International Journal of Engineering Trends and Technology Volume 69 Issue 11, 134-139, November, 2021
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I11P217

Original Article

Cardiovascular Disease Classification using ECG Signal

Salam Devayani Devi[1], Dr. Loitongbam Surajkumar Singh[2]

[1]*Lecturer, ECE Department, NIT Manipur, India*
[2]*Assistant Professor, ECE Department, NIT Manipur, India*

[1]devu2.sd@gmail.com, [2]surajloi@yahoo.co.in

***Abstract** - This paper presents an ECG signal monitoring system to classify normal and abnormal ECG signals. The system consists of pre-processing step followed by classification. In the pre-processing step, reduction of the noise contained in the ECG signal is performed. Then the filtered signal is given as the input to the classification block. A long short-term neural network is used for the classification of arrhythmia from the normal ECG signal beats. The benefit of this work is the reduction in the size and power consumption compared to other approaches. This monitoring system is implemented on Spartan 7 FPGA using Xilinx vivado software, achieving an accuracy of 99.92% with a power consumption of 0.009W. The ECG dataset used in this work is the MIT-BIH arrhythmia database.*

Keywords — *ECG, FPGA, LSTM, cardiovascular disease classification, abnormal ECG signal.*

I. INTRODUCTION

According to the health organization, the major death rates are happened by Cardiovascular Diseases (CVD) [1]. Heart attack, angina, stroke, peripheral vascular diseases, etc., are some cardiovascular diseases. Early detection of abnormalities related to heart diseases is needed as it can reduce the mortality rate. ECG is a commonly used non-invasive tool to detect various cardiovascular diseases[2]. In ECG, the electrical activity of the heart is measured by placing electrodes on the human body. The ECG waveform obtained from the human body is used as the source to decide the person's cardiovascular-related problems[3]. The ECG waveform is shown in figure 1. It consists of P, QRS, T, U waves. The amplitude level and duration of each of these component waves for the normal person and sick individual differs. The amplitude level P, R, T waves of the normal ECG is 0. 25 m V, 1.60mV, 0.1-0.5m V respectively[4]. Moreover, automated, efficient cardiovascular disease detection using an ECG system plays a major role in early accurate disease prediction[5]. ECG signals obtained from the human body may contain noise such as baseline wandering, motion artifacts, powerlines interference, etc. [6].

