A Wearable High Blood Pressure Classification Processor Using Photoplethysmogram Signals through Power Spectral Density Features

Abstract—**High blood pressure is a major source of health problems related to mental stress, cardiac issues, kidney problems, vision, and brain. High blood pressure bursts can damage and rupture blood vessels and cause strokes. Therefore, it is quite important to continuously monitor the blood pressure of high blood pressure patients. Conventional blood pressure monitoring devices can cause discomfort to the patients during the inflation process. The photoplethysmographic signals measure the volume changes in the human blood through human skin. This work presents a high blood pressure classification processor using photoplethysmographic signals through an artificial intelligence (AI) based boosted circuit. A data set of 25 participants was collected. Ten out of the 25 participants were high blood pressure patients. The AI boosted circuit calculates the power spectral densities, power spectral densities difference, and the sum of the consecutive difference between photoplethysmographic signals. The features are forwarded to a small 2-level DT classifier. The decision tree classifier classifies the systolic and diastolic high blood pressures with 96.2% classification accuracy on an Artix-7 FPGA.**

Index Terms—**Photoplethysmographic (PPG), Blood Pressure (BP), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Decision Tree**

I. Introduction

Human Blood Pressure (BP) quantifies the effort by blood to circulate in the arteries. Human arteries circulate blood from the heart to other organs in the body [1]. The pressure asserted by the blood on the arteries is measured as BP. BP measures in millimeters of mercury (mmHg). For example, the BP measurement of 120mmHg employs that the measured BP can drive $120mm$ of mercury liquid. BP is quantified as two different measures called systolic BP (SBP) and diastolic BP (DBP). The SBP and DBP measure the BP during the blood pumping and relaxing states of the human heart respectively [1]. Fig.1(a) shows how the blood cells put pressure on the arteries. Fig.1(b) depicts the SBP and DBP during the pumping state and relaxing state of the heart.

High BP is caused by several factors including genetic, obesity, dietary issues, work and/or family stress, etc [2]. It is reported that nearly half of the US adults suffer from high BP. It is not only reported as a major cause of death in the USA resulting in more than 0.5 million deaths annually but it also costs in excess of $131 billion per year. High BP can damage the human heart in several ways causing angina, heart attack, and heart failure [3]. It creates difficulties for the human heart to pump blood through the body due to high pressure in the blood vessels which damages the heart chambers [4]. Human kidneys contain different filtering units called nephrons [5]. These nephrons filter the waste material through different blood vessels. The high BP damages the blood vessels. The damaged blood vessels are unable to supply oxygen and necessary nutrition to the nephrons for the proper functioning of the human kidney [5].

