Arabian Journal for Science and Engineering
https://doi.org/10.1007/s13369-024-09202-3

RESEARCH ARTICLE-ELECTRICAL ENGINEERING

FPGA Implementation of PPG-Based Cardiovascular Diseases and Diabetes Classification Algorithm

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Received: 19 February 2024 / Accepted: 16 May 2024

Abstract
Photoplethysmogram is a noninvasive technique used to detect volumetric changes in the blood. Cardiovascular diseases, related to heart and blood supply problems, are one of the largest causes of death in the world. Our study explored the possibility of classifying different cardiovascular diseases using photoplethysmogram signals for quick diagnosis. Using the support vector machine technique, the classification is done at the software level, while Xilinx Zynq 7000 field-programmable gate array (FPGA) chip is utilized for hardware design. The overall accuracy for detecting cerebral infarction and cerebrovascular disease is 93.48% and 96.43%, respectively, using eleven features. In addition, diabetes which is linked to cardiovascular diseases is classified, and an accuracy of 88.46% is achieved. Considering the PPG signal with a higher signal quality index, the overall accuracy for all the diseases can be further increased. The resource and power utilization of the implemented system is analyzed, which shows that 0.693 W power is required. The developed prototype can be further extended as a point-of-care system for cardiovascular disease detection.

Keywords Cardiovascular disease (CVD) · Field-programmable gate array (FPGA) · Photoplethysmography (PPG) · Support vector machine (SVM)

1 Introduction

Cardiovascular diseases (CVD), a group of disorders of the heart and blood vessels, are one of the leading causes of death worldwide, taking approximately 17.9 million lives each year [1, 2]. CVD is an umbrella term that covers a range of pathologies, including heart attack, hypertension, stroke, heart failure, myocardial infarction, cerebral infarction, and cerebrovascular disease. Delay in detection and therefore late treatment can lead to death, which in recent years has increased with the spread of coronavirus. From March 2020 to March 2022, about 1,946,662 deaths have been reported by the National Centre for Health Statistics (NCHS) in the USA [3]. With the advancement in medical technology, it is expected to be in control though the lifestyle, food habits, and lack of physical activity have been worsening the situation. Despite recent developments in medication and management of CVDs, the challenge remains to detect CVDs due to the lack of an appropriate point-of-care system [4].

Among cardiovascular diseases, our study focuses on two diseases that are related to blood flow in the brain: cerebral infarction and cerebrovascular disease. Cerebral infarction is a medical condition that occurs when the blood flow to the brain is interrupted by issues with the arteries that supply it. It is also called ischemic stroke, which occurs when a blood clot blocks an artery leading to the brain. Being a frequently occurring disease, cerebral infarction is characterized by poor prognosis, high disability, and fatality rate [5]. Cerebrovascular disease is another type of CVD that represents a group of conditions which affect the blood flow and blood vessels in the brain. Blood vessel narrowing (stenosis), clot forma-

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Published online: 11 June 2024

tion (thrombosis), artery blockage (embolism), blood vessel rupture (hemorrhage), etc. can be causes of this serious issue. Cerebrovascular disease is the fifth leading cause of death in the USA, causing 486 fatalities per million people [6]. The spread of coronavirus has increased the rate in recent years, and it has been found to be associated with cerebrovascular disease [7–9]. Both diseases cause a lack of oxygen and nutrient supply in the brain region due to a shortage of blood flow. They can lead to severe damage like death of blood cells, while the ultimate result is death. So, the detection of these diseases at an early stage is necessary.

Another vital disease that is rapidly growing in the world is diabetes. It is a health condition that refers to the presence of high blood sugar. In this case, the body cannot make enough insulin or use it properly due to the incapability of beta cell production in the pancreas. Being a chronic disease, it tends to increase the risk of other diseases that negatively impact the brain, kidneys, eyes, and heart [10]. It is correlated with cardiovascular diseases as people with diabetes are likely to develop cardiovascular diseases 2 to 4 times more than others [11]. Detection and early-stage control of diabetes thus can prevent the build-up of cardiovascular diseases and help to grow consciousness about health. So, our study focuses on diabetes alongside cardiovascular diseases.

Medical technology is developing new techniques for detecting diseases using modern devices and systems. Disease detection through various biomedical signal analyses has been common over the years. Electrocardiogram (ECG) is mostly used for the diagnosis of cardiovascular diseases being a simple and invasive technique [12, 13]. However, ECG signals have the disadvantage of short boards with a short monitoring cycle and the problem of gathering [14]. Photoplethysmogram (PPG) is another biosignal which is, in contrast, suitable for long-term monitoring and can be acquired from wearable devices easily to analyze heart conditions. It is a noninvasive method making data acquisition at the surface of the skin and deals with the volumetric changes in blood in the peripheral circulation [15]. PPG makes use of infrared light, which is absorbed by bones, skin pigments, venous blood, and arterial blood. The nature of absorbing more light by blood than surrounding tissues is utilized by the PPG sensors, which produce an output voltage proportional to the quantity of blood flowing through blood vessels. Blood oxygen saturation, blood pressure, heart rate, and respiration rate can be detected by analyzing the PPG signal.

PPG signal has been analyzed by researchers for the detection of various diseases and health conditions. Neeraj et al. have used time domain analysis of PPG and its second derivative to extract features and a noninvasive technique for detecting coronary artery diseases [16]. They have achieved a sensitivity of 85% and specificity of 78%. Al Fahoum et al.[17] have used pre-trained deep learning models to classify hypertension and achieved a maximum of 99.5% accuracy. Prabhakar et al. achieved 99.48% accuracy in detecting CVDs from PPG signal using the Chi-square cumulative density function using logistic regression. They also got 98.96% accuracy using the Chi-square probability density function using Gaussian support vector machine (SVM) algorithm [18]. Oishee et al. have studied generating synthetic PPG signals and improved the coronary artery disease classification [19]. John et al. have applied a deep learning method to classify PPG signals for peripheral artery disease detection [20]. They have achieved 88.9 % accuracy with a specificity of 90.2% and a sensitivity of 86.6%. Cheng et al. have got an accuracy of 98.21% in identifying atrial fibrillation from PPG signals of 102 subjects [14]. They have used a combination of time–frequency analysis and deep learning methods in their study. As PPG is correlated with heart conditions, it can be used for the detection of various cardiovascular diseases. PPG has great potential to assess age-related changes in arterial stiffness which is an established risk factor of CVDs [21]. Chowdhury et al. have used the PPG signal for detecting different combinations of cardiovascular diseases [22]. They have considered 7 classes and achieved an accuracy of 79.83%. Ave et al. have designed a system for the early detection of cardiovascular disease [23]. Android-based application has been designed with user-friendly interface, which shows the result in color code; however, the accuracy of the system is not verified. Divya et al. achieved 97.88% accuracy in cardiovascular risk level detection from PPG signals [24]. They have used singular value decomposition (SVD) and statistical features with softmax discriminant classifier and Gaussian mixture model classifier for the CVD classification. Tariq et al. employed machine learning and deep learning methods to analyze CVD patients [25]. Their proposed model achieved 99.5% and 97.56% accuracy in detecting CVDs using PPG-BP and PPG DaLiA datasets, respectively. PPG signals are being analyzed for diabetes detection also. Yousef et al. classified diabetes based on PPG signal and achieved an accuracy of 92.3% [26]. They used logistic regression for the binary classification process to detect diabetic and non-diabetic subjects where the accuracy of detecting diabetic patients was 70% and the detecting accuracy of non-diabetic subjects was 96.4%. Serena et al. studied to detect type 2 diabetes with light CNN from raw PPG signal [27]. However, they achieved the best result when they took age and biological sex as input with raw PPG. Different deep learning and machine learning approaches have been applied for diabetes detection by researchers over the years [28–30].

