(activations);
    /* USER CODE_END 0 */
}
```

STM32Cube.Al APIs

- STM32Cube.Al provides an application template for its APIs for easier deployment
 - MX_X_CUBE_AI_Process() function used to run the model and get the results

```
float MX_X_CUBE_AI_Process(const float* in_data)
{
    /* USER CODE BEGIN 1 */
    int res;

    static float out_data[5];

    /* Perform the inference */
    res = aiRun(in_data, out_data);

    return out_data[0];

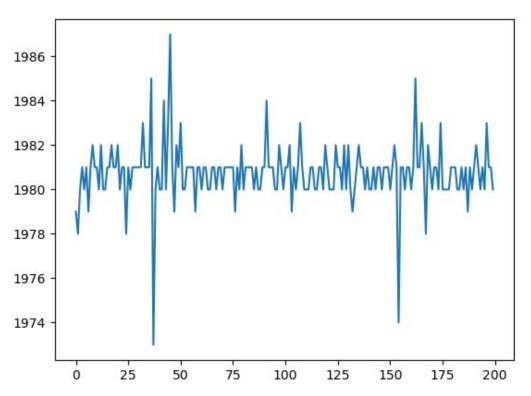
    /* USER CODE END 1 */
}
```

The normalized values are sent to the Al_Process API for prediction and are then returned and copied to the inference array. Based on the inference value "normal" or "abnormal" is transmitted to the UART.

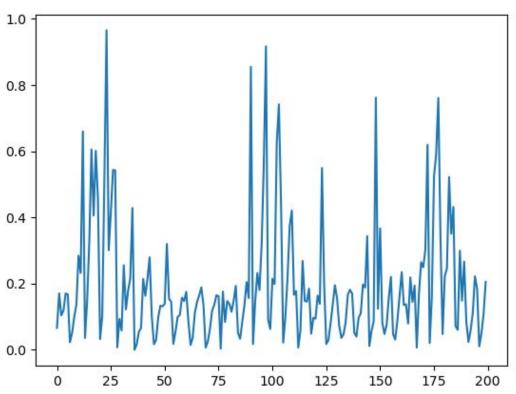
```
while (1)
  if(count>=187){ //if Counter exceeded 187 samples
    HAL ADC Stop IT(&hadcl); //stop ADC interrupts so no more values are read
     for (int j=0; j<187; j++) {
       norm in data[j] = (in data[j] min)/(max min),
      test = MX X CUBE AI Process(norm in data); //use the AI Process to get the prediction
      if(!isnan(test))
      {sprintf(inference, "%f\r\n", test); //copy the probability to inference array
      //HAL UART Transmit(&huart2, (uint8 t*)inference, sizeof(inference), HAL MAX DELAY);
      if((inference[2]=='9') || (inference[0]=='1')) //check if the probability is >=0.9
        HAL UART Transmit(&huart2, (uint8 t*) normal, sizeof(normal), HAL MAX DELAY); //transsmit normal
      else
        HAL UART Transmit(&huart2, (uint8 t*)abnormal, sizeof(abnormal), HAL MAX DELAY); //transmit/abnorma
      min=999999; //reset minimum
      max=-1; //reset maximum
      HAL ADC Start IT(&hadcl); //start ADC interrupt again.
```

Results

ADC Signal



ADC Signal Normalized



Final output Prediction:

```
Normal Good Job
Abnormal
Normal Good Job
Abnormal
Normal Good Job
Normal Good Job
Normal Good Job
```

Comments on the results

- The model performs the inference and returns the results to be displayed.
- The results achieved are not quite accurate due to a number of limitations.
 - Data coming from the sensor is noisy.
 - Memory limitations regarding the nucleo MCU led to the usage of a highly compressed model with somewhat degraded results.
 - Limitations regarding Keil IDE did not allow for full implementation of the required preprocessing tasks that are described by the Data set's paper
- Therefore, further work regarding the preprocessing of the data is required to allow for better results.

