A Smart Wearable for Real-time Cardiac Disease Detection using Beat-by-beat ECG Signal Analysis with an Edge Computing AI Classifier

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***Abstract*—This paper introduces a novel edge-computing wearable device for real-time beat-by-beat electrocardiogram (ECG) classification. Early detection of heart disease can prevent and improve the patient's health and minimize the load on healthcare professionals. The proposed wearable integrates the pre-trained artificial intelligence (AI) model with the device firmware to detect abnormal ECG beats. The wearable contains a custom printed circuit board (PCB) connected to a commercial Bluetooth system on chip (SoC) to process ECG signals. The AI-integrated firmware is programmed into 32 bit *ARM®* *Cortex™* based SoC. Data pre-processing, feature extraction, and inferencing are done on the SoC. The smart wearable is tested by passing the MIT-BIH test dataset through the wearable system as sample real-time data. The accuracy of the proposed device is assessed by testing normal and 4 abnormal ECG beats. The ANN model, after testing, provides an accuracy of 90.6% with a precision of 95.6% and a recall of 95.1%. The system consumes low power, a maximum of 128 mW, and offers a low latency of 6 ms for inferencing. The wearable is also tested on 5 subjects. The proposed wearable is smart, low-powered, and suitable for real-time regular cardiac monitoring. The performance indicates the device can effectively detect abnormal heart rhythms.**

***Index Terms*—smart wearable, edge computing, electrocardiogram, artificial neural network (ANN), real-time classification**

I. Introduction

Coronary heart disease can be critical and can lead to loss of life. With a rapidly increasing number of cardiac patients, many of these patients learn about their cardiac disease after they go through any symptoms or, certain illnesses [1]. Regular monitoring of the electrocardiogram (ECG) can prevent any underlying heart issues. Many clinical methods are already available to diagnose cardiac health. However, the users might not prefer clinical services for daily monitoring, especially those, who do not possess any symptoms of cardiac disorder. Wearable devices have been developed to store and analyze ECG data at a later time [2]. However, these applications lack real-time data classifications.

Several deep learning algorithms have already been introduced to detect the abnormalities from the cardiac signal [3-4]. ANN-based cardiac disease detection consumes less memory and processing power which makes it suitable for integration in smart wearable systems [5]. Mobile health (mHealth) applications are used to offer real-time detection but, with a cost of higher latency and more consumed power for inferencing [6].

The proposed wearable is a low-power device that offers real-time inferencing with a low latency of 6 ms. This implements an ANN-based model to detect 5 different beats of ECG: N (Normal), SV (Supraventricular Ectopic), V (Ventricular Ectopic), F (Fusion), and Q (Unknown) beats. The system takes low power and latency as all signal processing and inferencing are performed on a 32-bit Bluetooth low energy (BLE) system on chip (SoC). The MIT-BIH dataset is used for training and testing [7]. The ANN model is trained in *Edge Impulse®* platform suitable for developing AI models for edge devices [8]. The platform provides the pre-trained model as a C++ library [9]. The library is then merged into the SoC firmware to perform AI classification from the wearable.

II. System Architecture

In this section, the overall hardware-firmware codesign and the neural network (NN) architecture are discussed.

A. Hardware Design

The wearable device includes three main hardware blocks: the custom printed circuit board (PCB), the power unit, and a commercial board with the processing unit. Fig. 1 presents an overview of the system. The custom PCB incorporates an

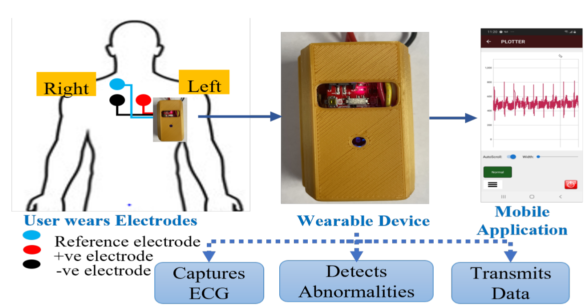

Fig. 1. Overall architecture of the proposed system.

AD8232 chip (Analog Devices, USA) and filtering circuitry to form an analog front end (AFE). The AFE captures the analog ECG data with the help of 3 commercial gel electrodes placed on the chest.

