ECG signal analysis using FPGA

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Abstract

Electrocardiogram (ECG) is considered to be a must have feature for a medical diagnostic system. This paper describes the software simulation of ECG signal for computing the rate of heart by utilizing Field Programmable Gate Arrays (FPGAs). The dataset is collected from the already existing online website MIT-BTH arrthyimia database. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia and later on loaded into B-RAM for Heart Rate analysis. By adopting the linear classification technique of machine learning for the analysis of ECG signal whether they are normal or abnormal in the FPGA. CORDIC algorithm applied in the FFT of DSP processor. The main objective of this paper is to design the high accuracy, low latency and develop low-complexity high-throughput CORDIC algorithms adopted in FFT. The power consumption and delay is mitigated to about 11% and 18% when compared to the existing method. Accuracy of heart analysis is around 99%.

Keywords : Data set , Block RAM, CORDIC algorithm, Machine Learning, Linear Classification.

Introduction:

Nowadays, cardiovascular disease, which includes the disease of heart and the stroke, stays as a main cause of death worldwide. Still, most of the heart attacks and the strokes is able be avoided if some form of pre-monitoring and pre-diagnosing is provided. If the abnormalities in the heart function are detected, then it could be beneficial for clinicians. The most dangerous conditions of cardiac can be understood by studying about the ECG signal. This commonly is centered on the study of arrhythmias, like disruption in the rate of heart, regularity of heart, and location of origin or conduction of electric impulse of cardiac. Some arrhythmias need urgent treatment to avoid problems that occur in further, since not whole arrhythmias are neither abnormal nor dangerous. This work speaks about the issues of analysing of ECG signals using FPGA.

Related Work:

Electrocardiogram:

Cardiologists utilize the ECG equipment to analyse the ECG signals by diagnosing different kind of diseases and to monitor the state of heart. By placing the electrodes which consists of conductive gel on patient's skin, ECG signals are collected, says J.J. Carr et al. [1]. It provides information of a human heart like disturbances in heart rhythm, abnormalities in the electrical impulses etc. At present's technological environment, keeping track of a person's health is difficult. Previously, entries of activity of cardiac were done manually which takes more time, now it got commercialized and digitalized into the form of wearable devices which will monitor the fitness of a person. External noise generated by ECG sensors has a considerable chance of corrupting the signal, resulting in incorrect analysis and identification of the beats. The ECG information of a patient is collected and saved by utilizing a portable Holter monitor that the individual wears. The non-linearity in the signals of ECG, as well as the wide variance in morphologies of ECG among patients, are the fundamental problems with automated analysis of ECG.

Shruti Jain proposed that FPGA is used to simulate the computation of rate of heart by utilizing the interval of R-R in hardware [2]. Faster executing and option of verification for executing latest design is enabled by the features of FPGAs such as reprogramming rapidly, cheaper and also they have feature of testability which is very easy. One more way proposes a processing module of signals of ECG signal that is executed in VHDL in a platform named FPGA.M. Ravi Kumar says that to test the modules that are executed on FPGA, already collected and saved signals of ECG will use the test input [3]. There is model in signal processing which says that processing of the signals of ECG consists of two stages: Feature Extraction and Pre-processing was discussed by L.V. Rajani Kumari et al.[4].

Abnormal ECG:

For analysis of ECG Signals the clear understanding about them is mandatory. The ECG signals will be having both normal and abnormal conditions. Arrhythmia is the medical term which is used for an abnormality in the rhythm of heart. Abnormal ECG signals comprises of mainly three types.

They are Trigeminy(T), Bigeminy(B), Ventricular Tachycardia (VT). Trigeminy is an abnormality in the rhythm of heart which results in an additional heartbeat. As a result of these Trigeminy, an abnormality in the rhythm of heart occurs at every third heartbeat. Trigeminy(T) can be an innocuous condition. Bigeminy is an arrhythmia related to cardiac in which each of the regular heartbeat is followed by an irregular heartbeat or single ectopic beat. This is most commonly caused by ectopic beats happening so regularly that one follows each normal heartbeat or sinus beat. [5]. Wenjun Suet al. explained that in the FPGA module processing, ECG signal survey and this method contains four different sections, the first one is pre-processing section, the second one is the feature extracting section, the third one is HRV analysis section, and fourth one is abnormal diagnosis section [6].

