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An Efficient VLSI Architecture Implementation Based on ECG Classification system

M.Sangeetha[1], S.Geetha[2]

[1]*PG Scholar, Er.Perumal Manimekalai College of Engineering, Hosur.*

[2]*Asst Professor,Er .Perumal Manimekalai College of Engineering, Hosur.*

Abstract: Recent medical field technologies are mainly used in advanced systems and equipments to analyze disease types and effectively classify the stages of diseases. This article says about the design of ASIC architecture for electrocardiogram (ECG) signal for the prophecy of ventricular arrhythmia. The unique set of ECG feature and a SVM Classifier is used. Real-time adaptive techniques are used for the recognition and the demarcation of the PQRS- T waves which were examined to extract the fiducially points. These performances are vigorous to any deviations in the ECG signal with high sensitivity and accuracy. Two of the heart signal recordings databases from the MIT PhysioNet are used as a substantiation set to calculate the performance. VLSI based DSP systems are used to modify the internal circuit structure level and to optimize the circuit complexity level and to improve the system quality. Most digital signal processing algorithms are specified with floating-point data types but they are finally implemented in Application Specified Integrated Circuit (ASIC) architectures in order to satisfy the cost and power consumption.

Index terms: Electrocardiogram (ECG), Application Specified Integrated Circuit (ASIC), ventricular arrhythmia, SVM (Support Vector Machine)

I. Introduction

Ventricular fibrillation (VF) is one of the main causes of sudden cardiac death in the Western world. It is a type of arrhythmia that causes the heart to beat chaotically, rendering it unable to pump blood. VF is usually preceded by ventricular tachycardia (VT), which is another type of arrhythmia that also constitutes a medical emergency. It is crucial for the patient to receive immediate medical intervention when either VF or VT occurs, so a method that predicts their occurrence even a few seconds sooner can prospectively save lives. The goal of this research is to investigate the possibility of predicting ventricular arrhythmias from an electrocardiogram (ECG) signal, which is a measurement of cardiac electrical commotion.

Recent advances in modeling the mechanism of VF initiation posit that the cardiac electrical dynamics leading to fibrillation is deterministic and chaotic. Even though passionate researches on ventricular arrhythmias, there have not been numerous existing efforts to apply current machine learning techniques on ECG signals for prediction. This electrical activity might leave detectable traces on the ECG which can be exploited by an appropriate learning technique to predict the imminence of the onset.

In the United States cardiac death rate has been increased account for approximately 300 000 deaths in per year and most cases due of ventricular arrhythmias, including ventricular fibrillation (VF) and ventricular tachycardia (VT). Ventricular arrhythmia is an abnormal ECG rhythm and is accountable for 75%–85% of unexpected deaths in persons with heart tribulations unless treated within seconds.

The main causes for ventricular arrhythmias are coronary heart syndrome, cardiomyopathy, or hypertension, and if not neither perfectly analyzed nor treated, instant death occurs. VT is a rapid rhythm of more than three successive beats beginning from the ventricles at a rate more than 100 beats/min. VF is one more rhythm differentiated by the chaotic inauguration of ventricles, and it causes instant cessation of blood circulation and deteriorates further into a pulse less or flat ECG signal indicating no cardiac electrical activity.

For the individuals with elevated danger cardiac activity, implantation of cardioverterdefibrillator has been considered as the best protection method against unexpected death due to ventricular arrhythmias. However, mainly unexpected deaths occur in personalities who do not have high-risk profiles. Long-standing ECG monitoring is the condition regular for the identification of ventricular arrhythmia. The 12- lead ECGs are acquired and examined to notice any changes in the characteristics of the ECG signal. By removing in order about intermissions, amplitudes, and waveform morphologies of the different P-QRS-T waves, the start of the ventricular arrhythmia can be distinguished.