The above discussion suggests that there are a lot of recent developments in PPG-based disease detection. However, there are fewer works on detecting cerebral infarction, cerebrovascular disease, and diabetes from PPG signals. Cerebral infarction and cerebrovascular disease are associated with cardiovascular diseases [31], and they affect the

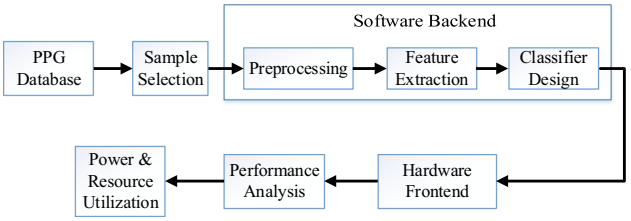


Fig. 1 Overall methodology of the study

blood flow in the brain. As the PPG signal can detect the volumetric change in blood flow, there is the scope of utilizing the PPG signal for detecting these diseases. Furthermore, most of the state-of-the-art research works are at the software level. Hardware implementation of these identification systems is necessary as compact digital systems are becoming popular as point-of-care systems. In this study, we have chosen two important cardiovascular diseases: cerebral infarction and cerebrovascular disease as well as diabetes, for classification based on PPG. The target is to design an FPGA-based pragmatic hardware system for classifying these diseases and thus identifying the diseases which will be helpful to patients and medical personnel. The rest of the paper follows methodology, performance analysis, and conclusions.

2 Methodology

For the purpose of the hardware implementation of FPGA-based CVD and diabetes classification, we need to develop the system at the software level first. Later, the hardware architecture needs to be designed and implemented. The hardware design performance will be compared and analyzed for validation. The total methodology of the study is shown in Fig. 1.

After selecting a suitable dataset it will go through a selection process as per Fig. 1. Then the signals will pass through a preprocessing stage to remove the undesired noises. After that, the selected features will be extracted from the preprocessed signals which will be utilized for designing the classifier to detect the diseases. To develop the system at the hardware level, FPGA implementation will be the next target. After the implementation, the system performance will be analyzed including the power and resource utilization of the developed prototype.

2.1 Dataset

For this study, we have chosen open-access "PPG-BP Database" [32]. The database contains 619 PPG data segments from 219 subjects. Among the subjects, 105 are males and the rest are females. Their age covers the range of 20 to 89 years. Each subject has 3 segments of PPG signal, each of 2.1 s in length. The dataset contains different CVDs like hypertension, cerebral infarction, cerebrovascular disease, and also diabetes of the subjects. All three segments went through a signal quality evaluation process. The signal quality index (SQI) of each signal was provided with the dataset. The SQI was measured after data collection to evaluate against the classification threshold of excellent, acceptable, or unfit PPG signals according to the following equation:

$$S_{\mathrm{SQI}} = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \frac{\mu_x}{\sigma}\right)^3 \tag{1}$$

where N is the sample number of PPG signal, and μ_x and σ are empirical estimates of the mean and standard deviation of x_i, respectively.

Table 1 Sample selection from the database for the study

	Available in database	Selected for the study (SQI equal or greater than 0.8)
Total subjects	219	
Available segments	657	331
Cerebral infarction	20 subjects	
	60 segments	23 segments
Cerebrovascular disease	25 subjects	
	75 segments	42 segments
Type 2 diabetes	38 subjects	
	114 segments	65 segments

2.2 Sample Selection

For this study, we have considered 3 types of diseases available in the dataset. Cerebral infarction, cerebrovascular disease, and type 2 diabetes are considered for the binary classification approach. Among the 219 subjects, 38 subjects were diagnosed with type 2 diabetes, 20 subjects were diagnosed with cerebral infarction, and 25 subjects were identified with the problem of cerebrovascular disease. As each subject has PPG data of 3 segments, there are in total 114 segments for type 2 diabetes, 60 segments with cerebral infraction, and 75 segments with cerebrovascular disease. However, we have also considered the signal quality index for our study. As high-quality signals will help to provide the result more accurately, we have decided to consider only the signals having SQI equal to or greater than 0.8 for our study. In this process, we have found 65 segments of 32 subjects having type 2 diabetes, 23 segments from 14 subjects with cerebral infarction, and 42 segments of 20 subjects with cerebrovascular disease. Table 1 depicts the subject selection process for our study.

2.3 Software Backend

For developing the system at the software level, we need to denoise the signal first, and then, the features are extracted. This is done using MATLAB which is a common tool for software-based signal analysis. Later the extracted features will be used for classifier design.

2.4 Preprocessing

Biosignals are contaminated with different noises which hinder the proper analysis of the signal. PPG is also affected by various noises like motion artifacts, baseline wander, power line noise, etc. To remove the noises, we need to design a preprocessor first. The signal is normalized first before given input to the preprocessor which is designed using a combination of low- and high-pass filters. As the PPG signal has a range from 0.5 to 15 Hz, we need to remove the frequency component below 0.5 Hz and above 15 Hz from the signal. FIR and IIR filters are usually used in digital system architecture. The response of an FIR filter is as follows:

$$y(n) = \sum_{i=0}^{N} b_i x(n-1) \tag{2}$$

where $x(n)$ is the input signal, $y(n)$ is the output signal, N is the order of the filter, and b_i is the impulse response at i_{th} instant for $0 \leq i \leq N$ of N_{th}-order filter.

To remove the baseline wander noises, a high-pass filter of 0.5 Hz is designed while a low-pass filter of 15 Hz has been developed to remove the high-frequency noises caused by electromyogram (EMG) and motion artifacts. Both the FIR filters have been designed in FDATool and the order of the filters has been selected such that the fast Fourier transform (FFT) of the preprocessed signals show the removal of all undesired noises. In the case of the high-pass filter the order is 50 while for the low-pass filter, the order is 81.

2.5 Feature Extraction

For designing a classifier, we need to find out the features from the PPG signal. As our final target is implementing the system in hardware, we have selected hardware-friendly features for our study. At first, they are extracted from MATLAB using the built-in function available. The details of the features are shown in Table 2.

Along with these statistical features, we have also considered two physical features for our study: age and body mass index (BMI) as these two have a relation with different types of CVDs and diabetes. So, here two systems have been considered: one with nine statistical features derived from the PPG signal and another one that includes two physical features along with the nine statistical features making a total of eleven features.

2.6 Classifier Design

Support vector machine (SVM) is a simple machine learning technique that avoids complexity during hardware implementation. Binary classification is a popular classification method for which SVM is commonly used.

The extracted features from the previous section have been used to train an SVM classifier. SVM works relatively well when there is a clear margin of separation between the two classes. It is also effective in high-dimensional space.

2.7 Hardware Frontend

The system has to be designed at the hardware level to fulfill the purpose of the study. Digital hardware systems can be implemented in various devices such as field-programmable gate array (FPGA) and complex programmable logic device (CPLD). We have chosen FPGA for our study as it is simple and easy to design as well as has the advantage of reprogrammable functionality [33]. We have targeted ZedBoard Zynq 7000 for developing the proof of concept of our system. It offers embedded system design and development at low cost and provides advantage of long life.