For detecting the abnormal ECG signals using FPGA the software chosen here is Xilinx Vivado. J. Bhasker suggested that pattern will be designed in three various styles. The styles are listed as: behavioral style – designed utilizing procedural constructs; dataflow style – designed utilizing the assignments in continuous form; structural style – designed utilizing module as well as gate instantiations [7]. But for the ECG signal analysis behavioral level modeling is being used in Verilog language. J. Gomez-Cornejo et al. proposes an approach which can write as well as read the content of the data collecting out of BRAMs (BLOCK RAMs) in FPGA depending on the designs just by performing the processing as well as reading the details which are already kept in form of bit stream [8]. Using the approach, the datasets can be easily read from the stored memory location of BRAM in FPGA. With the help of a method proposed by Zairi Hadjeret al. shows an remarkable attributes belittle mending, contrasting to already subsisting researches, that guides to lessen the size of a prototype in FPGA and thereby economizing the consumed energy [9].

For classifying whether the ECG signals are normal or abnormal a machine learning technique called linear classification has been used. A linear classification technique attains the required goal by building a classifying resolution depending on values obtained from the features of a linear combination. The characteristics of an object are even called as features or feature values. These features are generally given out to a machine in the form of vector; hence it is known as feature vector. This type of classification works as the best method for pragmatic problems, for example, in classifying the documents, and typically for situations where there are various characteristics to be considered. This results in attaining amazing levels of accuracy and also takes lesser time for testing and training. Saira Azizet al. stated that to instinctively categorize the disease of the heart, approximated peaks, time spans among various peaks, and some various features of ECG were utilized for training the model of machine learning [10]. For example, Qiao Li et al. (2014) executed the process of classifying data they trained the SVM model (support vector machine model) and then performed testing on an already executed dataset and approved the utilized data belonging to MIT-BIH arrhythmia database (MITDB) [11]. Alfaras Miquel et al. (2019) says that the utilization of aggregation of the ensemble data permits to make use of similarity for the training of classifier which results in with exceptional speeds [12].

For classifying data, S Celin et al. (2018) proposed a process which separates the features by utilizing Support Vector Machine, Artificial Neural Networks a classifier named as Naive Bayes to separate the datasets of ECG signal into two categories such as normal ECG and abnormal ECG [13]. This process is followed by the MIT-BIH for collecting abnormal and normal datasets and finally consolidating them. C. Ganesh Babu et al. (2021) described that an ECG is used for monitoring the heart's electrical activity and pulse rate [14]. For example, Qiao Li et al. (2014) executed the process of classifying data they trained the SVM model (support vector machine model) and then performed testing on an already executed dataset and approved the utilized data belonging to MIT-BIH arrhythmia database (MITDB) [15] [16]. Alfaras Miquel et al. (2019) says that the utilization of aggregation of the ensemble data permits to make use of similarity for the training of classifier which results in with exceptional speeds [17].

For classifying data, S Celin et al. (2018) proposed a process which separates the features by utilizing Support Vector Machine, Artificial Neural Networks a classifier named as Naive Bayes to separate the datasets of ECG signal into two categories such as normal ECG and abnormal ECG [18]. This process is followed by the MIT-BIH for collecting abnormal and normal datasets and finally consolidating them. C. Ganesh Babu et al. (2021) described that an ECG is used for monitoring the heart's electrical activity and pulse rate [19]. Tanoy Debnath et al. (2016) proposed a scheme, at first the QRS components have been extracted from the noisy ECG signal by rejecting the background noise. This is done by using the Pan Tompkins algorithm. The second task involves calculation of heart rate and detection of tachycardia, bradycardia, asystole and second-degree AV block from detected QRS peaks [20]. Shital L. Pingale et al. proposed a Matlab software for the Pan and Tompkins QRS detection algorithm for detection of diseases related to heart, implementation every stage processes the entire sample and then can the next stage begin [21]-[25].

Using all the methods a new technique for ECG signal analysis using FPGA is proposed in this paper. The rest of the paper is organized as follows: In section 2, brief introduction of overall methodology, collection of datasets, conversion of datasets and linear classification are discussed. In section 3, normal and abnormal ECG signals are classified based on the result, also power consumption and delay between each test sample for analyzing ECG signals are discussed. Finally, section 4 contains the conclusions.

