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Hardware and software co-design for detecting hypertension from photoplethysmogram

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ABSTRACT

Hypertension is one of the leading causes of cardiovascular disease morbidity in the world. If remains untreated, it may cause severe damage like heart attack or even death. Early detection is required to prevent the development of other cardiac abnormalities. Photoplethysmogram (PPG) is a bio signal that can be obtained optically by a sensor. It is studied to monitor the change of volume of blood and detect heart conditions. Previous studies have already applied PPG to detect hypertension at the software level. In this article, along with software-based detection, we have implemented a digital hardware-based system for detecting hypertension from signals recorded using PPG sensor. Xilinx ZedBoard Zynq-7000 field programmable gate array (FPGA) board is utilized for designing the embedded system. The hypertension detection accuracy is 98.02% at the software level while for the digital system, it is 96.05% consuming 0.374 W power. The study can be analyzed for other cardiac disease detection and medical equipment development.

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1. INTRODUCTION

Photoplethsmogram (PPG) is an optically obtained biosignal that is used to detect volumetric changes in blood volume [1]. It is a low-cost and non-invasive technique that uses a light and a photodetector to measure the volumetric blood flow [2], [3]. So, it can be used for detecting abnormalities related to blood and heart. Traditionally electrocardiography (ECG) is used for cardiac condition analysis. However, ECG needs a fixed amount of electrodes to be placed on the body which makes the data acquisition system stationary [4]. PPG signals can be obtained by a sensor which is very simple and easy. So, wearable devices are utilizing PPG sensors nowadays for measuring oxygen saturation, heart rate, and body temperature. from PPG signals [5]. So, PPG has the potential to explore cardiovascular diseases (CVDs) and heart conditions.

Hypertension is a type of cardiovascular disease that occurs when the systolic blood pressure is over 130 mmHg or the diastolic blood pressure is over 80 mmHg [6]. Higher blood increases the risk of health which leads to other heart diseases including heart failure [7]–[9]. It is the leading cause of other CVDs and myocardial infarction [10], [11]. It may show very little or even no symptoms at all in a patient. However, the World Health Organization (WHO) considers hypertension as a controllable risk factor [12]. Hence, early detection of hypertension is necessary to avoid further damage to cardiac health.

There are several studies on hypertension detection from PPG signals. Martinez-Ríos *et al.* [13] have achieved 71.42% accuracy in detecting normotension and prehypertension using support vector machine (SVM) method. The features of the signals have been derived from the wavelet scattering transform method and combined with different machine learning algorithms where SVM achieved the maximum accuracy. Tanc and Ozturk [14] have used synchrosqueezing transform and convolution neural network to achieve a 96.83% F1-score for separating normotensive patients from prehypertension and hypertension. Hasanzadeh *et al.* [15] have used random convolution kernels for hypertension detection from PPG signals. The random forest classifier has provided a maximum F1-score of 71.6%. Using 4 features from PPG signal Evdochim *et al.* [16] have detected hypertension with 72.9% accuracy. Liang *et al.* [17] have used risk stratification for hypertension detection using 10 features from PPG signals. They have achieved 92.31% F1-score for the normotension vs hypertension trial while a 72.97% F1-score has been achieved for the normotension vs hypertension approach. Sadad *et al.* [18] have detected hypertension using 30 features from the signals of the PPG-BP dataset. They have achieved 99.5% accuracy in detecting multiclass levels of hypertension using the decision tree algorithm and 97.7% using the ensemble classifier. Frederick *et al.* [19] have used different deep learning models for detecting hypertension from PPG signal. They have achieved the maximum accuracy of 80% for AvgPool (VGG-16) approach. An field programmable gate array (FPGA) implementation has achieved 79.83% accuracy in detecting multiclass diseases from PPG signals [20]. The study has included combination of four types of different diseases.