2.8 Preprocessor System Subsystem

The processes executed for software-level design will be followed in this case also. At first, the signal is normalized. Then, a high-pass filter of 0.5 Hz and a low-pass filter of 15 Hz are designed in the Xilinx system generator using the FDA tool. Filter orders are kept the same, 50 and 81, respectively, for the high-pass and low-pass filters, as per software design. These filters have successfully removed the noises, so higher-order filters are avoided for minimum resource and power utilization. The whole preprocessing system of the study is presented in Fig. 2.

2.9 Feature Extractor System Subsystem

In the next step, the features are needed to be extracted from the hardware design. The system architecture has been designed to extract the features which are already selected at the software level. Various mathematical and logic blocks are used for the implementation. The system architectures for feature extraction in the Xilinx system generator are depicted in Fig. 3.

In Fig. 3a, a multiplexer (mux) and a RAM are used to save the input signal data in memory which will be utilized in further feature extraction blocks. The output of the preprocessor prepo(i) is input to the data port of the RAM. Two counters

Table 2 Features selected for the study

Mean	Mean is the average value of all the samples in a signal. It can be expressed by the following equation: $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$	(3)
Mean absolute deviation (MAD)	The MAD is the mean or average difference between each data value and the mean of the dataset. It is presented by the following equation: $MAD = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i - \bar{x}\rvert$	(4)
Sum	SUM is the summation of all the samples of a signal. It is expressed by the following equation: $Sum = \sum_{i=1}^{N} x_i$	(5)
Absolute signal energy (AE)	AE is a way to represent the strength of the data and is defined as follows: $AE = \sum_{i=1}^{N} x_i^2$	(6)
Root mean square (RMS)	RMS is the square root of the arithmetic mean of the squares of a group value. It is defined by the following: $\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	(7)
Standard deviation (SD)	SD is a measure of the dispersion of the data in relation to the mean. It is expressed by the equation: $\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\bar{x})^2}{N}}$	(8)
Variance	Variance means the variability which is the measure of the spread between numbers in a dataset. It is defined as follows: $\sigma^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^2}{N}$	(9)
Skewness	Skewness is a measurement of the distortion of symmetrical distribution or asymmetry in a dataset. It is expressed by: $\text{Skewness} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^3}{(N-1)*\sigma^3}$	(10)
Kurtosis	Kurtosis is a measure of the tailedness of a distribution. It is defined as: $\text{Kurtosis} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^4}{(N-1)*\sigma^4}$	(11)

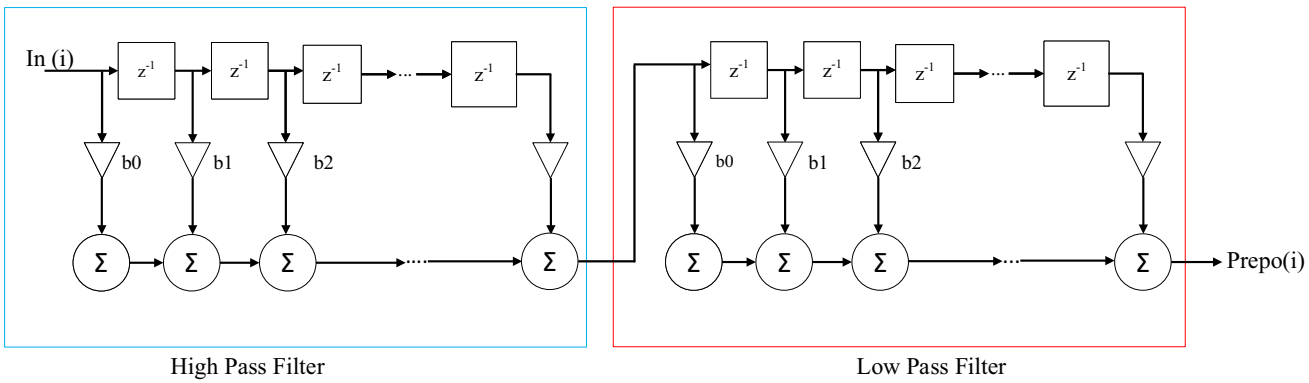
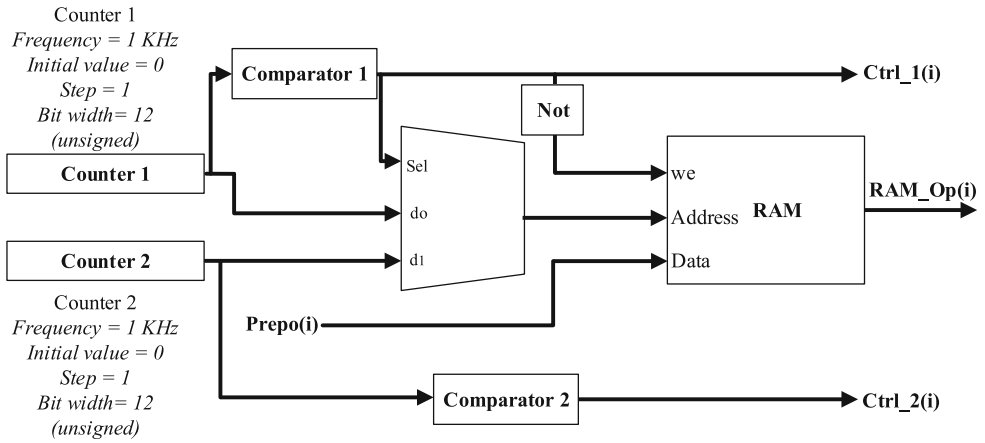
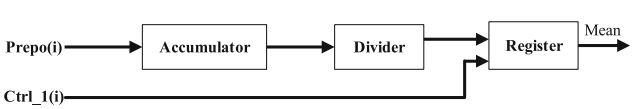


Fig. 2 Preprocessing stage of proposed the system

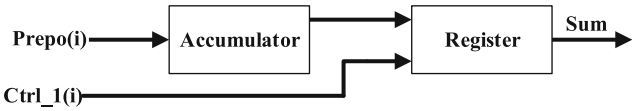
having the same frequency are used. Counter 1 starts counting from zero and it passes through a logic comparator. It continues to count till the total sample number of a PPG signal, 2100, and during that period, it keeps the writing enable (we) disabled due to the not gate. The logical comparator 1 also controls the selector switch. When the counter follows the comparator 1 logic, it is selected to d_o, and when the comparator logic breaks, it is selected to d_1 which is controlled by counter 2. Counter 2 is enabled and starts saving the data in the proper address after the comparator 1 logic breaks, that is, when counter 1 exceeds counting 2100, enabling the we port. Counter 2 counts to 4200 controlled by the logical comparator 2 and stores the 2100 sample of a PPG signal in the RAM address. The counters passing through the comparator's logic blocks create two control signals mentioned as Ctrl_1(i) and Ctrl_2(i). These control signals are used during feature extractions. In Fig. 3b, all the sample values of prepo(i) signal are added using an accumulator, which is later divided by the total number of samples to generate the mean value of the signal. The control signal Ctrl_1(i) helps to store the value in a register. The result of the accumulator gives the sum output shown in Fig. 3c. In the case of extracting AE, we need to square each sample value of prepo(i), and for the summation of the squared values, an accumulator is used in Fig. 3d. Ctrl_1(i) is also used to store the sum and AE value in a register. To determine the mean average deviation (MAD), the sample values of a signal, RAM_Op(i), are recalled from the RAM and the mean value is subtracted from each of the sample values of the signal using the block mentioned as subtractor in Fig. 3e. Then the absolute value, indicated by the Abs block in Fig. 3e, of the subtraction is added using an accumulator and later divided by the total number of samples to generate MAD. The feature is stored in a register using the Ctrl_2(i) signal. In Fig. 3f, the sample values of