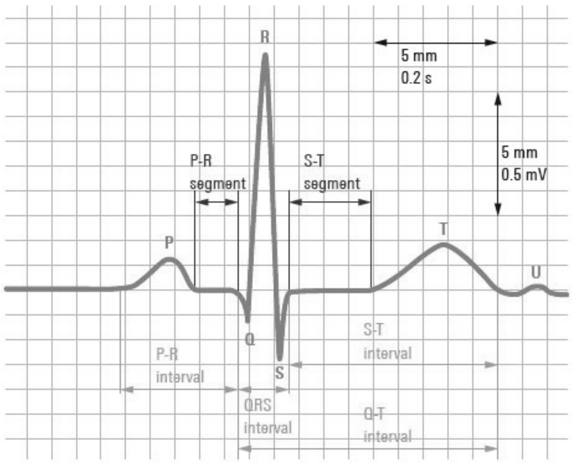

Fig: 1.1. P-QRS-T wave

Many methods have been residential to identify ventricular arrhythmia foundation on morphological spectral or mathematical features removed from the ECG signal. Machine learning techniques, such as neural networks and ANN have also been suggested as a useful tool to improve the detection efficiency. Even though these techniques have demonstrated recompense in the exposure of ventricular arrhythmia, they have some shortcomings. Some are too complex to put into practice or work out, some have low specificity in perceptive between normal and abnormal conditions, and all sustain late recognition interval, which is usually not enough to take an action.

II. Literature Review

Due to extraordinary encroachment in technology, the expansion of dedicated hardware for perfect ECG analysis and classification in real time has become possible. The major necessities are low-power utilization and low-energy procedure in order to have longer battery lifetime along with the tiny region. Several endeavors succeeded to execute ECG signal processing and classification schemes in hardware. Shiu et al [10]. Implemented an integrated electrocardiogram signal processor (ESP) for the identification of heart diseases using the 90-nm CMOS technology. The scheme engaged an instrumentation amplifier and a low-pass filter (LPF) to take away the baseline wander and the power line obstruction from the ECG and employed a time-domain morphological analysis for the feature extraction and classification based on the evaluation of the ST segment. The scheme was approved out in a field programmable gate array and consumed a total of 40.3-µW power and achieved an accuracy of 96.6%. The most important disadvantage of the scheme is that it uses fixed hunt window with predefined size to situate S and T fiducial points, which is not appropriate for real-time scenarios [12].

The system was fabricated on the 0.18-µm CMOS technology and completed special occupations for the three phases of preprocessing, feature extraction, and classification. The algorithm following these purposes was support on the quad level vector. Furthermore, the gatherings were all pipelined to enhance hardware consumption and shrink power utilization. The ECG processor consumed 6 µW at 1.8 V and 1.26 µW at 0.7 V, which is much better than the system due to the low-power techniques it employed. One latest classification for ECG was obtainable and embraced of three fragments. The initial chip restricted the body-end tracks that were the highpass sigma delta modulator-support bio-signal mainframe and the ON–OFF keying spreader. The next chip, the getting end, had the digital signal processing (DSP) and recipient division. The final chip was the classifier. Discrete wavelet transform was espoused by the DSP unit for the ECG element extraction and classification. The fragment was fabricated on the 0.18-µm CMOS expertise and obsessive a total power of 5.967 µW at 1.2 V for the DSP unit only. The precision of the beat recognition and the ECG classification was 99.44% and 97.25%, respectively.

The main benefit of such approach is that the impact of a person's motion and his daily activities is dramatically reduced. Chen et al. [6] proposed a syringe-implantable ECG system for arrhythmia classification based on the state-of-the-art 65-nm CMOS process. The system acquires the ECG signal, filters it, amplifies it, and digitizes it through the analog front-end (AFE) module. The AFE contains a low-noise instrumentation amplifier, a variable gain amplifier, and a successive approximation register analog-to-digital converter. The arrhythmia recognition is achieved using two looms. The first approach appraises the difference of the RR interval and be relevant a straightforward threshold method to distinguish between normal and abnormal intervals. In the next loom, the ECG signal is malformed into the frequency domain, and the deviation in the spectrum is examined. The propose consumed 92 nW at 0.4 V for the DSP unit. The accuracy of the classification was not stated.