The above state-of-the-art analysis verifies the use of PPG signals for hypertension detection. However, the previous hypertension detection studies were done at the software level. To develop a point-of-care system and medical equipment or wearable device for detecting hypertension hardware-based embedded systems are necessary. Hence, we have focused on designing a digital FPGA-based hypertension detection system. To the best of our knowledge, this is the first study on FPGA implementation for hypertension detection from PPG signal.

2. METHOD

The study's objective is to develop an FPGA-based system for hypertension detection from PPG signals. First, we need to find a PPG dataset labeled for hypertension. Then the signals need to be denoised from the artifacts incorporated during data acquisition. Next, features need to be extracted from the denoised signals and finally, a suitable classifier is needed for the detection of hypertension. The performance of the designed system will be analyzed. Resource utilization and power consumption studies are also discussed to verify the efficacy of the system.

2.1. Dataset and PPG signal selection

For our study we have selected the "PPG-BP" dataset [21]. It includes PPG signal of 219 subjects with information on height, weight, blood pressure and it is labeled with cardiovascular diseases and diabetes. Fingertip PPG waveforms were collected using SEP9AF-2 PPG sensor. The database contains 3 recordings of each subject with the signal quality index (SQI) of every signal. As higher SQI will provide better performance for training the system we have considered the signals with SQI equal to or above 0.8. A total of 38 PPG recordings have been found diagnosed with stage 1 or stage 2 hypertension. To train and test the proposed system, we also considered 38 normal recordings.

2.2. Tool selection for software and hardware design

We have selected MATLAB for the software-based hypertension detection system design and analysis. For designing a digital system, we have selected field programmable gate array. FPGA-based embedded systems are simple and easy to implement, change functionality, and test for validation [22], [23]. We have selected Xilinx system generator (XSG) for designing the system and ZedBoard Zynq-7000 FPGA board is selected for the implementation due to its low cost and reliability.

2.3. Normalization and preprocessing

Biosignals are generally contaminated with different noises [24], [25]. Hence, the selected signals are normalized first and then the normalized signal goes through a preprocessing stage for denoising as PPG signal is contaminated with different noises such as baseline wander, muscle noise, and motion artifacts [26]. For software-based preprocessing, we have applied a bandpass filter having a cutoff frequency of 0.5-15 Hz to remove the low-frequency baseline wander and high-frequency noises over 15 Hz. For the hardware system, we have utilized filter design and analysis tool (FDA tool) in XSG which allows us to select the type of filter with their frequency ranges. The frequency range is selected the same as the preprocessing system designed in MATLAB.

2.4. Feature extraction

Preprocessed signals are further analyzed to extract features from them. For this study five statistical features have been selected which are mean, mean absolute deviation (MAD), sum, absolute energy (AE), and root mean square (RMS) value of the signal. These are selected as they are easy for hardware implementation and also require fewer logic blocks, thus ensuring less resource utilization and power consumption. At the software level, the built-in functions of MATLAB are used to detect the features from the signals. For the hardware prototype, we have to design the feature extraction subsystem. The hardware architecture for preprocessing and feature extraction is shown in Figure 1. The preprocessed signal is stored in a random-access memory (RAM) by using a control signal and a multiplexer (MUX). The control signal is required to save the different features in registers also. An accumulator adds all the samples of a PPG signal to extract sum and this is divided by total sample numbers to provide mean value. Again, the square of each sample value is added using an accumulator to get the AE of the signal. The result of this accumulator is divided by total sample numbers and then root squared to get the RMS value. For MAD extraction the mean value stored in the register is subtracted from the stored sample of the signal in RAM. Then it goes through an absolute block to give us the absolute value.