The analog signal is processed by the nRF52840 Sparkfun mini (Sparkfun, USA) board. The board includes the Bluetooth 5.3 SoC that features a Raytac MDBT50Q-P1M module with a 32-bit *ARM*® *Cortex*™ CPU and 2.4 GHz Bluetooth radio. The power unit uses a rechargeable Lipo battery (Pkcell LP552530) of 350 mAhr. The Sparkfun mini board provides the charging circuitry. Fig. 2 presents key hardware modules.

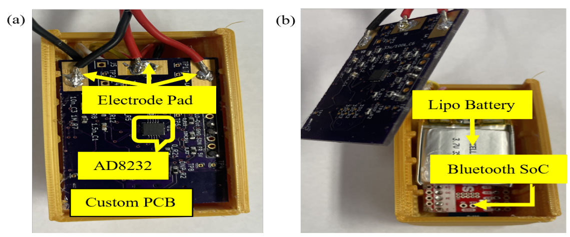

Fig. 2. Custom device: a) custom PCB and b) Bluetooth SoC and power unit.

The system uses timer interrupt and direct memory access for efficient data processing. A detailed hardware description is given in a previous work [10].

B. Firmware Design

The firmware of the wearable includes a deployed ANN model, ECG data processing, and Bluetooth transmission (Tx) protocol. After training the ANN model in the *Edge Impulse*® platform, the model is deployed as a C++ library. The library is integrated with the rest of the firmware code and programmed into the 32-bit *ARM*® *Cortex*™ CPU (64 MHz) SoC. An overall design of the device firmware is shown in Fig. 3.

1) Pre-processing: ECG data is obtained from the AFE at a sampling rate of 360 Hz, the same as the MIT-BIH data sampling rate. Sampled signals are filtered through a band pass filter (BPF). The lower cutoff frequency of the BPF is chosen 0.5 Hz to remove any DC offset and the higher cutoff frequency is chosen 150 Hz to remove any artifacts.

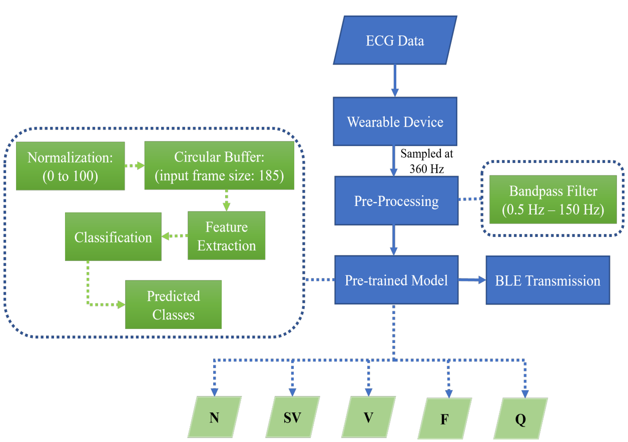

Fig. 3. Flowchart of the device firmware.

2) Pretrained model: As shown in Fig. 3, the filtered ECG data are normalized to a range of 0 to 100 and saved inside a circular buffer. The features are extracted when the buffer has stored 185 samples, equal to the input frame size of the NN. The inference thread is then executed to classify the ECG beats into 5 possible classes: N, SV, V, F, and Q. Data pre-processing, feature extraction, and classification are done in real-time, on SoC.

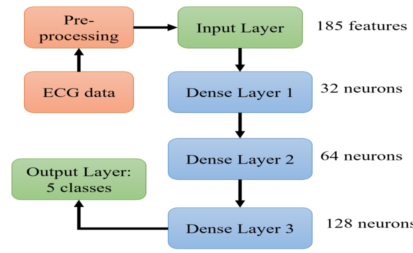

Fig. 4. The architecture of the ANN model.

Fig. 4 depicts the architecture of the ANN model. The pre-processed raw data are used as the input features. The input layer has 185 features followed by 3 dense layers. The number of neurons is 32, 64, and 128 respectively at each dense layer. The deployed ANN model is trained by 100 epochs. The model takes 77.6 kB of flash, 2.3 KB usage of peak RAM, and $\sim$ 6 ms for inferencing.

3) BLE data transmission: The BLE data Tx starts once the inference result is ready. Each BLE packet contains the ECG samples and the predicted label. A BLE gatt Nordic UART service (NUS) is used to transmit the data to the mobile application at a rate of 115200 baud. The device utilizes a BLE data rate of 1 Mbps. The firmware is developed under *Visual Studio Code*® environment. USB bootloading technique is used to flash the firmware code. Required compiler and linker flags are added to the makefile to merge C++ libraries to the project. The size of the application is $\sim$ 137 KB.