III. Methodology

The system taken is like a guard for patients who are susceptible to ventricular arrhythmia by alerting them for immediate attention to their medical condition. Disparate additional schemes that attain the ECG signal and broadcast it for supplementary analysis, the anticipated scheme aspires to propose and expand an integrated biomedical structural design that is proficient of acquiring the ECG signal from the heart along with dispensation and analyzing it on the similar chip without any exterior interface. Thus, the patient would have immediate alert to his situation and that is very important, especially in critical situations. Furthermore, the local processing of the data would reduce the amount of the data to be transmitted in case of any further checkup. This system consists of three main stages, which are the ECG preprocessing, feature extraction, and classification, as shown in Fig. 2.1. In the first stage, the ECG preprocessing is responsible for three tasks: 1) ECG filtering; 2) QRS complex detection; and 3) T and P wave delineation.

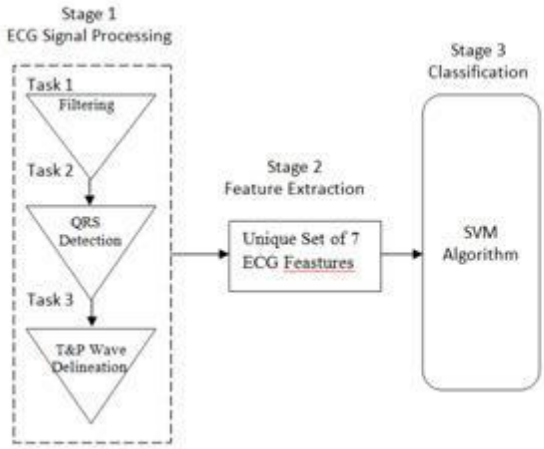

Fig.2.1Schematic representation of the proposed ventricular arrhythmia Prediction system.

The ECG filtering removes the noise coupled with the ECG signal and prepares it for further analysis. After that, the QRS complex is detected

The T and P waves are delineated, and the corresponding fiducial points such as P onset, P peak, P offset, T onset, T peak, and T offset are extracted. In the second stage, seven features are extracted from the ECG signal and grouped together to construct a unique set. All the skin texture symbolizes special intervals from the ECG signal, and they are RR, PQ, QP, RT, TR, PS, and SP intervals.

Usually, the reported systems in the literature build their systems depending on one feature only, such as the heart rate interval [8], the variability of the timing delay of the ECG segments [7], or the QT interval variability [5]. To enhance the robustness of the system, multiple features are necessary. Thus, the unique set of ECG intervals is constructed and used as input for the final stage.

The combination of these features has never been used in any published detection or prediction method, yet it was proved to be the most significant combination. In the final stage, SVM algorithm is used to identify the signals that are susceptible to ventricular arrhythmia. There are many reasons for choosing the SVM algorithm [4]. First, the ECG features have shown strong potential in the prediction of ventricular arrhythmia with a p-value < 0.001. Second, it was intended to investigate the performance of the system without introducing the strong biasing effect of a classifier. Finally, SVM algorithm is the simplest classification method that can be easily implemented in hardware. The methodological block diagram is as shown in Fig 2.2.