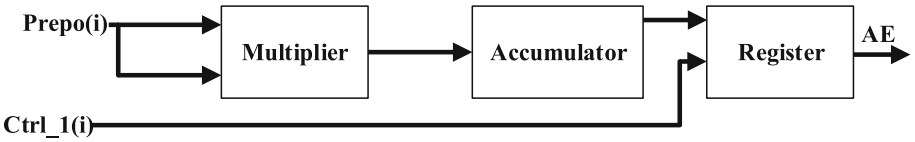
(a) Memory unit



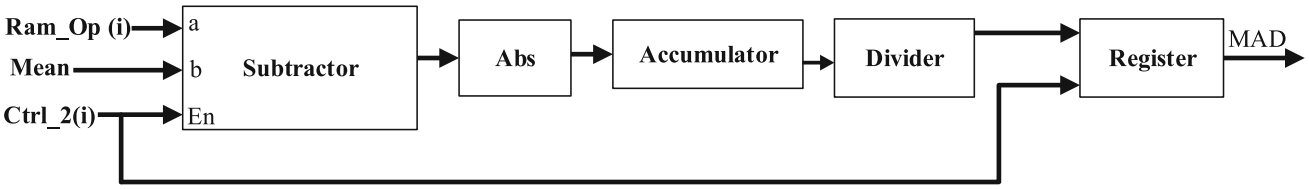
(b) Mean extraction



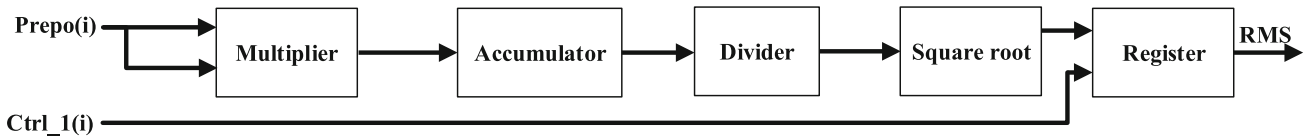
(c) SUM extraction



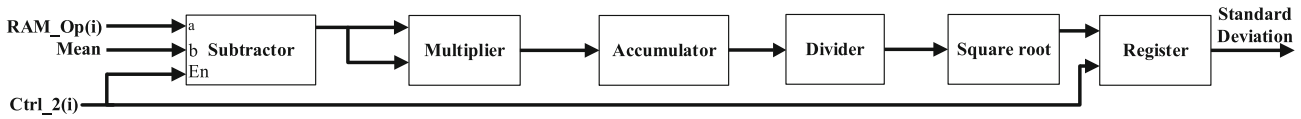
(d) AE extraction



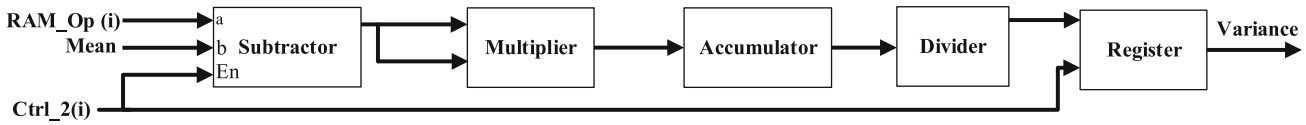
(e) MAD extraction



(f) RMS extraction

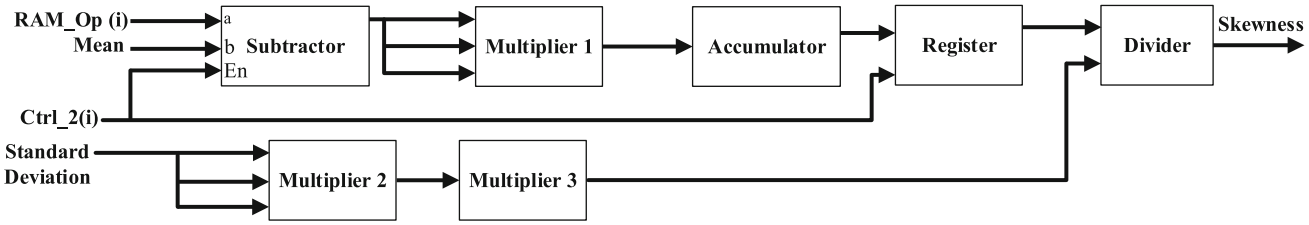


(g) Standard deviation extraction

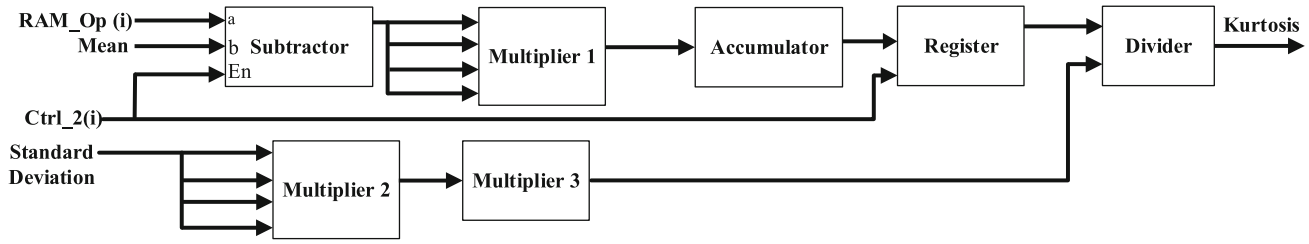


(h) Variance extraction

Fig. 3 Feature extraction system architecture



(i) Skewness extraction



(j) Kurtosis extraction

Fig. 3 continued

prepo(i) are squared using a multiplier block and then added using an accumulator. The result is divided by the total number of sample values and later square rooted for generating RMS value which is stored in a register and Ctrl_1(i) is used for controlling this. For determining the standard deviation, mean value of each prepo(i) signal is subtracted from all the samples and squared. The squared values are added using an accumulator followed by a divider dividing the accumulator output by the total number of samples. Later the result of the divider is root squared to get the standard deviation of the input signal. The extraction of the feature called variance is almost the same process as extracting standard deviation except for the square root process. So, it is the square of the standard deviation, which is shown in Fig. 3h. In the case of skewness, the mean value of a PPG signal is subtracted from the sample values preserved in the RAM, RAM_Op(i). Then the same result is multiplied three times and added to an accumulator each time. The standard deviation, extracted previously, is also multiplied three times and then multiplied with 1 less than the total number of samples. This multiplication output divides the accumulator output to get the skewness value. For kurtosis, the process is almost the same, except here, we need to multiply the values four times instead of three times, as in the case of determining skewness. In the case of standard deviation, variance, skewness, and kurtosis, the Ctrl_2(i) signal is used to control registers that store the values, respectively.

2.10 Classifier System Subsystem

The extracted features have to be utilized for developing a classifier to classify the PPG signal for the detection of diseases. For this, we have chosen the SVM classifier as it is easy and simple to implement in hardware due to its simple function.

$$f(x) = x'\beta + b \tag{12}$$

where x is an observation corresponding to a row of x indicating the features. b is the bias term, and β represents the weight values of the features.