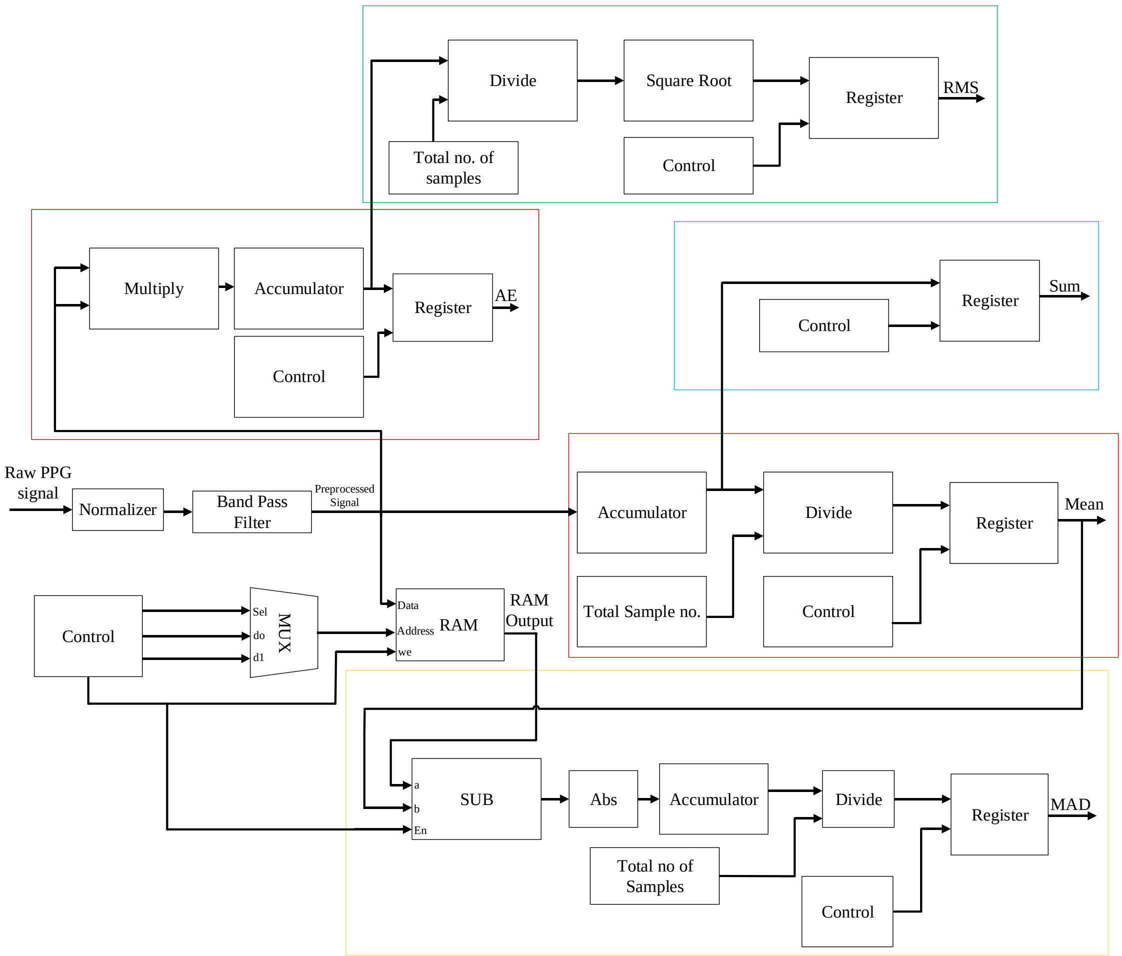

Figure 1. Hardware architecture for preprocessor and feature extraction

2.5. Classifier design

Many machine learning algorithms are available for classifying the PPG signal. We have selected linear support vector machine algorithm for our system design as it is easy to apply at the hardware level due to its simple function.

$$c(x) = x'\beta + b \quad (1)$$

where β represents the weight values of the features, b is the bias value and x is the vector of features.

At the software level, the SVM classifier has been applied where 80% of the selected signals have been used for training and 20% for testing. The hardware architecture has been designed as per the SVM function equation. It is presented in Figure 2. The weight and bias values have been taken from the model designed in the software. The result of c(x) is divided by its absolute value which results in either 1 or -1. 1 indicates the signal to be a normal case while -1 indicates the signal to be a hypertensive case.