a. METHODOLOGICALBLOCK DIAGRAM

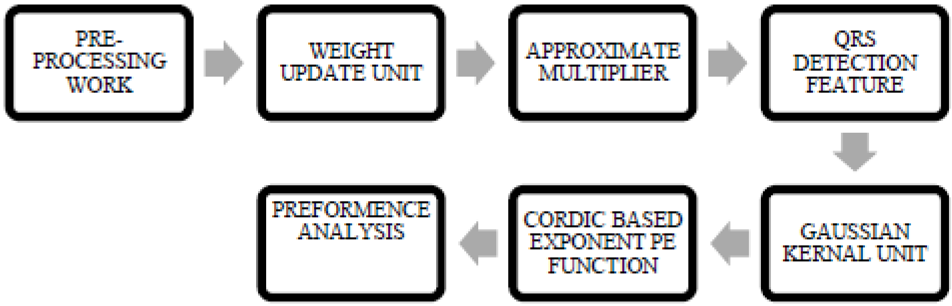

Fig2.2 Methodological Block Diagram

b. ECG PREPROCESSING STAGE

The raw ECG signal is filtered by Band pass filter which isolates the predominant QRS energy centered at 10 Hz, and attenuates the low frequencies characteristic of the P and T waves, baseline drift, and higher frequencies associated with electrographic noise and power line interference. The major factor is not to lose the information carried by the ECG signal after being filtered out. The difference equations of the LPF and high-pass filter (HPF) the cutoff frequency of the LPF filter is 11 Hz, and it introduces a delay of six samples, whereas the HPF has a cutoff frequency and delay of 5 Hz and 16 samples, respectively. To detect the QRS complex, the PAT method was used [7]. The PAT algorithm which is support on the amplitude threshold procedure abusing the fact that R peaks have superior amplitudes evaluated with extra ECG wave peaks [8]. This technique is extremely proficient of distinguishing the R peaks in each heartbeat by means of two threshold levels. The demarcation of T and P waves is support on an original technique anticipated in [17]. The scheme is based on adaptive hunt casements all along with adaptive thresholds to exactly distinguish T and P peaks from noise peak. These regions are then used to form the forward and backward search windows of the T and P waves, respectively, as shown A forward search window is assumed to contain the T wave, and the limitations are enlarged from the QRS offset to two third of the previously detected RR distance. Correspondingly, a backward hunt casement for the P wave is recognized and extensive from the QRS onset backwardly to one third of the earlier RR interval. The position of T and P peaks is demarcated in their respective search windows by finding the local maximum or/and local minimum that are above the associated thresholds.

c. FEATURE EXTRACTION STAGE

Most important constraints measured while budding a recognition or forecast system are the difficulty and the accuracy of the feature extraction technique for effective results. For example, if the technique that is used for the feature extraction requires complex transformation or data analysis of the ECG signal, this would increase the overall cost and complexity of the system, and thus, it will not be suitable for wearable biomedical devices[12]. For example, a technique reported in [6] is based on ECG morphology and RR intervals, leading to a simple and easily realizable detection system. On the other hand, Jen and Hwang [9] and Zhao and Zhang [15] used neural networks and a combination of wavelet transform and SVM to extract the features from the ECG signal, correspondingly. These procedures are additional complex-to-realize and resulted in high cost of the system. Moreover, the take out ECG features should illustrate a significant relevance in the (prediction or detection) of the targeted arrhythmia to guarantee maintaining a high accuracy. Usually, there is a tradeoff between the complexity and the accuracy. For instance, the accuracy of the system in [12] is lower compared with the one presented in [9] and [15].

In this study, both the complexity and the accuracy are taken in account simultaneously. On behalf of, achieve statistical scrutiny techniques with the intention of well-known in the conclusion making in the biomedical research to select the most excellent discriminative ECG features that would maintain low system complexity and high accuracy to obtain effective architecture. These statistics assist the researchers to conclude about the significance of a conducted research, and it included the mean error and standard deviation, the two-sided unpaired t-test [16], and the area beneath the recipient operative distinguishing curve [17]. The features include RR, PQ, QP, RT, TR, PS, and SP interval Fig. 2.3 demonstrates these distances on ECG evidence [12]. It is importance mentioning so as to the skin texture is extorted from two successive heartbeats, unlike other techniques that practice every heartbeat independently.

d. CLASSIFICATION STAGE

Support vector machine (SVM) is a machine learning system that is extensively second-hand for pattern recognizing and information analyzing. The algorithm was invented by Vladimir Vapnik and the current normal personification was anticipated by Corinna Cortes and Vladimir Vapnik. Organizing statistics has been one of the most important parts in machine learning. The idea of support vector machine is to generate a hyper plane in among information sets to point out which class it belongs to the consequective signals. The dispute is to instruct the machine to identify with formation from mapping and data with the right class label, for the most excellent result, the hyper plane has the biggest detachment to the adjacent training data points of some class.

e. svm classifier

The SVM is one of the for the most part supervised culture algorithms for solving categorization problems. The basic of SVM involves the adoption of a nonlinear kernel function to transform input data into a high dimensional feature space, which is easier to separate data rather than at the original input space. Thus, depending on input data, the iterative learning process of SVM will finally devise optimal hyper planes with the maximal margin between each class in a high dimensional feature space. Hence, the maximum margin hyper planes will be the decision boundaries for distinguishing different data clusters. Therefore, the larger distance between hyper planes and group data will result in better classification performance.