We need to find the weight values and bias of the model. The total classifier system architecture designed in the Xilinx system generator is shown in Fig. 4. The weight values (w1,w2,....w11) and bias values (b) are chosen from the model found in MATLAB by training the dataset at the software level. The extracted features are multiplied by the weight values and added together. Finally, the bias value is added and the total summation is divided by the absolute value of the sum. If it results in 1, it is considered a normal case, and if the result is -1, it is considered a signal of a patient of a particular disease.

3 Performance Analysis

The PPG signal from the database is given input to the prepocessing stage designed in the Xilinx system generator. The high- and low-pass filters remove the undesired noises from the signal. Figure 5a shows that the noisy PPG signal, which is noise-free in the case of Fig. 5b after passing through the filter. Also, the signal is normalized first before giving input to the preprocessing stage.

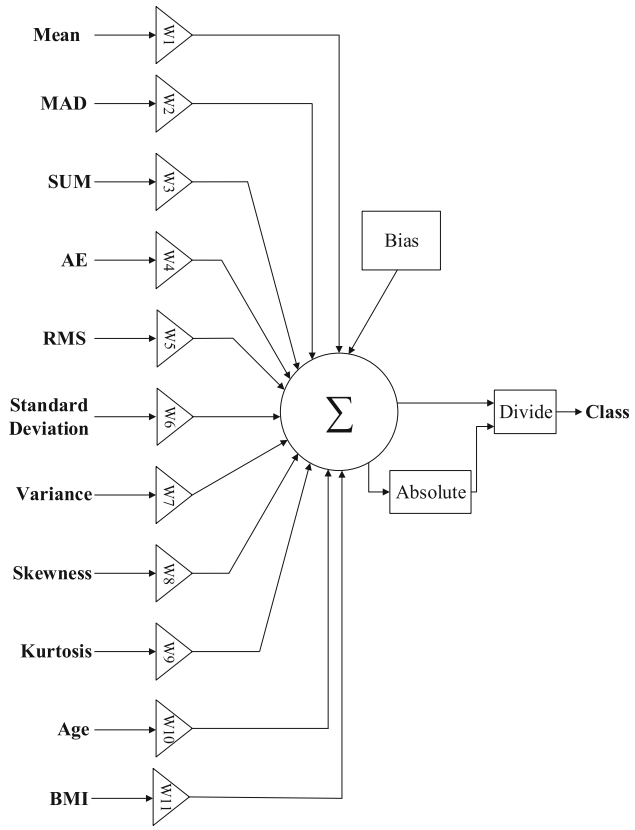


Fig. 4 Classifier system architecture

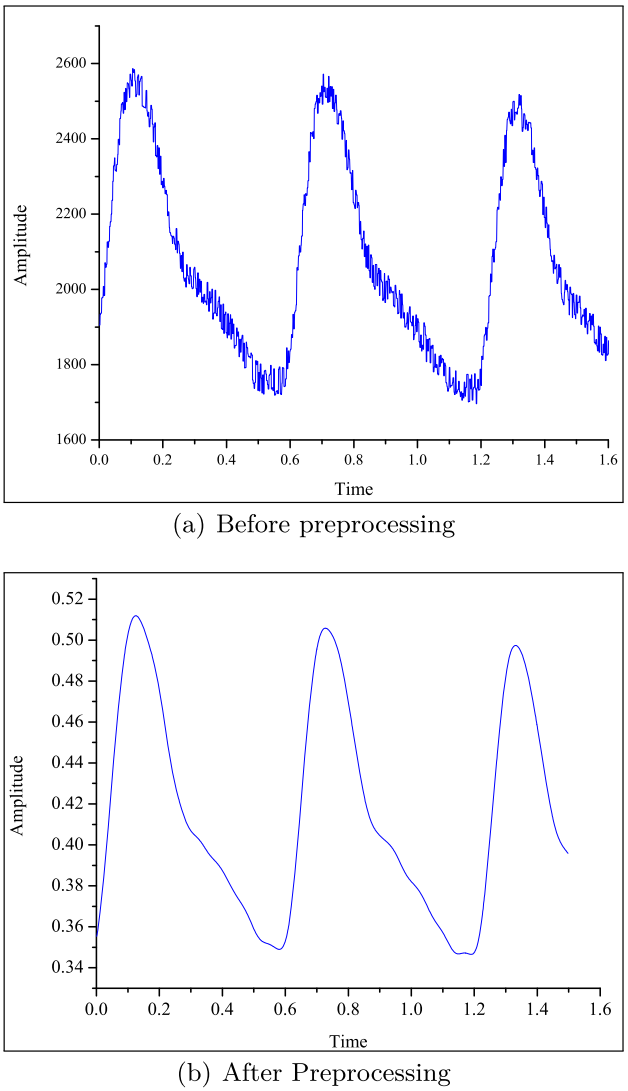


Fig. 5 PPG signal before and after preprocessing stage

3.1 Performance of the Designed System

The developed system takes the PPG signal as input and gives the output of class 1 or −1 for various diseases. Class 1 indicates a normal subject, while class −1 indicates the subject is affected by a disease. In the software-level design, five-fold cross-validation has been applied. It resulted in 97.39% accuracy for 9 statistical features and 96.08% accuracy for 9 statistical and 2 physical features in the case of cerebral infarction detection. In a similar approach, 97.85% and 98.57% accuracy have been achieved, respectively, for cerebrovascular diseases while 96.85% and 97.49% accuracy, respectively, for diabetes detection. The hardware system has been checked for all the selected segments. For the performance analysis of the hardware design, we have to determine the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) cases where:

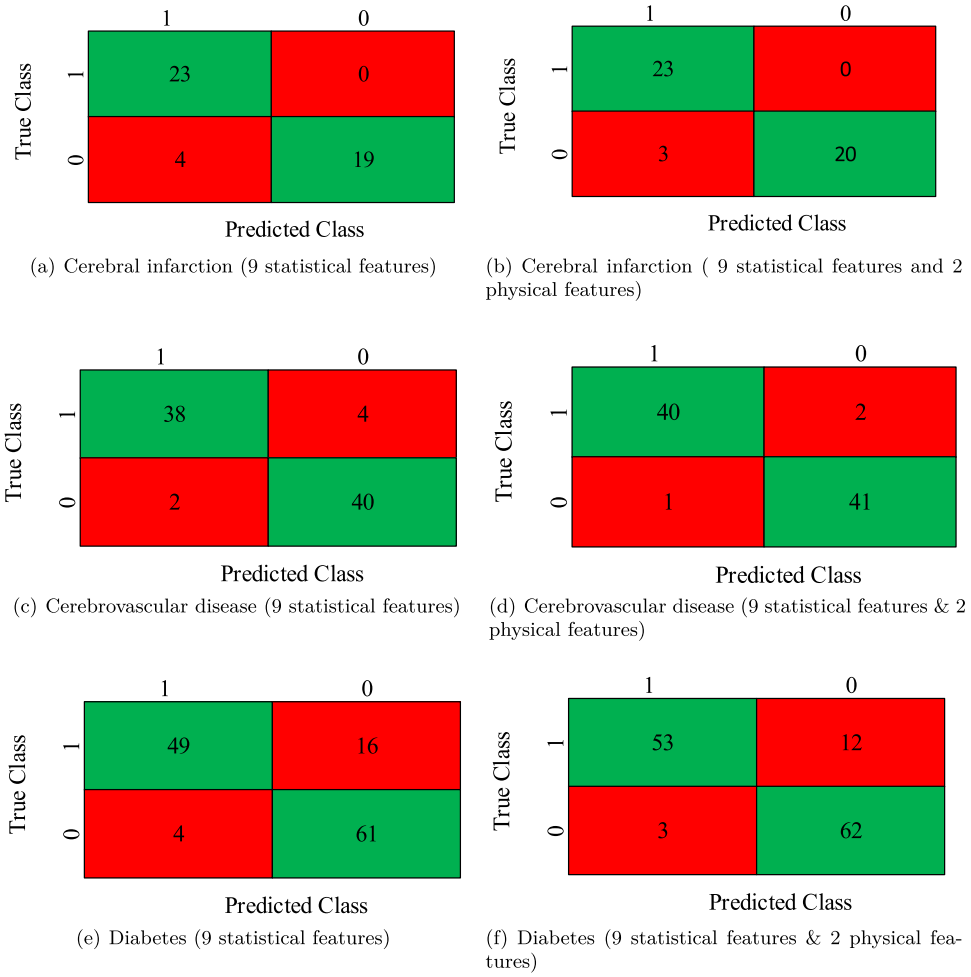
True positive (TP): Normal instances correctly identified as normal
False negative (FN): Normal instances that are identified as abnormal
True negative (TN): Abnormal instances that are identified as abnormal
False positive (FP): Abnormal instances that are identified as normal