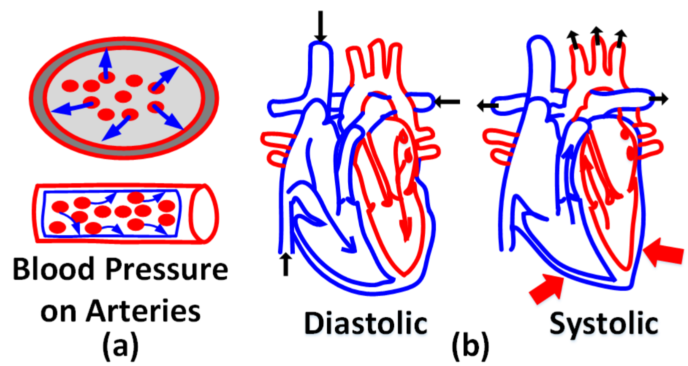

Fig. 1. (a) BP measurement (b) Systolic and Diastolic BP

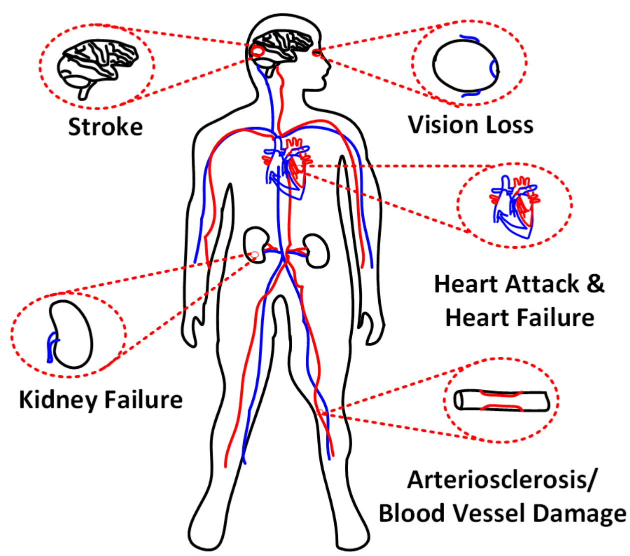

Fig. 2. Effect of High BP on Human Body

The human brain requires a healthy supply of blood to work [6]. The high BP disrupts that supply and affects the proper functioning of the human brain in several ways. High BP damages the blood veins. The damaged blood veins are highly likely to be ruptured causing brain stroke or a mini-stroke called a transient ischemic attack or cognitive impairments [6]. High BP can also damage human eyesight by rupturing the retina or the optical nerves [7]. These damages can cause temporary or permanent vision loss. Fig.2 portrays the effect of high BP on the human body including vision loss, strokes, heart attack, heart failure, kidney failure, and blood vessels damage.

The American heart association advises high BP patients to frequently monitor their blood pressure at home [8]. The hypertension patients or the patients who have suffered from transient ischemic attack in the past need to monitor their blood pressure continuously and vigilantly because of being at a higher risk of brain stroke.

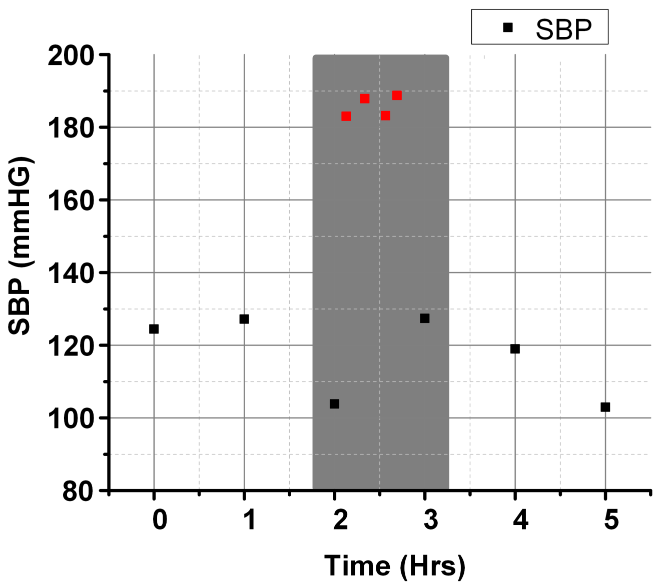

Fig. 3. SBP Values of a patient

Fig.3 depicts the SBP values of a high BP patient monitored hourly between 0 to 5 hours. It can be observed that the SBP of the patient is close to the normal value (120 mmHg) if monitored hourly. However, the patient may suffer from intermediate-high BP bursts highlighted in red. These high BP values can be left unnoticed in hourly monitoring. However, these patients can feel discomfort due to the pressure asserted by inflation on arm for frequent BP monitoring. Therefore, there is a dire need for continuous and noninvasive high BP prediction methods for hypertension patients [9].

Photoplethysmography (PPG) signals have shown a great potential for non-invasive and continuous BP prediction in recent studies [9]. PPG is an optical signal used to measure the blood volume changes during circulation and has shown a strong relationship with BP. This work focused on a prototype for a wearable device to predict high BP using PPG signals. The proposed device can timely predict the high BP of a patient after suitable features extraction and machine learning classification using PPG signals. The proposed method shows promising results for high BP prediction with a classification accuracy greater than 95%. It classifies the SBP and DBP using the features of power spectral densities (PSD) in 0-2 Hz, 2-5 Hz, PSD difference between both PSD bands (0-2 Hz and 2-5 Hz), and sum of consecutive PPG signals,

II. Data Set Collection

The blood pressure of 25 subjects aged between 20 to 45 years was measured using a commercially available BP measurement device. The PPG signals of the subjects were recorded in parallel for ten minutes using MAX30102 PPG sensor integrated with ATMEGA 32 micro-controller. Fig.4 shows the BP and PPG measurements of a subject during the data set collection. The recorded data set was then utilized for the high BP classification using an artificial intelligence boosted circuit. The SBP and DBP values greater than or equal to 140 and 90 mmHG respectively were classified as high SBP or high DBP respectively.

Fig. 4. BP Measurement of a subject

III. Previous Contributions

Wearable healthcare devices have gained a lot of attention from researchers in recent years [11]- [15]. These healthcare devices play a key role in monitoring health conditions at home. The recent Covid-19 epidemic significantly highlighted the importance of these devices for real-time diagnosis and treatment of patients of different diseases at home. The blood pressure classification using PPG signals is also a hot topic and different researchers have proposed different machine learning algorithms for BP classification [11]- [15].