III. Results

In this section, the train-test performance of the pre-trained ANN model is presented as well as the real-time data acquisition from the smart wearable is illustrated.

Table I gives the performance over the validation set, the time, and memory consumption by the BLE SoC for different ANN architectures. The MIT-BIH dataset is split into 60%-20%-20% for training, validation, and testing respectively. NN

TABLE I
Validation Set Performance of the BLE SoC for the ANN Model with 3 Dense Layers: Layer 1, 2, 3 (L1, L2, L3)

Number of neurons (L1, L2, L3)	Inference time (ms)	RAM usage (KB)	Flash usage (KB)	ANN Accuracy (%)
16, 32, 64	6	2.2	34.3	95.8
24, 48, 96	6	2.2	53.8	96.0
32, 64, 128	6	2.3	77.6	97.4
64, 128, 256	16	2.9	224.1	97.5

with less number of layers can infer fast but provide low accuracy. With 3 dense layers, the accuracy tends to increase as the number of neurons is incremented. Meanwhile, NN models with a higher number of neurons tend to provide similar accuracy but consume more RAM, flash memory, and inferencing time. Considering all the constraints, the ANN model with 32, 64, and 128 neurons is chosen for the proposed wearable. Table I refers to the validation set accuracy after 100 epochs for the unoptimized float32 model. The performance data are provided by the *Edge Impulse*® studio.

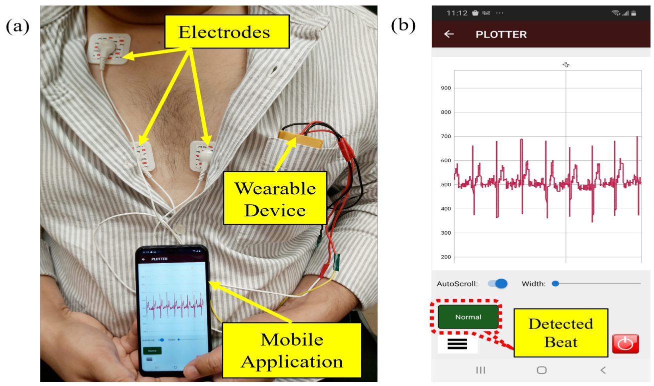

Fig. 5. Smart wearable: (a) setup of the wearable, (b) classification results sent to the mobile application

Fig. 5(a) shows the real-time data acquisition setup where the custom wearable is put on the chest pocket. 3 commercial gel electrodes are used to get the electrical activity of the heart. The wearable is responsible for data capture, pre-processing, feature extraction, and beat classification. The predicted beat as well as the ECG samples are sent by the wearable to a custom mobile application. The purpose of the mobile application is only to visualize the wearable performance. As presented in Fig. 5(b), the ECG data and classification results transmitted by the BLE are observed in the mobile application.

TABLE II
THE PERFORMANCE METRICS OF THE ANN MODEL FOR VALIDATION SET

	N	SV	V	F	Q
N	14219	36	64	27	31
SV	123	326	10	0	10
V	72	4	1066	12	3
F	14	0	10	107	0
Q	23	1	6	1	1346

87,555 ECG beats of 5 classes are used to train and validate the ANN model. The model is tested by passing 21,892 MIT-BIH test samples into the wearable device as mock data. The training, validation, and test split ratio is 60%-20%-20% respectively. The validation set performance of the ANN model is depicted in Table II. The table provides the confusion matrix for all 5 classes, where, the rows represent the true or, expected classes and columns represent the predicted classes. The values inside each cell indicate the number of ECG beats predicted for different classes. For the validation set, the overall accuracy of the ANN model is found 97.4%.

TABLE III
THE PERFORMANCE METRICS OF THE PRETRAINED ANN MODEL FOR TEST DATASET IMPLEMENTED ON SOC FIRMWARE

	N	SV	V	F	Q
N	17581	41	319	130	47
SV	134	356	57	0	9
V	72	4	1276	19	77
F	31	5	6	114	6
Q	38	56	3	0	1511

The ANN model is tested from the wearable device with a minimum confidence rating of 0.8. The MIT-BIH test dataset is added to the SoC firmware for classifying ECG beats. Table III provides the wearable performance for the test dataset where rows and columns have the same representation as Table II. The smart wearable has successfully detected 17581 N (Normal) beats out of 18118 N beats. Similarly, 356, 1276, 114, and 1511 beats are successfully detected out of 556, 1448, 162, and 1608 SV, V, F, and Q beats respectively.