Methodology:

The overall methodology of this process is clearly explained using the block diagram is displayed in the Figure 1.

Initially two types of datasets should be collected. The first type of dataset is a real-time dataset collected using the instrument CMC DAQ ECG. These signals are collected in the csv file format. Simultaneously another type of dataset is collected from the online website UCI Machine Learning Repository[26] and MIT BIH arrhythmia dataset [27]. These ECG Signals are also collected in the csv file format. Later these two signals are consolidated into single csv file format. Then the consolidated csv file is converted into text file with each sample having a specific address of BRAM.

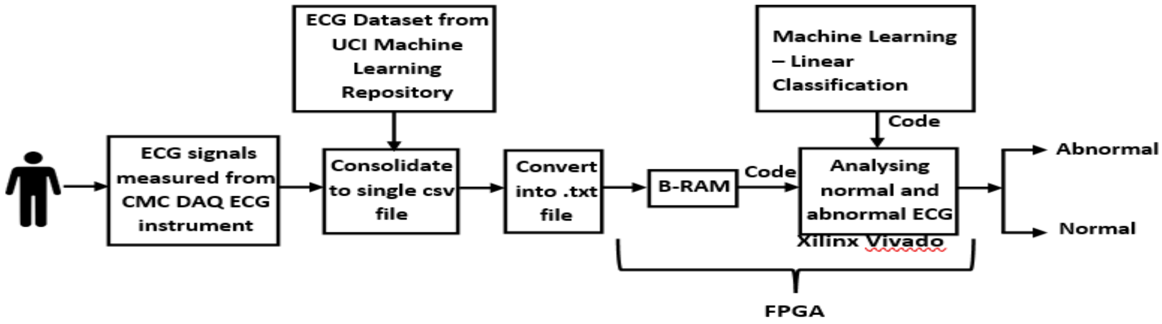

Figure 1. Block Diagram

For classifying whether the signal is normal or abnormal a machine learning technique called linear classification is used. This is a model which is best suited for separating two or more samples. The code for predicting the abnormality of ECG signals has been written in Verilog language. In the source code the code regarding the prediction is done where as in the test bench code the code regarding the linear classification and Bram address have been called for data intake.

Finally, the output is obtained in the waveform. If the output is 0 then the signal is abnormal and if the output is 1 then the signal is normal. Hence the normality and abnormality of ECG signals will be made at the end of the process. Each step of this block diagram is clearly explained in the further sections.

The overall block diagram for the process involved in Machine Learning is shown in Figure 2

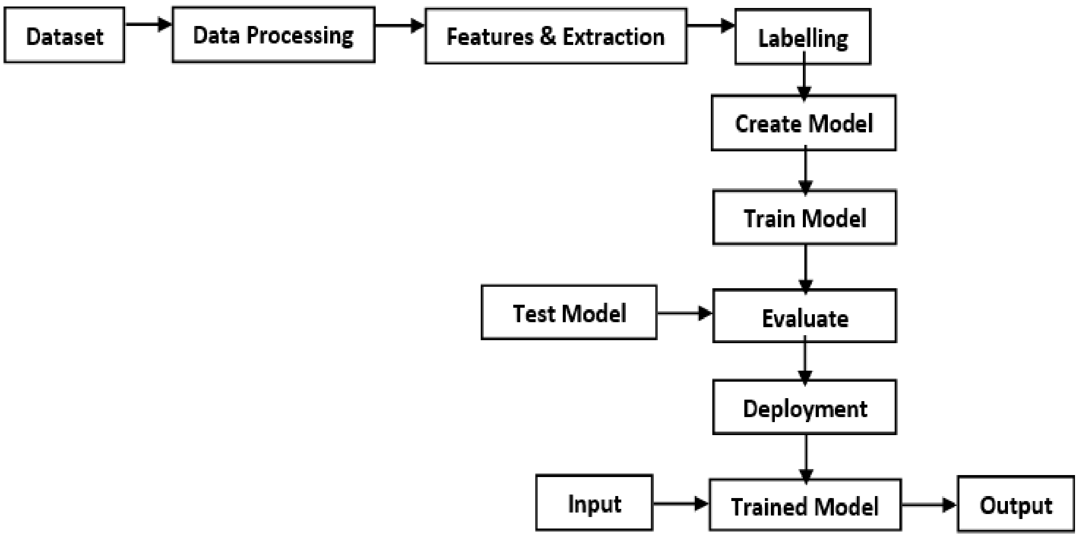

Figure 2. Over all Machine Learning block diagram

Collection of Datasets:

The datasets required for the testing and training have been collected in two ways. One type of dataset is collected the already existing online website. Another type of dataset is the collection of real time ECG signals.