The training algorithm is an important part of the SVM model. A good topology can be inefficient if trained by an inappropriate algorithm. A suitable training algorithm has a short training process, while achieving better accuracy. This algorithm modernizes the weight and bias rates according to Levenberg–Marquardt optimization.

The assessment of the anticipated method on classification problems is strong-minded by computing the statistical parameters of sensitivity, specificity and classification precision. The descriptions of these restrictions are as:

Sensitivity: Number of correctly detected positive patterns/total number of actual positive patterns. A constructive sample point outs distinguished seizure.

Specificity: Number of correctly detected negative patterns/total number of actual negative patterns. A unenthusiastic sample point outs detected normal/non-seizure.

Classification accuracy: Amount of correctly classified samples/whole number of patterns.

The major benefit of this proposed work is that, the morphological divergences between numerous types of ECG signal are highlighted and the extracted features show the differences more clearly. Another advantage of this study is that the reduction of the dimension of data by applying SVM leads to the most appropriate input vector for classifier which improved the concert of SVM classifier significantly. Also this work can be extended by applying appropriate preprocessing algorithm with ECG signal for the noise removal can promise more efficiency.

IV. Results & Discussion

For effective extraction of ECG signal taken from the Physionet database, MATLAB is used in which the raw signals are converted into datasets for further processing .as the initial step the raw signal shown in fig 4.1 has been filtered.

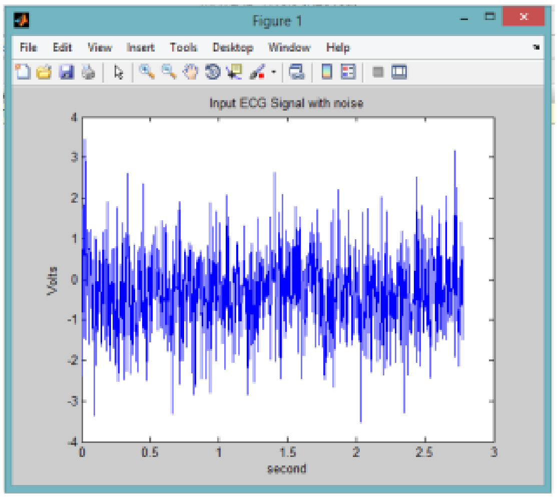

Fig4.1ECG Raw signal

The noise free ECG signal (fig4.2) is further processed to the stages through Verilog coding with help of Xilinx. The coding are directly linked from mat lab to Xilinx

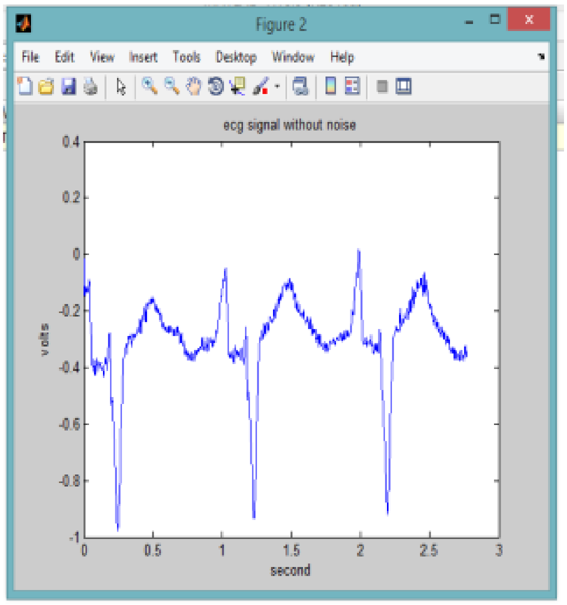

Fig4.2 ECG signal after noise removal.