Riaz et al. [11] classified the high BP patients with ≈95% accuracy using linear support vector and different wavelet transform-based features. Another related work [12] classified the high BP using a k-nearest neighbor classifier and different PPG and ECG-based features including waveform area, power area, slope, etc., and ECG R-wave. Similarly, there are several other studies targeting blood pressure classification using PPG signals. However, either these works lack hardware implementation or they use ECG signals along with PPG signals.

IV. Proposed High BP Classification Processor

The proposed high BP classification processor classifies a patient with high SBP or high DBP after suitable features calculation and decision tree (DT) classification. Fig.5 shows the overall flow diagram of the proposed high BP classification processor.

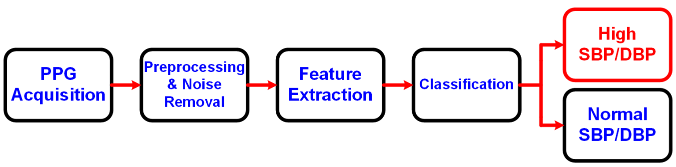

Fig. 5. BP Classification Using PPG Flow Chart

The feature selection is based on the best choice after a detailed analysis of a large set of features. The selected features include power spectral density in 0-2 Hz (F1), 2-5 Hz (F2), PSD difference between 0-2 Hz and 2-5 Hz (F3), and the sum of consecutive PPG samples (F4). Eq (1)-(4) shows the mathematical equations to calculate the selected features.

Fig.6 shows the hardware unit for feature calculation. The acquired PPG signal is pre-processed to remove noise and other artifacts. The preprocessed signal is forwarded to the feature calculation unit for features extraction. The calculated features are forwarded to the classification unit for high or low/normal SBP and DBP classification.

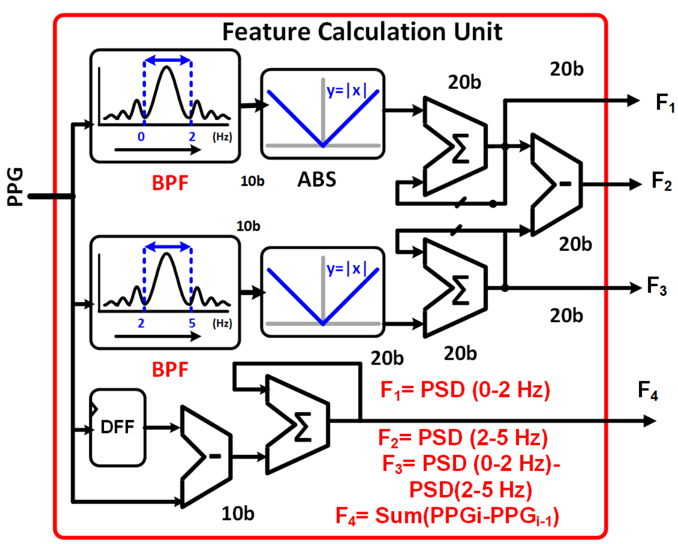

Fig. 6. Feature Calculation Unit

The PPG signal is forwarded to the feature calculation unit. Two 50th order finite impulse response filters are used to calculate the PSD in 0-2 Hz and 2-5 Hz [10]. The absolute filtered PPG signals are accumulated to calculate the PSD's (F_1,F_2). The PSD difference is calculated after subtracting both PSD's (F_3). The sum of consecutive PPG samples (F_4) is calculated after accumulating the current PPG sample and previous PPG sample using a D flip-flop and accumulation unit. The calculated features are forwarded to the DT classifier for high BP classification.

$$F_1 = \sum_{i=1}^{n} X_{0-2Hz} \quad (1)$$

$$F_2 = \sum_{i=1}^{n} X_{2-5Hz} \quad (2)$$

$$F_3 = \sum_{i=1}^{n} X_{0-2Hz} - \sum_{i=1}^{n} X_{0-2Hz} \quad (3)$$

$$F_4 = \sum_{i=1}^{n} (X_i - X_{i-1}) \quad (4)$$

The calculated features are normalization with zero mean and unit standard deviation using Z-score normalization technique. The normalized features are forwarded to the DT classifier for high SBP or DBP classification.