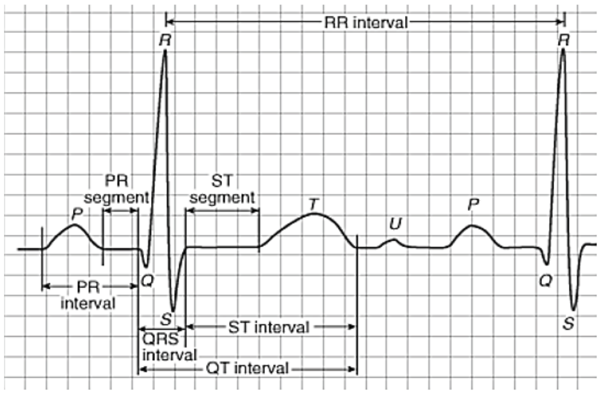

Fig. 1 ECG waveform

Such noisy ECG signal is needed to be pre-processed before it is applied to the detection system [7]. In some cases, diseases such as arrhythmias, a small duration of ECG waveforms is not sufficient to diagnose a patient, so continuous monitoring is required, say more than 24 hrs time duration[8]. Many research works have been done in the field of detection and classification of various ECG signals in the software domain using a platform such as MATLAB, python. On the hardware platform, smaller numbers of work related to ECG signal analysis are developed as well [9]. FPGA is considered as the platform for hardware implementation as it is cost-effective, smaller processing duration, reconfigurable. FPGA(field-programmable gate array) consist of CLBs(configurable logic blocks) which are connected through programmable interconnects[10]. To ease the work of doctors and patients, it is necessary to develop a portable wearable system that can detect the electrical signal of the heart [11]. In Pan, Tomkins method used the band-pass filter to remove noise such as muscle noise, 60Hz interference, baseline wander, and T-wave interference [12-13]. For the detection step, derivative filter, squaring function, moving window integrator, and thresholding method are employed to obtain the ECG signal [14]. This method is efficient, but its accuracy is lesser as compared to other algorithms. S.M. Rayavarapu used the ordinal pattern analysis method to develop a less complex hardware system on the FPGA platform for ECG signal classification. The author computes the conditional entropy, which is then compared with a threshold value [15]. Madam Aravind Kumar employed a bandpass filter followed by a first-order differentiation filter for the filtering step[16]. In the slop detection, Shannon energy envelope extraction, zero-phase filtering method is used. Hilbert transform method is applied in the R peak finding from the ECG signal obtained with an accuracy of 99.87 %. Many works employed the Wavelet transform method in the pre-processing stage as well as in feature extraction. The wavelet transform is implemented in the form of filter banks, consisting of low pass filters and high pass filters, thus extracting the approximate co-efficient and details co-efficient [17]. Most of the paper considered Daubechies wavelet, haar wavelet as the mother wavelet [18]. In Daubechies wavelet decomposition, the decomposition is done up to the third level. Thus the detail co-efficient, d1, d2, d3 with the very low frequency, very frequency are excluded for the further steps [19-20]. The approximation co-efficient a3 is considered as the input for the classifier block. The wavelet transform method achieved better SNR in denoising, better accuracy in the detection of normal and abnormal ECG signals. But this technique is computationally complex, which is not an efficient choice for the design of wearable hardware systems with lesser power consumption and memory space. In [21], L.V.Rajani Kumari used the empirical mode decomposition method (EMD) is used for the removal of noise from the ECG signal. The raw ECG signal is decomposed into a series of IMF's. By calculating the spectral flatness of the IMF's and comparing them with a threshold value, the IMF's which contained noisy signals are removed. Thus by using a bandpass filter of 40-60Hz and a low pass filter with a cut-off frequency of 60Hz, IMF's are filtered. Then for the R peak detection thresholding method is used. This system obtained an overall accuracy of 94.76%. Karim Meddah[22] proposed an arrhythmia detection system by calculating the heart rate from the ECG signal detected. The author used the Pan Tomkins method in the pre-processing stage. For the QRS complex detection stage, the author applied derivative filter, maximum peak detection, adaptive amplitude, and time thresholding method. Thus the heart rate is calculated using the R-R interval obtained, achieving the accuracy of 99.26% and 99.39% in software and hardware architecture, respectively. Hamza Baali [23] used the sparsity measurement technique to determine the ventricular ectopic beats, thus classifying the beats in 69.3 ms using only 0.934 W energy.

In recent years deep learning-based algorithms for the classifications of various types of ECG signals have been developed. Paweł Pławiak [24] has designed an automatic cardiac disease prediction system using an evolutionary neural system based on an SVM classifier. Here 17 classes of sinus rhythms are trained to the system, which is normal ECG signals. This system obtained an accuracy of 98.85%. Nahian Ibn Hasan[25] have employed an empirical mode framework to classify the multiple Cardiac diseases from the trained ECG signal. Hence, to recognize the severity rate from the trained ECG signal, the convolution model was projected. Finally, it has been reported that the projected convolution model has gained 99.7% accuracy for classifying the abnormal ECG signal. But it takes more time to execute. M. Yin [26] applied AI technology and IoT to develop a remote ECG monitoring system with good accuracy. In this work, IoT is used to link all the devices, and a convolutional neural network is issued for the classification. Hassan Sharabaty [27] used threshold decision (TD) and Numeral Virtual Generalizing Random-Access Memory (NVG-RAM) classifier to determine the abnormal and the normal ECG signals. NVG-RAM achieved higher accuracy compared to TD, while the TD method required less computation time. The deep learning-based method attained better accuracy as compared to other methods, as well as the features were extracted automatically[28]. In deep learning algorithms, feature extraction and classification are done collectively by a system.

In this paper, a deep learning-based classification method with the implementation in the hardware domain is proposed. The recurrent neural network is best suited for the analysis of time series. The recurrent neural network used previous input to determine the present output. In this work, the long-short term neural network (LSTM) is used to classify ECG signals, explained in section II. Then, the experimental results are shown in section III, followed by a conclusion in section IV.

II. METHODOLOGY

The cardiovascular disease classification system consists of two steps: pre-processing stage and classification. But in some cases, the noise in the ECG signal might minimize the disease prediction rate. Thus, the denoising of the ECG signal is necessary, and then the filtered output is fed to the LSTM model. The architecture of the projected design is described in fig.2.