The confusion matrix for different diseases is shown in Fig. 6 for 9 features and 11 features.

To analyze the performance of our designed system, we have determined different parameters. Sensitivity, specificity, accuracy, false alarm (FA), error rate (Err), precision, F-measure, and false positive rate (FPR) are different parameters to analyze the performance of a system [34]. The equations of these parameters are given below:

$$\text{Sensitivity(Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100 \tag{13}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} * 100 \tag{14}$$



(a) Cerebral infarction (9 statistical features)

(b) Cerebral infarction (9 statistical features and 2 physical features)

(c) Cerebrovascular disease (9 statistical features)

(d) Cerebrovascular disease (9 statistical features & 2 physical features)

(e) Diabetes (9 statistical features)

(f) Diabetes (9 statistical features & 2 physical features)

Fig. 6 Confusion matrices from hardware implementation

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} * 100 \tag{15}$$

$$\text{Err} = \frac{\text{FN} + \text{FP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} * 100 \tag{16}$$

$$\text{FA} = \frac{\text{FP}}{\text{TN} + \text{FP}} * 100 \tag{17}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100 \tag{18}$$

$$\text{F} - \text{measure} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} * 100 \tag{19}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} * 100 \tag{20}$$

According to the equations, the parameters are measured for our designed system. The values of these parameters are shown in Table 3.

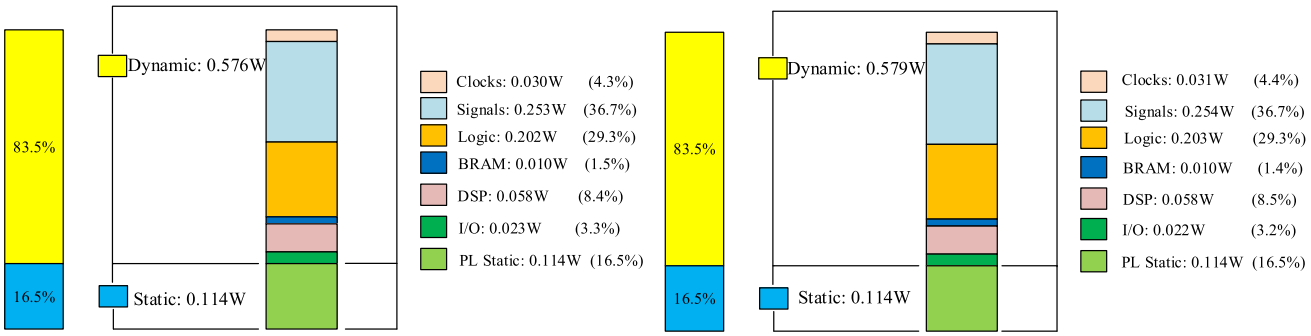
Table 3 shows that in all cases the performance parameters show better results for cases of combined statistical and physical features. The error rate and false alarm percentage are lower also which validates the inclusion of the two physical features in our system design. However, all the performance parameters can be improved by taking the PPG signals having SQI above 0.9 or higher. The software implementation provides better accuracy due to the conversion between fixed value to float value through casting in Xilinx, and precision cannot be maintained accurately at the hardware level during feature extraction. This affected the performance of the hardware design and provided lower accuracy in detection than the software design.

3.2 Resource and Power Analysis

The system has been implemented in the Xilinx system generator targeting ZedBoard Zynq xc7z020-1clg484. It utilizes lookup table (LUT), lookup table random access memory (LUTRAM), flip-flop (FF), block random access memory (BRAM), digital signal processing (DSP), input/output (IO), and global buffer (BUFG). The resources used for our implemented system are presented in Table 4. It can be seen that more LUT and flip-flop are required when we use the physical features along with the statistical features. The amount of LUTRAM, BRAM, DSP, IO, and BUFG requirements are the same for both cases.

Table 3 System performance analysis

	Cerebral infarction		Cerebrovascular diseases		Diabetes	
	9 features (%)	11 features (%)	9 features (%)	11 features(%)	9 features(%)	11 features (%)
Sensitivity	100	100	90.48	95.24	75.38	81.54
Specificity	82.61	86.96	95.24	97.62	93.85	95.38
Accuracy	91.3	93.48	92.86	96.43	84.62	88.46
Err	8.7	6.52	7.14	3.57	15.38	11.54
FA	17.39	13.04	4.76	2.38	6.15	4.61
Precision	85.19	88.46	95	97.56	92.45	94.64
F-measure	92	93.88	92.68	96.39	83.05	87.6
FPR	17.39	13.04	4.76	2.38	6.15	4.62



(a) Power utilization considering 9 features (b) Power utilization considering 11 features

Fig. 7 Power utilization of the total system

Table 4 Resource utilization analysis

Resource	For 9 features		For 11 features	
	Utilization	Available	Utilization	Available
LUT	19,849	53,200	20,349	53,200
LUTRAM	501	17,400	501	17,400
FF	3921	106,400	3990	106,400
BRAM	7.50	140	7.50	140
DSP	134	220	134	220
IO	65	200	65	200
BUFG	1	32	1	32

The power utilization of the designed system is also depicted in Fig. 7. It can be seen that in the case of utilizing nine statistical features the power utilization is slightly less than in the other case of utilizing 2 extra physical features. In both cases, the static power is 0.114 W which is about 16.5% of the total system power. Dynamic power is slightly higher for eleven features than for the nine features system. The maximum of the dynamic power is utilized for signals which are about 36.7% while 29.3% of total power is used for the logic portion.

3.3 Comparative Study

To the best of our knowledge, this is the first work of detecting cerebrovascular disease and cerebral infarction from PPG signal. There are some studies that worked on the detection of various cardiovascular diseases and diabetes. The comparison study is presented in Table 5.