Collection of Datasets from Online Database:

The dataset is collected from the already existing online website UCI Machine Learning Repository [15][23].

Collection of Real-Time Datasets :

The collection of real time datasets has been done in biomedical department of the Vel Tech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology. The equipment used for collecting ECG signals is CMC DAQ ECG and is shown in Figure 3.

The electrodes which are the small patches that are made of plastic, stick to the skin when placed at certain spots on the arms and legs. Conductive gel in electrodes is used for better conductivity between the electrodes that monitor the electrical activity of heart and the skin of a human. Contractions that occur in various parts of a human heart are coordinated by the natural electrical impulses for proper blood flow. These impulses are then recorded by connecting the electrodes to the CMC DAQ ECG instrument through the lead wires.

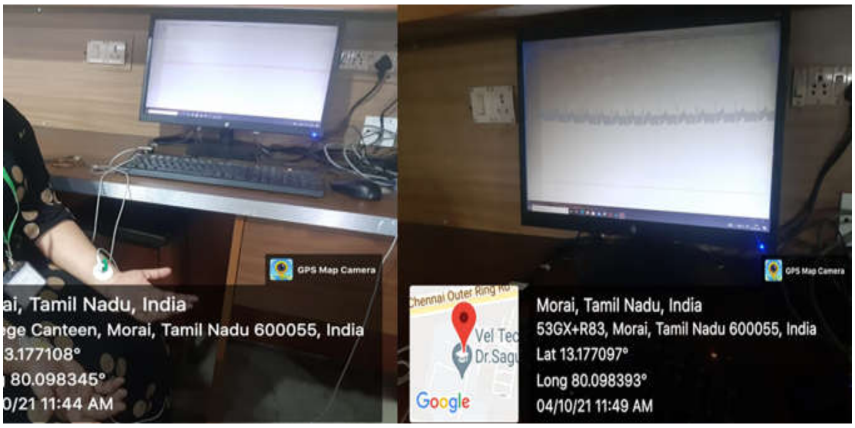

Figure 3. Real time ECG signals collection

Conversion of Datasets:

The datasets collected from the online website as well as the real-time time datasets are consolidated into single .csv file. The total samples obtained after consolidating into excel file is 3672. Out of these 3672 samples 5 samples have been taken to testing process and remaining samples have been used for training purpose. These samples have six features

They are Amplitude, RR, Speed, Age, Sex, Medicine and Arrhythmia. Based on these six features the prediction will be made whether the ECG is normal or abnormal. Generally, these features are plotted on x-axis and output on y-axis such that a clear classification of normal and abnormal samples can be seen on either side of a linear curve

Amplitude is the height of R wave and is measured in milli volts. RR determines the interval of R-R. The time between the complexes of QRS is the interval of RR. Normal RR value should be between (0.6-1.00 sec). Speed of ECG signals which is the normal resting heart rate is between 60 to 100 for adults of age 18 and above. The consolidated csv file is converted into .txt file with memory addresses on the top of each sample using Python programming.

Linear Classification:

In machine learning field, the aim of quantitative classification is to utilize the characteristics of the object to detect whether it is part of which group or which class. A linear classification technique attains the required goal by building a classifying resolution depending on values obtained from the features of a linear combination. The characteristics of an object are even called as features or feature values. These features are generally given out to a machine in the form of vector; hence it is known as feature vector. This type of classification works as the best method for pragmatic problems, for example, in classifying the documents, and typically for situations where there are various characteristics to be considered. This results in attaining amazing levels of accuracy and also takes lesser time for testing and training. The linear classification used in this process is explained in the block diagram shown in Figure 6

The six features of the sample such as Amplitude, RR, Speed, Age, Sex, Medicine, and Arrhythmia. Based on these six features the prediction will be made whether the ECG is normal or abnormal. So, these features are given as input to the multipliers,M_1, M_2, M_3 …… M_n. Each multiplier is given an input of each sample. Therefore, number of samples will be same as the number of multipliers used. Later each multiplier is given to the input of n adders namely A_1, A_2, A_3 …..A_n as shown in the block diagram. Each adder has the input of all the n samples and then further hidden layers of adders will be created according to the requirements. Finally, an activation function is generated. From that activation function a prediction is made to analyze whether the ECG signals are normal or abnormal.