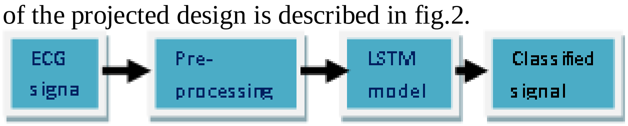

Fig. 2 proposed architecture for CVD detection system.

A. Pre-processing

The technique which is used to convert the raw dataset into a clear dataset is known to be Dataset pre-processing. Data pre-processing is used to eliminate the contaminated data and to filter the noise. For filtering muscle interference, the value of frequency used in high filter threshold frequency is 0.5Hz, and for low filter threshold frequency is 50Hz. In this work, FIR band-pass filter is used to remove the unwanted signals present in the ECG signal.

B. Classification model

Long Short-term neural network is one of the variants of recurrent networks in which there are recurrent connections of neurons, thus forming a memory unit. This type of neural network is useful in the analysis of series data, such as speech signal, time series, etc. Each computational unit is called the cell, consisting of neurons. The memory unit present in the LSTM is also called cell state, which solves the vanishing and exploding problem. The LSTM network includes input gate, new input gate, forget gate, output gate. The architecture of the LSTM model is shown in fig. 3.

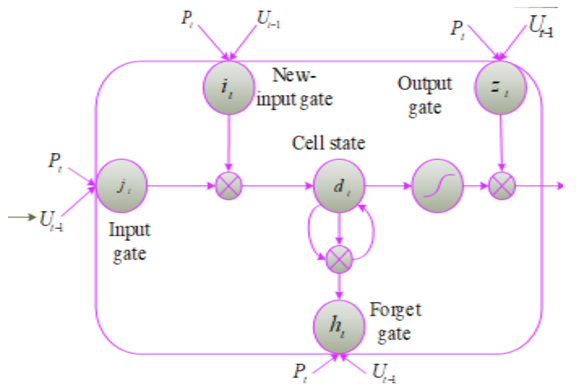

Fig. 3 LSTM model

The network is expressed mathematically as follows:

$$j_t = sigm(w_{pj}p_t + w_{uj}u_{t-1} + b_j) \quad (1)$$

$$i_t = tanh(w_{pi}p_t + w_{ui}u_{t-1} + b_i) \quad (2)$$

$$h_t = sigm(w_{ph}p_t + w_{uh}u_{t-1} + b_h) \quad (3)$$

$$z_t = sigm(w_{pz}p_t + w_{uz}u_{t-1} + b_z) \quad (4)$$

$$d_t = j_t \odot i_t + h_t \odot z_{t-1} \quad (5)$$

$$u_t = z_t \odot tanh\, d_t \quad (6)$$

In order to accelerate the performance of this model, the three sum term in equations (1), (2), (3), (4) are concatenated instead of calculating them explicitly. Thus, the equation can be written as,

$$j_t = sigm(\tilde{j}_t) = sigm(w_j \tilde{p}_t) \quad (7)$$

where j_t represents the pre-activation term of the input signal, p_t represents the concatenation of pre-processed signal, hidden state signal, and bias value

III. RESULTS AND DISCUSSION

The dataset used in this work is taken from the MIT-BIH arrhythmia database, which is a standard dataset to estimate the performance of this proposed work. The ECG recordings are sampled at 360 samples per second. The ECG signals were obtained from 45 patients. The dataset is first converted into binary form and split the dataset for testing and training in MATLAB. The planned research work is executed in the XILINX vivado using the Spartan 7 FPGA platform. Consequently, the novel LSTM model is structured in the Xilinx environment to separate the disease signal from the normal signal. To validate the successive score of the projected scheme, one ECG signal was taken into account and processed with the designed model. Moreover, the attained waveform of that particular signal is described in fig.4.