In the table, we can see that maximum cardiovascular disease and diabetes detection works have been done at the software level where different machine learning algorithms have been used. Ave et al. [23] designed a hardware-based system to detect cardiovascular disease at an early stage, but the study lacks their system performance analysis. Our proposed study mainly focuses on implementing the disease detection system at the hardware level. We have achieved a maximum of 96.43% accuracy for cerebrovascular disease and a minimum of 88.46% accuracy for diabetes using eleven features. If we consider only the statistical features, the accuracy percentage slightly decreases in each case. 91.3%, 92.86% and 84.62% accuracy are found, respectively, for cerebral infarction, cerebrovascular disease and diabetes using nine features. In both cases, the accuracy can be further improved by considering higher SQI-indexed PPG signals.

Table 5 Comparative study

Reference	Disease type	Features used	Implementation level	Method	Accuracy (%)
Divya et al. [24]	CVD risk level	10	Software	Gaussian mixture model	99.65
Sadad et al. [25]	Hypertension	–	Software	Decision tree	99.5
Wang et al. [35]	CVDs	4	Software	SVM	78.84
Fahoum et al. [36]	Coronary artery disease	14	Software	Naive Bayes	94.44
Prabha et al. [28]	Diabetes	107	Software	RBF Kernel-based SVM	92.38
Qawqzeh et al. [26]	Diabetes	3	Software	Logistic Regression	92.3
Hettiarachchi et al. [37]	Diabetes	4	Software	Linear Discriminant Analysis	79
Chowdhury et al. [22]	CVDs	11	Hardware	SVM	79.83
Ave et al. [23]	CVDs	5	Hardware	Signal processing	–
Proposed work	Cerebral infarction	11	Hardware	SVM	93.48
	Cerebrovascular disease				96.43
	Diabetes				88.46

4 Conclusions

Cardiovascular diseases and diabetes are a growing concern for human health all over the world. Early detection can save a lot of human lives from fatal damage. Therefore, we have focused on designing and implementing a digital system using PPG signal for the detection of two vital cardiovascular diseases: cerebral infarction and cerebrovascular disease. We have further detected diabetes, a disease closely related to heart conditions. The system has been designed at the software level using a support vector machine algorithm and later at the hardware level using Xilinx system generator. Xilinx ZedBoard has been targeted for the implementation of the system. The system has a detection accuracy of over 90% on average for the selected diseases. The resource utilization study proves that the implemented system is capable of performing its purpose within the available resources of the onboard FPGA. A maximum of 0.693 W power requirement shows its efficiency in power management. The performance analysis proves that physical features like age and BMI can certainly improve the accuracy in the detection of the selected diseases. However, the number of subjects is not sufficient in this study and real-time data analysis is also required for effective validation of the system. In future, more subjects along with real-time data incorporation can be done. Robustness and sustainability analysis of the designed system for minimizing static power consumption is another scope for further studies. FPGA has the advantage of reprogramming over other hardware platforms. So, the system has the scalability potential of utilizing other biosignals like ECG, which will help to detect cardiovascular diseases more effectively. Also, the system design can be further utilized for the detection of other types of cardiovascular diseases from PPG signal and can be implemented as a point-of-care system which will help physicians in the quick detection of different diseases. The FPGA-based system can be embedded in smartwatches and other medical equipment for clinical analysis and treatment.

Acknowledgements CityU Architecture Lab for Arithmetic and Security (CALAS), City University of Hong Kong, Kowloon, Hong Kong, has supported for the implementation of this work.

Author Contributions Aditta Chowdhury contributed to conceptualization, formal analysis, methodology, and writing the original draft; Mehdi Hasan Chowdhury was involved in visualization and writing the original draft; Diba Das was responsible for methodology and writing the original draft; Sampad Ghosh took part in visualization and writing—reviewing; and Ray C. C. Cheung participated in supervision and writing—reviewing and editing.

Funding The authors have no relevant financial or non-financial interests to disclose.

Declarations

Conflict of interest The authors have no conflict of interest to declare that is relevant to the content of this article.

Ethics Approval This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by ethics committee of the Guilin People Hospital and the Guilin University of Electronic Technology in China.

References

1. Meenal, M.R.; Vennila, S.M.: Bidirectional recurrent network and neuro-fuzzy frequent pattern mining for heart disease prediction. SN Comput. Sci. **4**(4), 379 (2023). https://doi.org/10.1007/s42979-023-01711-6
2. Mani, V.; Durmus, C.; Khushaim, W.; Ferreira, D.C.; Timur, S.; Arduini, F.; Salama, K.N.: Multiplexed sensing techniques for cardiovascular disease biomarkers - a review. Biosens. Bioelectron. **216**, 114680 (2022). https://doi.org/10.1016/j.bios.2022.114680
3. Han, L.; Zhao, S.; Li, S.; Gu, S.; Deng, X.; Yang, L.; Ran, J.: Excess cardiovascular mortality across multiple COVID-19 waves in the