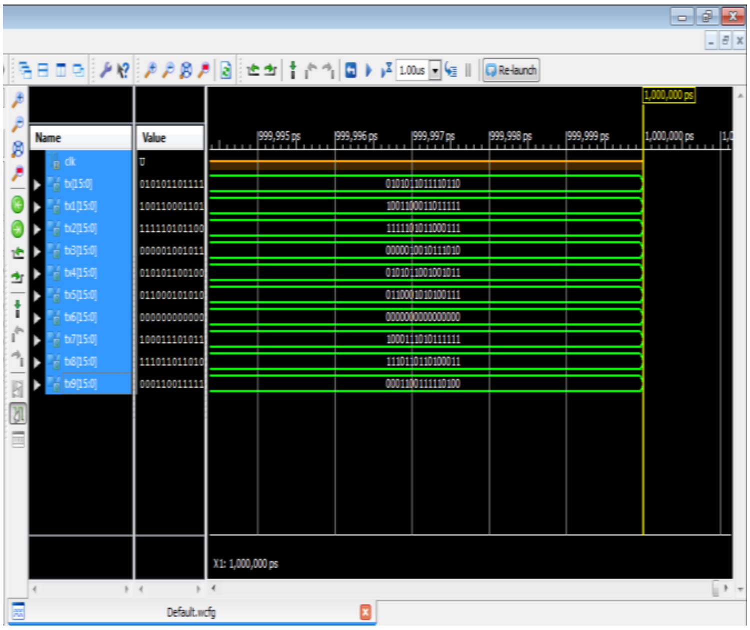

Fig4.3 low power and compact VlSI architecture implementation using ModelSim

V. Conclusion

This work is to achieve a VLSI architecture that reduces the system complexity and improves the classification performance level compare to existing methodologies both effective to cost and low power consumption. For which selection of filtering technique, feature extraction and classifier is done .In the preprocessing stage, task of selected filter performance is analyzed and a final output of filtered signal is obtained, the furthermore tasks such as complex demarcation and detection is done. The preprocessed ECG signals are brought to the next stage, feature extraction of ECG signals and then implementation of SVM Classifier and its performance analysis is done. Moreover, the proposed ESP achieved an outstanding capability of predicting the arrhythmia up to 3 h before the onset. A prediction accuracy of 94% was obtained.

Table4.1: Comparison with other design implementations

Sl no	Methods	YOP	Cmos Technology	Power	Operating voltage	Accuracy	Disadvantages
1	Quad level vector	2010	0.18µm	6µw	1.8v	97%	The system engaged clock gating methods to enable and disable every processing unit character according to the require and its applied voltage
2	FPGA & ST Segment	2013	90nm	40.3µw	not stated	96%	The main disadvantage of the system is that it uses fixed search window with predefined size to locate S and T fiducial points, which is not suitable for real-time scenarios.
3	state-of the art	2015	65nm	92nw	0.4v	NA	syringe-implantable ECG system
4	Discrete wavelet transform	2015	0.18µm	5.967µw	1.2v	97.25%	three chips are used for each process so it consumed high power
5	Naïve Bayes classifier	2015	65nm	2.78µw	1v	86%	Power reduction techniques not implemented, mis detection of any of the PQRS-T waves cannot be identified.
6	SVM	2017	If we use 65nm	Power can be reduces (approximately) to 1.68µw	It will operate with low voltage (approximately) of 0.5v	Simulated accuracy 94%	**Advantage of proposed system** Speed of the processor is increased, and also it detects the types of Arrhythmia

VI. Future Scope

In future, this architecture may be implemented in a suitable processor or embedded system for making it a wearable device for the cardiac patients. The tiny area, squat power, and high performance of the planned ESP make it appropriate for inclusion in organization on chips targeting wearable mobile medical devices.

VII. Referances

[1]. Amann, R. Tratnig, and K. Unterkofler, "Detecting ventricular fibrillation by time-delay methods," IEEE Trans. Biomed. Eng., vol. 54, no. 1, pp. 174–177, Jan. 2007.

[2]. A. Lay-Ekuakille, P. Vergallo, A. Trabacca, M. De Rinaldis, F. Angelillo, F. Conversano and S. Casciaro,"Low-frequency detection in ECG signals and joint EEGErgospirometricmeasurements for precautionary diagnosis", Measurement, Vol. 46, pp. 97–107, 2013.]

[3]. B.-Y. Shiu, S.-W. Wang, Y.-S. Chu and T.-H. Tsai, "Low-power lownoise ECG acquisition system with dsp for heart disease identification, "in Proc. IEEE Biomed.