Table. I Database Description

	Patients no	Fragments number	Test set	Training set
Ventricular bigeminy	4	44	13	31
Ventricular flutter	1	10	3	7
Atrial flutter	2	17	5	12
Idioventricular rhythm	1	10	3	7
Ventricular trigeminy	4	13	4	9
Pre-excitation	1	21	6	15
Atrial fibrillation	3	93	28	65

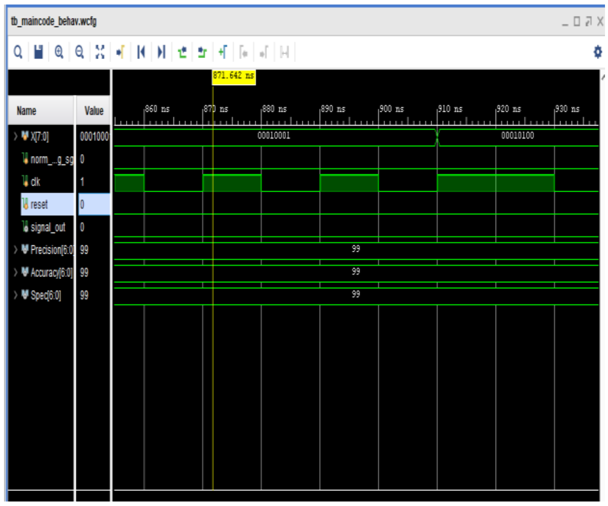

Fig.4 ECG signal classification

This projected approach is designed in the Spartan-7 family, and it has utilized very few resources while comparing the other gadget families. The Xilinx platform has a different device family; each family has specific and unique features to execute the circuit model. Based on that, the device parameter gets varied. Fig.5. represent the schematic diagram of the proposed work. Hence, the utilization of Artix-7 device resources is detailed in the table.II, Kintex 7gadget resource usage is illustrated in the table.III and Spartan-7device utilization is described in the table. IV.

Table. II Artix-7 device (xc7a100t fgg676-1 (active)

Device utilization table			
Device parameter	**Resource Utilization**	**Available**	**Utilization %**
LUT	3610	63400	5.7
FF	201	126800	0.16
Signals	19	240	7.92
IO	39	300	13

Table III Resource usage of Kintex 7 (xc7k160t fbg484-3) device

Resource	Utilization	Available	Utilization %
LUT	66	101400	0.07
FF	104	202800	0.05
Signals	19	600	3.17
IO	38	285	13.33

Moreover, the proposed design is structured in the Spartan-7 family; hence, comparing all those devices, it has utilized few resources to execute the function. It is quite better than the compared device. But, while comparing the power consumption, Kintex 7 device has recorded the low power consumption as 16.17W, Spartan-7has consumed 0.079W power to run the process, and the device Artix-7 device has consumed a wide measure of power as 0.1 W.

In addition, for the circuit model, the validation of power is very crucial to value the device's reliability. The time taken by a system to generate the output after applying the input is known as Latency.

Table.IV Spartan-7(xc7s50fpga484-2 (proposed)

Resource	Utilization	Available	Utilization %
LUT	66	32600	0.20
FF	104	65200	0.16
Signals	19	120	15.83
IO	38	250	15.20

It measures the design's delay response, and if the value of latency is high, it slows the system. In the synchronous method, the latency was measured with regard to clock cycles based on numbers. In a non-pipeline model, improvement of latency is a significant space of concern. In common terms, latency is described as the difference of time between input and output. The device performance was compared with other models such as SII [23] and TDG [28]. By the evaluation, the proposed device Spartan-7 has recorded the lowest latency as 2.518ns, 0.2% LUT usage, 0.16% FF usage, and 0.009W power consumption for 50 MHz frequency. Moreover, the TDG approach has taken 629.8ms for execution, 9.9% LUT usage, 1.25% FF and 0,13W power for 25MHz frequency. Also, the method SII has obtained 0.934W power, 69ms latency, 47% LUT utilization, and 41%FF for 300Hz frequency. These statistics are shown in the table. V.

A. Accuracy

The parameter accuracy is the chief metric to validate the algorithm proficiency; here, the exactness score was validated for accurate disease signal specification. By comparing the old approaches, the proposed strategy has earned the finest results. Moreover, the metrics are valued with the incorporation of some basic parameters, such as true positive (P_t), False negative (N_f), False positive(P_f), and true negative (N_t); the parameter accuracy was measured by eqn. (8).

$$Accuracy = \frac{P_t}{P_t + N_f + P_f} \qquad (8)$$

The designed scheme has gained 99.92% accuracy; the TDG method has earned 98% accuracy, the CFL the method has attained 98.4% accuracy, and AA has earned 94.6% accuracy[29].