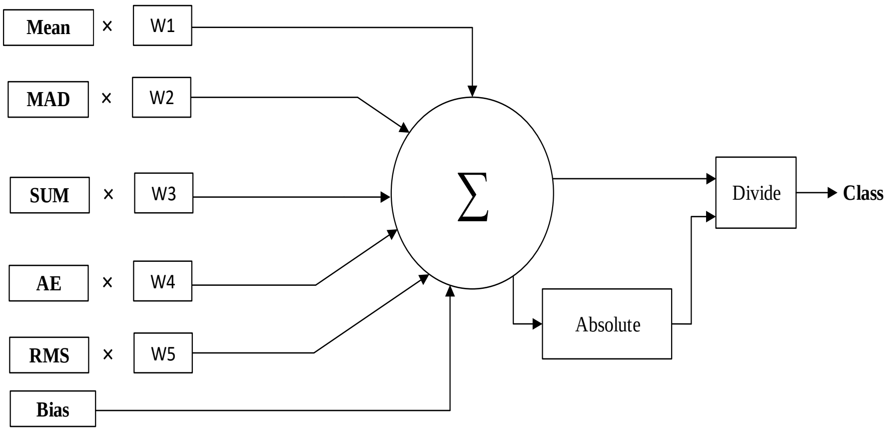

Figure 2. System architecture of the SVM classifier

3. PERFORMANCE AND ANALYSIS

The performance of the designed systems is analyzed by testing the models. At the software level, 5-fold cross-validation is utilized and it results in an accuracy of 98.02%. It verifies the selected features are correlated with hypertension detection from PPG signals. For verifying the performance of hardware system analysis of the designed system is necessary.

3.1. System performance

At the hardware level, the system is tested with all the PPG signals. The confusion matrix is shown in Figure 3. So, the hardware system shows an accuracy of 96.05% for hypertension detection. Also, the F1-score of the system is 96.2%. These are measured by (2) and (3).

$$Accuracy = \frac{True\ Positive+True\ Negative}{True\ Positive+False\ Positive+True\ Negative+False\ Negative} \tag{2}$$

$$F1-score = \frac{True\ Positive}{True\ Positive+\frac{1}{2}(False\ Positive+False\ Negative)} \tag{3}$$

The accuracy is slightly less than the software system because the extracted feature values slightly mismatch with the software-extracted features. This is due to different datatype conversions during operation in the hardware design.

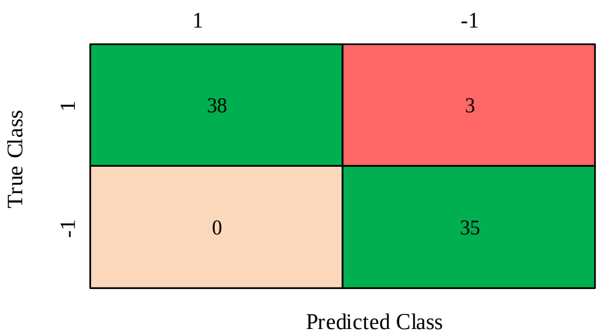

Figure 3. Confusion matrix for hypertension detection at hardware level

3.2. Resource utilization

The resource utilization of the FPGA board is shown in Figure 4. The system utilizes global buffer (BUFG), input-output (IO), digital signal processing (DSP), look up table (LUT), look up table random access memory (LUTRAM), block random access memory (BRAM), flip flop (FF) for the implementation of the works. The resource utilization analysis verifies that the ZedBoard Zynq-7000 has enough resources to implement the designed system.