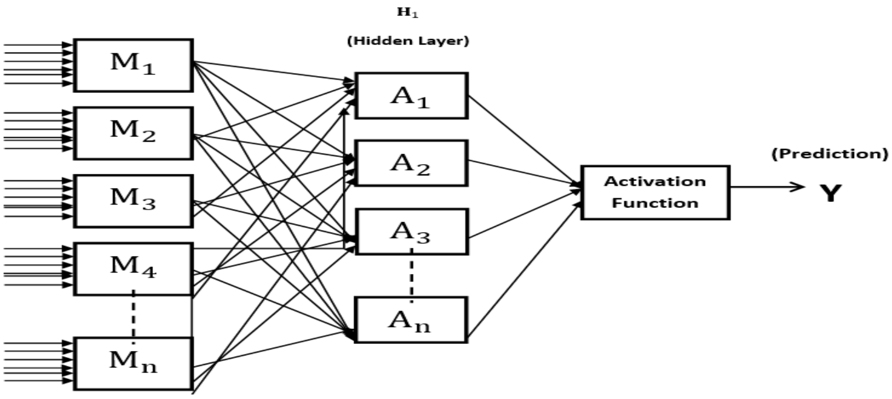

Figure 4. Linear Classification Block Diagram

Results and Discussion:
Simulation Process:

The five samples have given to test the model. They are displayed below. The predicted output obtained for first test sample with speed of 1fcb is 1 which means the ECG signal is normal. The simulation time taken for this simulation is 500 ns at 28,727,200 ns after beginning of simulation. The waveform for this output is shown in Figure 8.

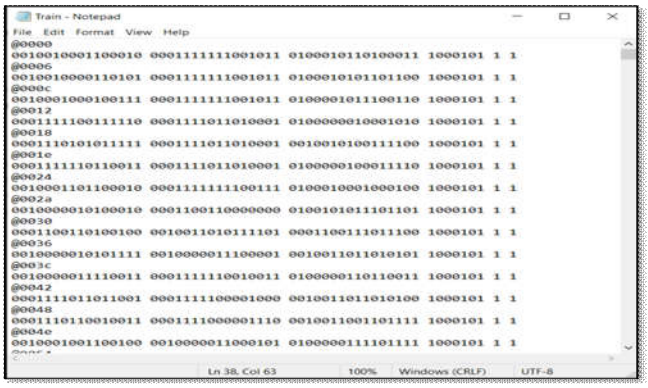

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Figure 5. Training data samples in .txt format

The sample consisting six features so, the memory address for the first sample ranges from the address of 0-5, the second sample ranges from 6-11 and so on. These are the addresses which a particular sample should take in the BRAM during the storing process. The result of this is access a particular sample by directly using its address in the code. The example of this addressing process is that to conversion is shown in the Figure 4 and Figure 5 for both test and train samples respectively

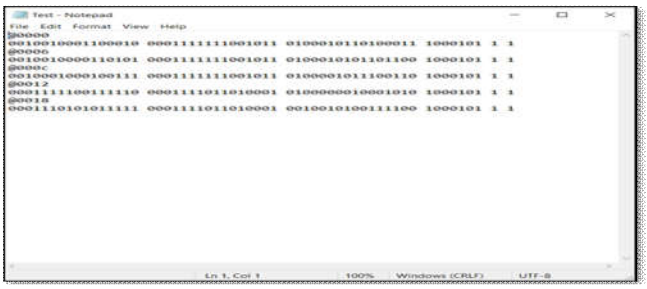

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Figure 6. Testing data samples in .txt format