Table. V Comparison validation device resource utilization

Methods	Power (W)	area	delay	LUT (%)	FF (%)	frequency
sparse inequality indexes (SII) [23]	0.934	-	69 ms	47	41	300 Hz
Time discrete grouping (TDG) Scheme [28]	0.013	0.925	629.8ms	9.90	1.25	25 MHz
Proposed : work (Spartan-7)	0.009	0.4	2.518ns	0.2	0.16	50 MHz

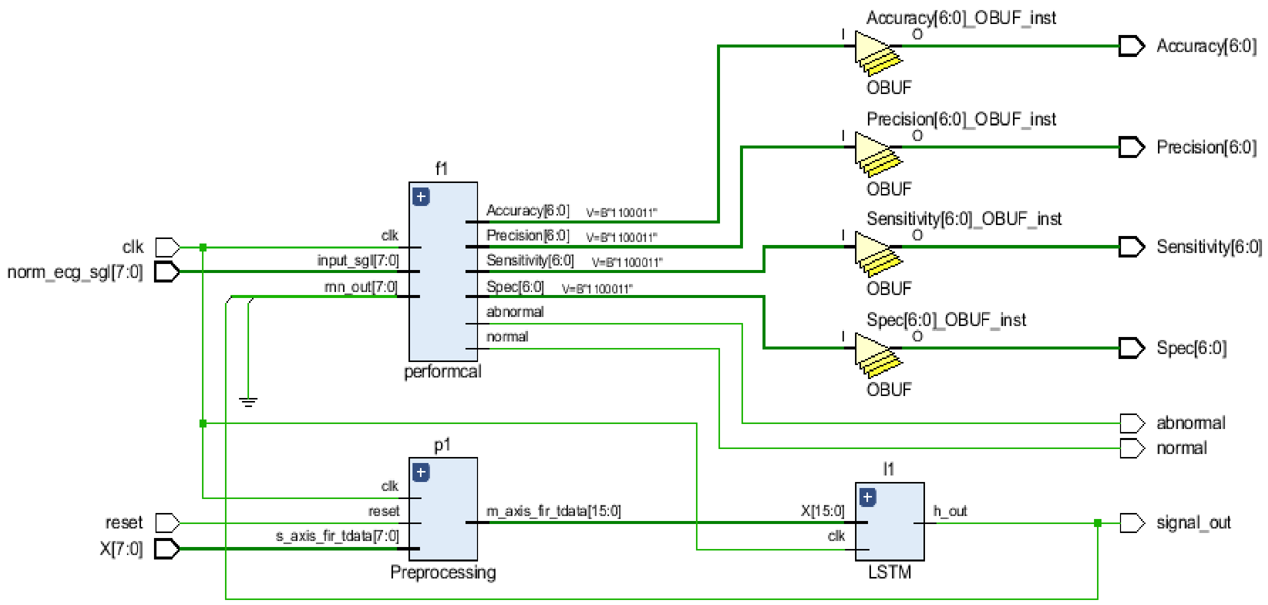

Fig.5 Schematic diagram of the proposed work

B. *Precision*

The metrics precision is valued by calculating the predicted disease signal; hence, the precision score is measured by eqn. (9).

$$precision = \frac{p_t}{p_t + p_f} \quad (9)$$

The designed approach has earned 99.91% precision; the TDG algorithm scored 94% precision, the CFL scheme has achieved 98.3% precision, and the AA approach has yielded 97.6% precision. Compared the compared conventional models, the designed approach has earned the finest precision measure.

C. *recall*

To measure the severity range of the disease affection, the parameter sensitivity was evaluated. Hence, the score of sensitivity is estimated by eqn. (10).

$$SEN = \frac{abnormal}{abnormal + normal} \quad (10)$$

The parameter recall was estimated to quantify the exact disease specification, which is valued on the basis of true positive scores. Moreover, the recall validation is proportional to the correct disease specification cases. The designed approach has earned 99.92% recall.

D. Discussion

To measure the magnificent sore of the presented design, several key parameters are validated with replicas in terms of both classification and device utilization parameters. In the Xilinx Vivado software for the FPGA platform, the designed scheme is validated in three device families, which are KIntex 7, Spartan 7, and Artix 7. While comparing these 3 devices, the gadget family Spartan 7 has used fewer resources than other devices. Moreover, the device Spartan 7 has earned marvelous outcomes by occupying fewer resources.