United States from March 2020 to March 2022. Nature Cardiovasc. Res. **2**(3), 322–333 (2023). https://doi.org/10.1038/s44161-023-00220-2
4. Mohamed, N.A.; Marei, I.; Crovella, S.; Abou-Saleh, H.: Recent developments in nanomaterials-based drug delivery and upgrading treatment of cardiovascular diseases. Int. J. Mol. Sci. (2022). https://doi.org/10.3390/ijms23031404
5. Sun, Z.; Xu, Q.; Gao, G.; Zhao, M.; Sun, C.: Clinical observation in Edaravone treatment for acute cerebral infarction. Niger. J. Clin. Pract. **22**(10), 1324–1327 (2019). https://doi.org/10.4103/njcp.njcp_367_18
6. Centers for Disease Control and Prevention [CDC] Underlying Cause of Death 2018-2021, Single Race Results (2021)
7. Li, Y.; Li, M.; Wang, M.; Zhou, Y.; Chang, J.; Xian, Y.; Wang, D.; Mao, L.; Jin, H.; Hu, B.: Acute cerebrovascular disease following COVID-19: a single center, retrospective, observational study. Stroke Vasc. Neurol. **5**(3), 279–284 (2020). https://doi.org/10.1136/svn-2020-000431
8. Goldberg, M.F.; Goldberg, M.F.: Cerebrovascular disease in COVID-19. AJNR Am. J. Neuroradiol. 1170–1172 (2020)
9. Aggarwal, G.; Lippi, G.; Michael Henry, B.: Cerebrovascular disease is associated with an increased disease severity in patients with Coronavirus Disease 2019 (COVID-19): A pooled analysis of published literature. Int. J. Stroke **15**(4), 385–389 (2020). https://doi.org/10.1177/1747493020921664
10. Theerthagiri, P.; Ruby, A.U.; Vidya, J.: Diagnosis and classification of the diabetes using machine learning algorithms. SN Comput. Sci. **4**(1), 72 (2022). https://doi.org/10.1007/s42979-022-01485-3
11. Lathief, S.; Inzucchi, S.E.: Approach to diabetes management in patients with cvd. Trends Cardiovasc. Med. **26**(2), 165–179 (2016). https://doi.org/10.1016/j.tcm.2015.05.005
12. Chowdhury, A.; Das, D.; Cheung, R.C.; Chowdhury, M.H. Hardware/software co-design of an ecg- ppg preprocessor: A qualitative & quantitative analysis. In: 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), 1–6 (2023). https://doi.org/10.1109/ECCE57851.2023.10101536
13. Liu, X.; Wang, H.; Li, Z.; Qin, L.: Deep learning in ECG diagnosis: A review. Knowl.-Based Syst. **227**, 107187 (2021). https://doi.org/10.1016/j.knosys.2021.107187
14. Cheng, P.; Chen, Z.; Li, Q.; Gong, Q.; Zhu, J.; Liang, Y.: Atrial fibrillation identification with PPG signals using a combination of time-frequency analysis and deep learning. IEEE Access **8**, 172692–172706 (2020). https://doi.org/10.1109/ACCESS.2020.3025374
15. Chowdhury, A.; Das, D.; Eldaly, A.B.M.; Cheung, R.C.C.; Chowdhury, M.H.: Photoplethysmogram-based heart rate and blood pressure estimation with hypertension classification. IPEM-Translation p 100024 (2024) https://doi.org/10.1016/j.ipemt.2024.100024
16. Paradkar, N.; Roy Chowdhury, S.: Coronary artery disease detection using photoplethysmography. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS pp. 100–103 (2017) https://doi.org/10.1109/EMBC.2017.8036772
17. Al Fahoum, A.; Al Omari, A.; Al Omari, G.; Al Zyout, A.: PPG signal-based classification of blood pressure stages using wavelet transformation and pre-trained deep learning models. In: 2023 Computing in Cardiology Conference (CinC) 50:1–4 (2023) https://doi.org/10.22489/cinc.2023.360
18. Prabhakar, S.K.; Rajaguru, H.; Lee, S.W.: Metaheuristic-based dimensionality reduction and classification analysis of PPG signals for interpreting cardiovascular disease. IEEE Access **7**, 165181–165206 (2019). https://doi.org/10.1109/ACCESS.2019.2950220
19. Mazumder, O.; Banerjee, R.; Roy, D.; Bhattacharya, S.; Ghose, A.; Sinha, A.: Synthetic PPG signal generation to improve coronary artery disease classification: study with physical model of cardiovascular system. IEEE J. Biomed. Health Inform. **26**(5), 2136–2146 (2022). https://doi.org/10.1109/JBHI.2022.3147383
20. Allen, J.; Liu, H.; Iqbal, S.; Zheng, D.; Stansby, G.: Deep learning-based photoplethysmography classification for peripheral arterial disease detection: A proof-of-concept study. Physiol. Meas. (2021). https://doi.org/10.1088/1361-6579/abf9f3
21. Allen, J.; Overbeck, K.; Stansby, G.; Murray, A.: Photoplethysmography assessments in cardiovascular disease. Meas. Control **39**(3), 80–83 (2006). https://doi.org/10.1177/002029400603900303
22. Chowdhury, A.; Das, D.; Hasan, K.; Cheung, R.C.C.; Chowdhury, M.H.: An fpga implementation of multiclass disease detection from ppg. IEEE Sensors Lett. **7**(11), 1–4 (2023). https://doi.org/10.1109/LSENS.2023.3322288
23. Ave, A.; Fauzan, H.; Adhitya, S.R.; Zakaria, H.: Early detection of cardiovascular disease with photoplethysmogram(PPG) sensor. In: Proceedings - 5th international conference on electrical engineering and informatics: bridging the knowledge between academic, industry, and community, ICEEI 2015 pp. 676–681 (2015) https://doi.org/10.1109/ICEEI.2015.7352584
24. Ramachandran, D.; Ponnusamy Thangapandian, V.; Rajaguru, H.: Computerized approach for cardiovascular risk level detection using photoplethysmography signals. Meas. J. Int. Meas. Confeder. **150**, 107048 (2020). https://doi.org/10.1016/j.measurement.2019.107048
25. Sadad, T.; Bukhari, S.A.C.; Munir, A.; Ghani, A.; El-Sherbeeny, A.M.; Rauf, H.T.: Detection of cardiovascular disease based on PPG signals using machine learning with cloud computing. Comput. Intell. Neurosci. (2022). https://doi.org/10.1155/2022/1672677
26. Qawqzeh, Y.K.; Bajahzar, A.S.; Jemmali, M.; Otoom, M.M.; Thaljaoui, A.: Classification of diabetes using photoplethysmogram (PPG) waveform analysis: logistic regression modeling. BioMed Res. Int. (2020). https://doi.org/10.1155/2020/3764653
27. Serena, Z.; Ammi, M.; Hallab, M.; El Yacoubi, M.A.A.: Type 2 diabetes detection with light CNN from single raw PPG wave. SSRN Electron. J. (2022). https://doi.org/10.2139/ssrn.4145219
28. Prabha, A.; Yadav, J.; Rani, A.; Singh, V.: Non-invasive diabetes mellitus detection system using machine learning techniques. In: Proceedings of the confluence 2021: 11th international conference on cloud computing, data science and engineering pp. 948–953 (2021). https://doi.org/10.1109/Confluence51648.2021.9377138
29. Avram, R.; Tison, G.; Kuhar, P.; Marcus, G.; Pletcher, M.; Olgin, J.E.; Aschbacher, K.: Predicting diabetes from photoplethysmography using deep learning. J. Am. Coll. Cardiol. **73**(9), 16 (2019). https://doi.org/10.1016/s0735-1097(19)33778-7
30. Susana, E.; Ramli, K.; Murfi, H.; Apriantoro, N.H.: Non-invasive classification of blood glucose level for early detection diabetes based on photoplethysmography signal. Information (Switzerland) (2022). https://doi.org/10.3390/info13020059
31. Nakai, M.; Iwanaga, Y.; Sumita, Y.; Wada, S.; Hiramatsu, H.; Iihara, K.; Kohro, T.; Komuro, I.; Kuroda, T.; Matoba, T.; Nakayama, M.; Nishimura, K.; Noguchi, T.; Takemura, T.; Tominaga, T.; Toyoda, K.; Tsujita, K.; Yasuda, S.; Miyamoto, Y.; Ogawa, H.: Associations among cardiovascular and cerebrovascular diseases: Analysis of the nationwide claims-based JROAD-DPC dataset. PLoS ONE 17(3 March):1–13 (2022) https://doi.org/10.1371/journal.pone.0264390
32. Liang, Y.; Chen, Z.; Liu, G.; Elgendi, M.: A new, short-recorded photoplethysmogram dataset for blood pressure monitoring in China. Sci. Data **5**, 1–7 (2018). https://doi.org/10.1038/sdata.2018.20
33. Gandhare, S.; Karthikeyan, B.: Survey on FPGA Architecture and Recent Applications. In: 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), 1–4, (2019) https://doi.org/10.1109/ViTECoN.2019.8899550

34. Al Fahoum, A.S.: Enhanced cardiac arrhythmia detection utilizing deep learning architectures and multi-scale ECG analysis. Tuijin Jishu/J. Propul. Technol. **44**(6) (2023)
35. Wang, Y.: Identification of cardiovascular diseases based on machine learning. ACM Int. Conf. Proc. Ser. **1**(1), 531–536 (2022). https://doi.org/10.1145/3570773.3570855
36. Al Fahoum, A.S.; Abu Al-Haija, A.O.; Alshraideh, H.A.: Identification of coronary artery diseases using photoplethysmography signals and practical feature selection process. Bioengineering (2023). https://doi.org/10.3390/bioengineering10020249
37. Hettiarachchi, C.; Chitraranjan, C.: A machine learning approach to predict diabetes using short recorded photoplethysmography and physiological characteristics. Lecture Notes Comput. Sci. 11526 LNAI:322–327 (2019) https://doi.org/10.1007/978-3-030-21642-9_41