V. Classification Unit

The proposed high BP classification processor classifies a person using a DT classifier. The DT classifier employs the Z-score normalized features. Fig.7 shows the architecture of the 3 level DT for high SBP classification. A similar DT was utilized for the DBP classification. The feature F_1 was compared with a threshold (T_1) and if the feature is lesser than that threshold, a high SBP class is assigned. If the feature is higher or equal to (T_1) then F_2 is compared similarly. The complete DT architecture is shown in the Fig.7

Fig.8shows the hardware unit for the DT classification. The four normalized features are forwarded to the DT classification unit. Four 16-bit comparators compare the z-score normalized features F_{1-4} with the thresholds T_{1-4} and generates one bit signals S_{1-4} if the features are lesser than the thresholds. These signals act as a selection input of a 16-to-1 multiplexer and assigns a class zero (Low/Normal) or 1 (High) to the SBP or DBP. Two similar hardware units are utilized for the SBP and DBP prediction. This low complexity DT architecture utilizes only eight 16-bit comparators and two 16-to-1 multiplexer for the SBP and DBP prediction.

VI. Results and Comparison

The proposed high BP classification processor was implemented on Xilinx Artix-7 FPGA. This is the first work (to the best of our knowledge) for a hardware based high BP classification processor using PPG signals. A data set for 25 participants was collected including 20 male and 5 female participants. The proposed processor provides excellent

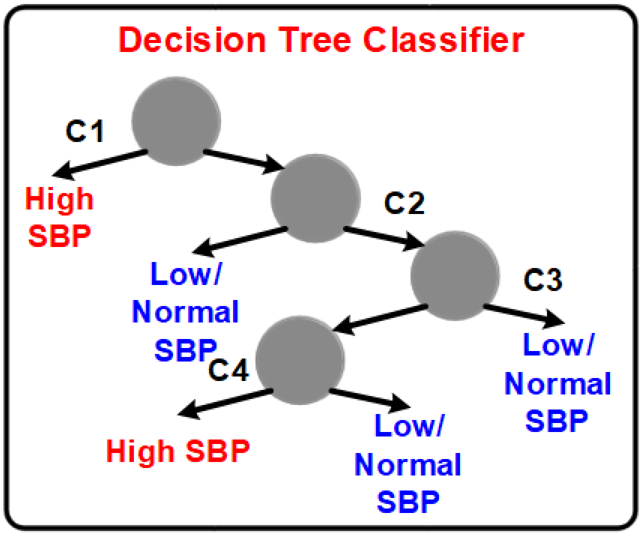

Fig. 7. DT Architecture

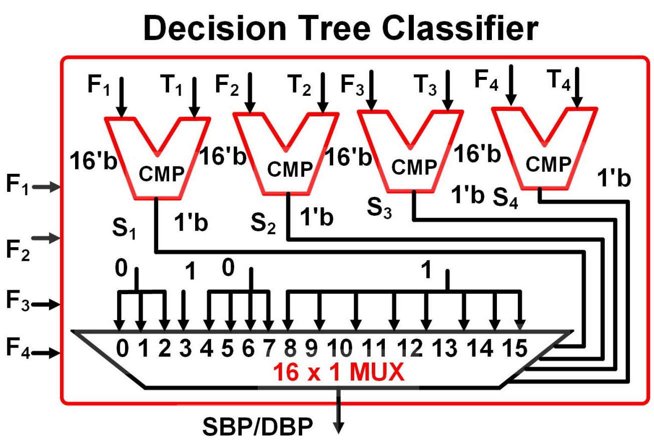

Fig. 8. DT Classification Unit

classification results. The overall power consumption of the processor was 5.23 μW using 5 fold cross validation.

Table I show the comparison of this work with the previous related works. The proposed processor provides higher classification results than similar works [11],[12],[14] and utilizes only PPG signals. Some of the other works also require ECG signals [12], while other works does not provide any hardware based solution for the high BP classification [13],[15].

TABLE I
COMPARISON WITH THE RELATED WORKS

Parameters	FGCS'19 [11]	Diagnostic'18 [12]	ACCESS'20 [13]	iSES'18 [14]	JNM'21 [15]	This Work
Classifier	LSVM	KNN	BLSTM	RF	BP-NN	DT
Accuracy	95%	94.8%	97.3%	90.8%	98.2%	96.2%
Physiological Signals	PPG	ECG+PPG	PPG	PPG	PPG	PPG
Hardware Solution	No	No	No	No	No	Yes
Power (µW)	----	----	----	----	----	5.23

VII. CONCLUSION

Wearable blood pressure prediction processors can be a major step-forward in biomedical healthcare. They can predict the BP of patients in real-time to avoid serious medical issues after timely medical aid. The implemented DT classifier utilizes only 8 16-bit comparators and two 16-to-1 multiplexer. These classification results and the processor performance is quite encouraging to expand the research towards a large data-set collection, extensive analysis and a fully integrated on-chip solution development.

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