Table.VI Overall Parameter validation

Methods	accuracy	recall	precision
automated algorithm [29]	94.6	98.3	97.6
Convolution Focal Loss[30]	98.4	98.4	98.3
Time discrete grouping (TDG) Scheme [23]	98%	97%	94%
Proposed work	99.92	99.92	99.91

Besides, the disease specification process parameters analysis statistics are described in the table. VI. From all the outcome validation, the presented method has gained a magnificent outcome. This verified that the projected design is applicable for disease specification systems by ECG signals.

IV. CONCLUSIONS

Classifying the disease with the use of ECG signals became a trending topic in today's medical field. Hence, to specify the disease severity and types with a better exactness rate, a novel LSTM model is implemented in the Xilinx Vivado using the Spartan 7 FPGA family. Consequently, to check the robustness of the designed model, the LSTM technique was implemented in two family devices, such as Artix-7 and Kintex 7. Finally, a comparison has been done for these three devices. In that, the Spartan device platform has occupied fewer resources to execute the function. In addition, the proficiency score of the disease specification module is estimated by evaluating the chief metric like accuracy, sensitivity, precision. Hence, the earned accuracy by the presented model is 99.92%. Thus it has enhanced the disease signal specification ratio by 0.3% than the previous model.

REFERENCES

[1] Satria Mandala, Tham Cai Di, ECG Parameters for Malignant Ventricular Arrhythmias: A Comprehensive Review, J. Med. Biol. Eng., (2016).

[2] R.Shankari, S. Asha Safana, M. Kaviya, Lynda Charles, FPGA-based electrocardiography (ECG) signal analysis system using infinite impulse response (IIR) filter, in International Journal of Applied Engineering Research, 14 (2019).

[3] Dipeeka Kalamkar, S.S. P., Ecg Signal Noise Reduction Using FPGA, in International Journal Of Current Engineering And Scientific Research, 4(6) (2017).

[4] Md. Merajul Islam, Md. A. R., ECG Signal Based Angina Pectoris Detection Using Statistical and Machine Learning Approach, in International Journal of Scientific & Engineering Research, 10(1) (2019).

[5] Wissam Jenka, R.L., Abdelhafid Elouardi, S. M., FPGA Implementation of the Real-Time ADTF process using the Intel-Altera DE1 Board for ECG signal Denoising, in 4th World Conference on Complex Systems (WCCS), (2019).

[6] N. S. Madiraju, N. Kurella, R. Valapudasu, FPGA Implementation of ECG feature extraction using Time domain analysis, in Electrical Engineering and Systems Science, (2018).

[7] Safa Mejhoudi, R. L., Wissam jenkal, Real-time ECG Signal Denoising Using the ADTF Algorithm for Embedded Implementation on FPGAs, 4th World Conference on Complex Systems (WCCS), (2019).

[8] M. Yin, R. T., Miao Liu, K. Han, X. Lv, M. Huang, P. Xu, Y. Hu, B. Ma, and Y. Gai, Influence of Optimization Design Based on Artificial Intelligence and Internet of Things on the Electrocardiogram Monitoring System, on Internet of Medical Things for Healthcare Engineering, (2021).

[9] El Hassan El Mimouni, Mohammed Karim**,** Novel Real-Time FPGA-Based QRS Detector Using Adaptive Threshold with the previous smallest peak of ECG signal, in Journal of Theoretical and Applied Information Technology, Vol. 50(1) (2013).

[10] Savita Jadhav, B. P., Chaudhari Asawari, C. N., FPGA Based ECG Signal Noise Suppression using Windowing Techniques, in International Journal of Engineering Trends and Technology (IJETT) , 4 (2017).

[11] Wai-Chi Fan, I-Wei Chen, An Integrated PPG and ECG Signal Processing Hardware Architecture Design of EEMD Processor, in International Conference on Consumer Electronics (ICCE), (2019).

[12] Sachin Singh, Netaji Gandhi. N, Pattern analysis of different ECG signal using Pan-Tompkin's algorithm, in International Journal on Computer Science and Engineering 02(7) (2010) 2502-2505.