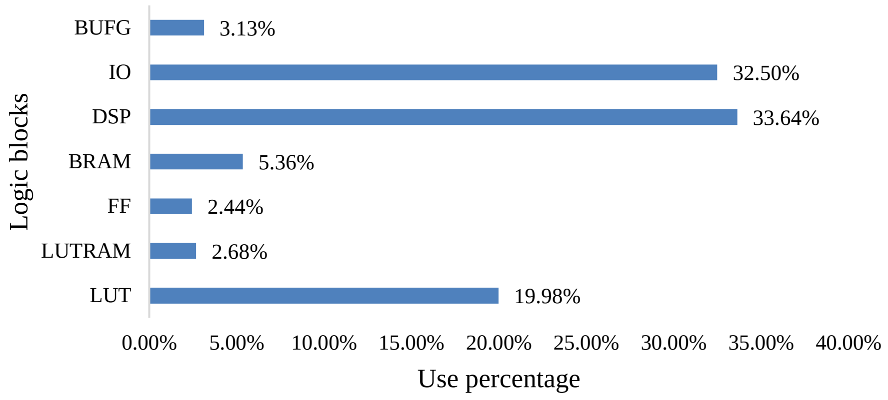

Figure 4. Resource utilization for different logic blocks in hardware architecture

3.3. Power utilization

Table 1 shows the power consumption for various logical processes. Dynamic power is the power required during active operation and static power is the power dissipated independent of the device activity. The system uses 0.374 W of power in total, of which 0.109 W is used for static operation and 0.265 W for dynamic operation. This analysis validates the system as a power efficient hardware system.

Table 1. Power utilization by the FPGA

Logic operation	Power (W)	Percentage
Static	0.109	29.14%
IO	0.023	6.15%
DSP	0.019	5.08%
BRAM	0.01	2.67%
Logic	0.089	23.8%
Signals	0.107	28.61%
Clocks	0.017	4.55%
Total	0.374	100%

3.4. Comparison study

A comparative study with previous works is presented in Table 2. Different machine learning and deep learning strategies have been applied in different works. However, our system has better accuracy than most of the works. Though there are some works that have achieved better performance than ours, they are done at the software level. We have designed both software-based and hardware-based systems for detecting hypertension with significant accuracy. However, the system has been developed with signals having SQI above 0.8. With the development of PPG sensors, the signal quality index of collected PPG signals can be improved which will give better results in disease detection.

Table 2. Comparison of hypertension detection from PPG

Reference	Dataset	Method	Implementation level	Accuracy
Martinez-Ríos *et al.* [13]	PPG BP	SVM	Software	71.42%
Tanc and Ozturk [14]	---	CNN	Software	96.83% F1-score
Hasanzadeh *et al.* [15]	MIMIC III	Random forest	Software	71.6% F1-score
Evdochim *et al.* [16]	PPG BP	Quadratic SVM	Software	72.9%
Liang *et al.* [17]	---	Risk stratification	Software	91.31% F1-score
Yen *et al.* [27]	PPG BP	Xception+BILSTM	Software	76%
This work	PPG BP	SVM	Software	98.02%
			Hardware	96.05%

4. CONCLUSION

Hypertension is a severe disease that can lead to other fatal cardiovascular diseases. Early detection can prevent this to a great extent. Previous studies are focused on software-based analysis for hypertension detection. Hence, this study aims to develop an FPGA-based digital system for detecting hypertension from photoplethysmogram signal. The software-based system is designed at first using SVM classifier and 5 features extracted from the signal, and it achieved an accuracy of 98.02%. Then the hardware system is developed utilizing Xilinx ZedBoard Zynq FPGA. The resource utilization analysis proves the effectiveness of this FPGA. The power consumption analysis also verifies the device as power efficient. The system can detect hypertension with an accuracy of 96.05% consuming 0.374 W power. However, the static power of the designed system is still high. Also, there is scope of improving the accuracy from the analysis of other features. The system can be further developed to improve detection accuracy with low static power consumption for medical equipment and wearable device applications. Detection of other cardiovascular diseases from PPG signal can be studied in future.

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