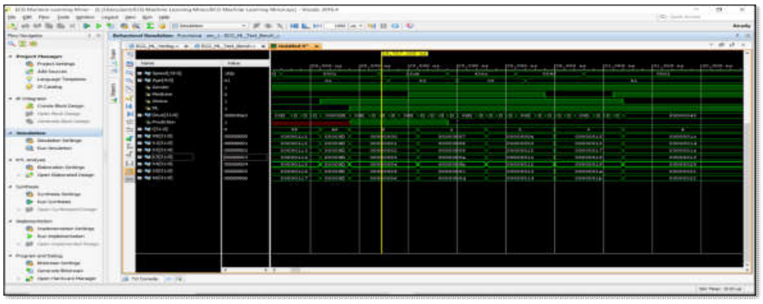

Figure 7. Output for first test sample

The predicted output obtained for second test sample with speed of 456c is 0 which means the ECG signal is abnormal. The simulation time taken for this simulation is 500 ns at 29,462,200 ns after beginning of simulation. The waveform for this output is shown in Figure 9.

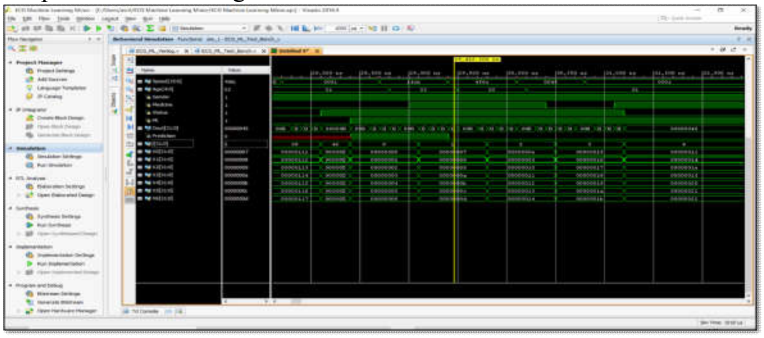

Figure 8. Output for second test sample

The predicted output obtained for third test sample with speed of 0045 is 0 which means the ECG signal is abnormal. The simulation time taken for this simulation is 500 ns at 30,142,200 ns after beginning of simulation. The waveform for this output is shown in Figure 10

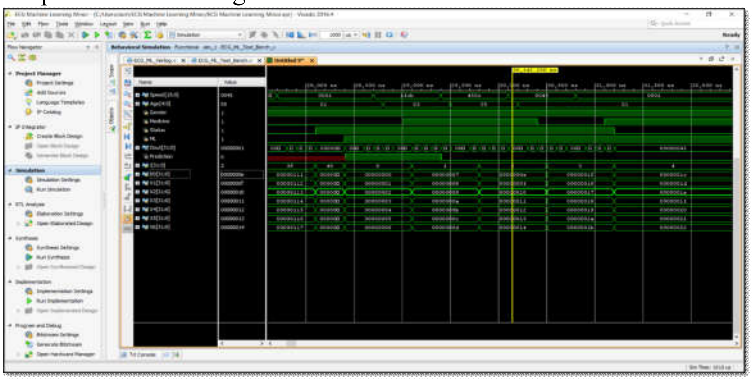

Figure 9. Output for third test sample

The predicted output obtained for fourth test sample with speed of 0001 is 0 which means the ECG signal is abnormal. The simulation time taken for this simulation is 500ns at 30,857,200 ns after beginning of simulation. The waveform for this output is shown in Figure 11.

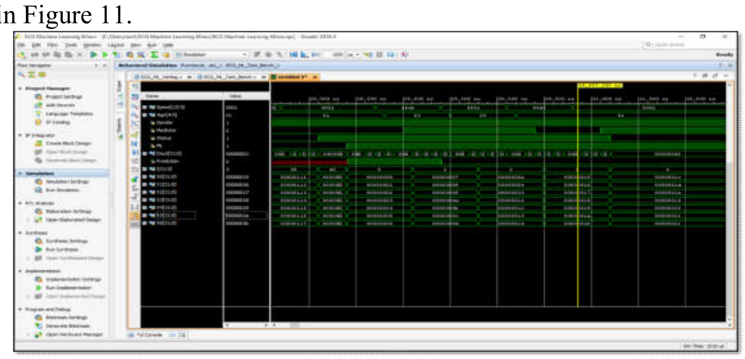

Figure 10. Output for fourth test sample

The predicted output obtained for fifth test sample with speed of 0001 is 0 which means the ECG signal is abnormal. The simulation time taken for this simulation is 500 ns at 32,457,200 ns after beginning of simulation. The waveform for this output is shown in Figure 12