[13] D. Alhelal and M. Faezipour, Denoising and Beat Detection of ECG Signal by Using FPGA, in International Journal of High-Speed Electronics and Systems, 26 (2017).

[14] Jiapu Pan, W.J.T., A Real-Time QRS Detection Algorithm, in IEEE transactions on Biomedical Engineering, 32(3) (1985).

[15] S. M. Rayavarapu, D Bikshapathi, Samrat L Sabat, J.S.Armand Eyebe Fouda, FPGA implementation of Ordinal Pattern Analysis algorithm for Early Detection of Cardiovascular diseases, in International Conference for Convergence in Technology (I2CT), Pune, India, 29-31 (2019).

[16] K. Meddah, M. Kedir Talha, M. Bahoura, H. Zairi, FPGA-based system for heart rate monitoring, in IET Circuits, Devices & Systems, 13 (6) (2019) 771-782.

[17] Safa Mejhoudi, R. L., Wissam jenkal, Real-time ECG Signal Denoising Using the ADTF Algorithm for Embedded Implementation on FPGAs, 4th World Conference on Complex Systems (WCCS), (2019).

[18] Agostino Giorgio,C. g.: ECG Signal Denoising using Wavelet for the VLP effective detection on FPGA, AEIT International Annual Conference, (2018).

[19] Padmavathi C, Veenadevi S V, An Optimized FPGA Based System Design for the Arrhythmia Detection using ECG, in International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, 9 (2019).

[20] Syed Muhammad Anwar, Maheen Gul, Muhammad Majid, and Majdi Alnowami, Arrhythmia Classification of ECG Signals Using Hybrid Features, in Comput Math Methods Med. (2018).

[21] L.V.Rajani Kumari, Y.Padma Sai, N.Balaji, K.Viswada, FPGA Based Arrhythmia Detection, in 3rd International Conference on Recent Trends in Computing, Procedia Computer Science 57 (2015) 970 – 979 .

[22] K. Meddah, M. Kedir Talha, M. Bahoura, H. Zairi, FPGA-based system for heart rate monitoring, in IET Circuits, Devices & Systems, 13(6) (2019) 771-782.

[23] Baali, Hamza, et al., Inequality indexes as sparsity measures applied to ventricular ectopic beats detection and its efficient hardware implementation, in IEEE Access 6 (2017) 9464-9472.

[24] Pławiak, Paweł, and MoloudAbdar, Novel methodology for cardiac arrhythmias classification based on long-duration ECG signal fragments analysis, in Biomedical signal processing. Springer, Singapore, (2020) 225-272.

[25] Nahian Ibn Hasan, Arnab Bhattacharjee, Deep Learning Approach to Cardiovascular Disease Classification Employing Modified ECG Signal from Empirical Mode Decomposition, in Biomedical Signal Processing and Control 52 (2019) 128-140.

[26] M. Yin, R. T., Miao Liu, K. Han, X. Lv, M. Huang, P. Xu, Y. Hu, B. Ma, and Y. Gai, Influence of Optimization Design Based on Artificial Intelligence and Internet of Things on the Electrocardiogram Monitoring System, on Internet of Medical Things for Healthcare Engineering, (2021).

[27] Hassan Sharabaty, Ihab Ahkam, Abdellatif Baba, FPGA-Based Multi-Heart Diseases Classification System with the Aid of LabVIEW, in 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)

[28] hubham Srivastava, Himanshu Bhardwaj, Aman Dixit, Prof. Namita Kalyan Shinde, ECG Pattern Analysis Using Artificial Neural Network, in SSRG International Journal of Electronics and Communication Engineering 7.5 (2020).

[29] Zhao, Yang, Zhongxia Shang, and Yong Lian, A 13.34 μW event-driven patient-specific ANN cardiac arrhythmia classifier for wearable ECG sensors, in IEEE transactions on biomedical circuits and systems 14.2 (2019) 186-197.

[30] Moridani, M. K., M. Abdi Zadeh, and Z. Shahiazar Mazraeh, An efficient automated algorithm for distinguishing normal and abnormal ECG signal, IRBM 40.6 (2019) 332-340.

[31] Romdhane, Taissir Fekih; Alhichri, Haikel; Ouni, Ridha; Atri, Mohamed Electrocardiogram heartbeat classification based on a deep convolutional neural network and focal loss, in Computers in Biology and Medicine, (2020).