TABLE IV
PERFORMANCE EVALUATION OF THE PRE-TRAINED MODEL

ECG beats	MIT-BIH test samples	Precision (%)	Recall (%)	F1 score (%)
N	18118	98.45	97.03	97.73
SV	556	77.05	64.02	69.93
V	1448	76.82	88.12	82.08
F	162	43.34	70.37	53.64
Q	1608	91.58	93.97	92.76
Overall	21892	Accuracy: 90.6 %		

Table IV provides the performance of the pre-trained model on the wearable device. The device can effectively detect all 5 classes. The MIT-BIH dataset contains limited instances of SV and F beats. The performance of SV and F beat detection can be enhanced if more data are added. SV, V, and F beats are the three forms of arrhythmia that can be used to detect abnormalities from the ECG stream.

TABLE V
PERFORMANCE OF THE PROPOSED WEARABLE ON 5 SUBJECTS (SX)

Subjects (Sx)	Detected ECG Beats				
	N	SV	V	F	Q
S1	147	0	2	0	2
S2	161	1	2	0	0
S3	175	0	0	0	1
S4	162	0	3	0	1
S5	153	1	2	0	1

The proposed wearable is used for real-time cardiac beat detection on 5 different subjects for a 2-minute duration. The project has IRB approval (Texas Tech University IRB approved IRB2020-783) and written consent was taken before taking the data. The subjects were 3 male and 2 female aged between 20 to 30 years with no known cardiac abnormalities. As shown in Table V, most of the beats are detected as normal beats.

IV. Discussion

The proposed wearable implements a pre-trained ANN model to detect the heartbeats. The device consumes a maximum of $\sim$ 128 mW power during the BLE data transfer process making it suitable for low-power applications. An oscilloscope (Model. Rigol MS05104) is used to measure the power consumption. Similarly, the average power is measured as $\sim$ 15 mW during an active session and $\sim$ 1.5 mW of power during sleep mode. The device offers a low latency of 6 ms for inferencing, a major requirement for real-time operation. The latency is also measured with the help of an oscilloscope. To measure the latency, a digital output pin of the SoC is turned on and off respectively, before and after the inference thread. The corresponding duration of voltage shift is noted from the oscilloscope to find out the actual latency.

TABLE VI
Performance Comparison between the Proposed Work and Other AI Implemented Hardware

Properties	Enériz *et al.* [11]	Kwiatkowski et al. [12]	Wang et al. [13]	Huang et al. [14]	Ezekiel et al. [15]	This work
Hardware	Xilinx 7020 FPGA, 100 MHz	ARM Cortex M7 CPU, 100 MHz	GRU-MT-ABN	STM32F7, 216 MHz	TE0802 FPGA, 133 MHz	ARM Cortex M4 CPU, 64 MHz
Application	SHW	SHW	Cloud	SHW	SHW	SHW
Signal type	PCG	PCG	ECG	ECG	ECG	ECG
NN model	U-Net CNN	Tiny CNN	RNN	LSTM	ANN	ANN
# of class	4	3	2	6	2	5
Accuracy, %	90.5	91.6	95	90	95.9	90.6
Inference, ms	29	12	250	1000	41.99	6
Power	722 mW	-	1200 J/s	137.4 mW	-	128 mW

Table VI provides a comparative analysis of this work with other smart wearable devices. Applications are mostly based on either CPU or, FPGA-based smart hardware (SHW) or cloud computation. Mainly two types of signals, phonocardiogram (PCG) and ECG are analyzed by existing works. The proposed device offers a reasonable testing accuracy of 90.6% compared to other devices as well as, provides lower latency and lower power during real-time cardiac monitoring.

V. Conclusion

An AI-integrated edge computing wearable device is proposed in this paper. The device is a low-power solution with fast computational ability. The smart wearable shows promising performance in real-time ECG beat classification. The MIT-BIH dataset is used to train the ANN model and the results indicate that the wearable can effectively and accurately detect different heart-beats. The performance is evaluated by the MIT-BIH test dataset and 5 volunteer data. The wearable can serve as a system for early detection and continuous monitoring of cardiac abnormalities.

The wearable shows great potential for cardiovascular health management. By completing an extensive amount of computation with a limited resource, the device is offering a fast and low-power solution. In the future, we will focus on optimizing the NN model for efficient operation. We intend to validate the real-time ECG beat detection by an expert cardiologist.

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