[4]. Davide Anguita-2012 "In–sample Model Selection for Support Vector Machines" Davide Anguita, Alessandro Ghio, Luca Oneto and Sandro Ridella are with the Department of Biophysical and Electronic Engineering, University of Genova, Via Opera Pia 11A, I-16145 Genova, Italy.

[5]. G. Genov et al., "Kerneltron: Support vector machine in silicon," IEEE Trans. Neural Network, vol. 14, no. 5, pp. 1426–1434, Sep. 2003.

[6]. Hsun-Hsien Chang and Jos´ M. F. Moura, "Biomedical Signal Processing", 2nd Edition of In Biomedical Engineerng and Design Handbook,McGraw Hill, Vol. 1, No. 22, pp. 559-579, 2010.

[7]. H. Khandoker, M. H. Imam, J. P. Couderc, M. Palaniswami, and J. F. Jelinek, "QT variability index changes with severity of cardiovascular autonomic neuropathy," IEEE Trans. Inf. Technol. Biomed., vol. 16, no. 5, pp. 900–906, Sep. 2012.

[8]. H. Kim, R. F. Yazicioglu, P. Merken, C. Van Hoof, and H.-J. Yoo, "ECG signal compression and classification algorithm with quad level vector for ECG holter system," IEEE Trans. Inf. Technol. Biomed., vol. 14, no. 1, pp. 93–100, Jan. 2010.

[9]. J. Pan and W. J. Tompkins, "A realtime QRS detection algorithm," IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[10]. K. Jen and Y. Hwang, "ECG feature extraction and classification using cepstrum and neural networks," J. Med. Biol. Eng., vol. 28, no. 1, p. 31, 2008.

[11]. Linquan Zhang, Chuan Wu, Zongpeng Li-2013 "VLSI Design of an SVM Learning Core on Sequential Minimal Optimization" Algorithm IEEE TRANSACTIONS ON VERY LARGE SCALE.

[12]. Christos-Savvas Bouganis and Markos Papadonikolakis, Member, IEEE “Novel Cascade FPGA Accelerator for Support Vector Machines Classification” IEEE TRANSACTIONS ON NEURAL NETWORKS

[13]. Muhammad bn Ibrahimy,“Biomedical Signal Processing and Applications”, International Conference on Industrial Engineering and Operations Management, Dhaka, Bangladesh, 2010.

[14]. Nourhan Bayasi,et al.,“Low power Ecg based Processor for PredicatingVenticular Arrhythmia”,IEEE TRANSACTIONS ON VLSI SYSTEMS,2015

[15]. P. de Chazal, M. O’Dwyer, and R. B. Reilly, “Automatic classification of heartbeats using ECG morphology and heartbeat interval features,” IEEE Trans. Biomed. Eng., vol. 51, no. 7, pp. 1196–1206, Jul. 2004.

[16]. P. Tadejko and W. Rakowski, “Mathematical morphology based ECG feature extraction for the purpose of heartbeat classification,” in Proc. IEEE 6th Int. Conf. Comput. Inf. Syst. Ind. Manage. Appl. (CISIM), Jun. 2007, pp. 322–327.

[17]. Q. Zhao and L. Zhang, “ECG feature extraction and classification using wavelet transform and support vector machines,” in Proc. IEEE Int. Conf. Neural Netw. Brain (ICNN&B), vol. 2. Oct. 2005, pp. 1089–1092

[18]. R. Kumar and A. Indrayan, “Receiver operating characteristic (ROC) curve for medical researchers,” Indian Pediatrics, vol. 48, no. 4, pp. 277– 287, 2011

[19]. T. Heeren and R. D’Agostino, “Robustness of the two independent samples t-test when applied to ordinal scaled data,” Statist. Med., vol. 6, no. 1, pp. 79–90, 1987.

[20]. Y.-P. Chen et al., “An inject able 64 nW ECG mixed-signal SoC in 65 nm for arrhythmia monitoring,” IEEE J. Solid-State Circuits, pp. 375–390, Jan. 2015.

[21]. Yakoub Bazi, and Farid Melgani “Classification of Electrocardiogram Signals with Support Vector Machines and Particle Swarm Optimization”, Biomed” SEPT 2008, pp.667.