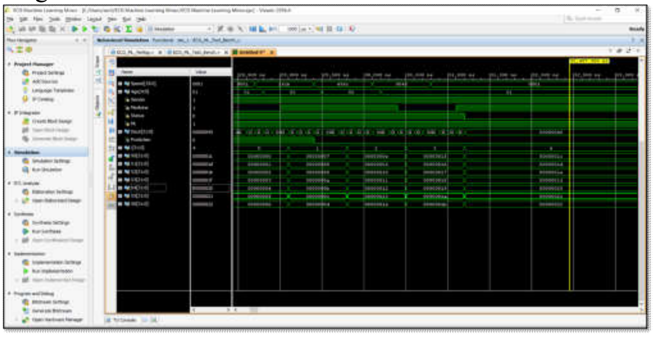

Figure 11. Output for fourth test sample

The comparison between the power and delay of both the proposed methodology and existing methodology is shown in the Table 1. The units of power and delay are measures in milli watts and micro seconds respectively. The graphical representation of delay and power for both existing methodology and proposed methodology are shown in Figure 13 and Figure 14 respectively.

Table 1. Comparison of Power and Delay of proposed methodology to existing methodology

Parameters	Existing method (Madhav P. Desai et al. (2021)) [24], (Shivani Mehrotra et al. (2015)) [25]	Proposed method
Power (mW)	28	25
Delay (µs)	1691	1400

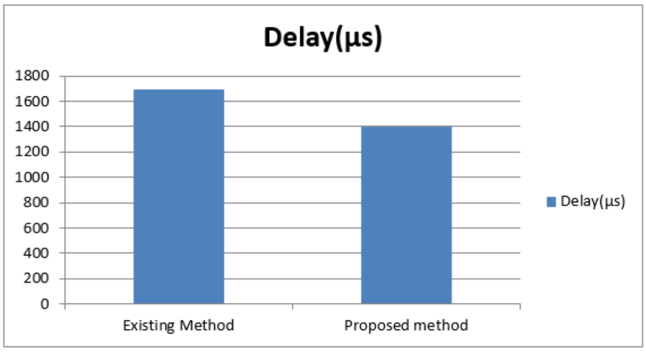

Figure 12. Graphical representation of delay for both existing and proposed methods

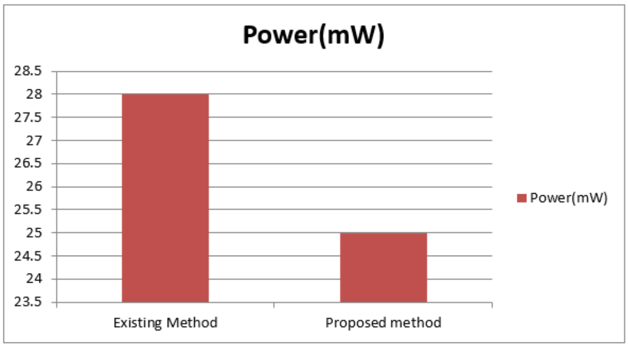

Figure 13. Graphical representation of power for both existing and proposed methods

CONCLUSIONS:

The analysis for determining whether the ECG signals are normal or abnormal using FPGA is successfully simulated. The time taken for each sample to undergo simulation is 500 nano seconds. The datasets are stored in B-RAM for

Heart Rate analysis. The code for predicting the abnormality of ECG signals has been written in Verilog language. By adopting the linear classification technique of machine learning for the analysis of ECG signal whether they are normal or abnormal in the FPGA, the power consumption and delay is mitigated to about 11% and 18% when compared to the existing method. Finally, the output is obtained in the waveform. If the output is 0 then the signal is abnormal and if the output is 1 then the signal is normal. Out of the 5 samples which have been taken for testing, the output of one sample is obtained as 1 which means the ECG is normal and remaining four sample's output is 0 which means the ECG is abnormal. By adopting CORDIC architecture in FFT, performance will be improved.

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