FPGA-Based System for Real-time Epileptic Seizure Detection using KNN Classifier

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***Abstract*: Epileptic seizure detection is a crucial task in the field of biomedical signal processing. Seizures are abnormal electrical discharges in the brain that can lead to various symptoms, such as convulsions, loss of consciousness, and cognitive impairment. People with epilepsy experience repeated seizures that happen suddenly and without warning. More than 70 million people worldwide suffer from epileptic seizure illness. Health professionals examine and identify the epilepsy in electroencephalography (EEG) signal using visual perception. The real time visual analysis of EEG signal is tough and challenging process. Therefore, it is essential to identify seizure event in EEG signal using a real time system in order to prevent patient from unexpected death. In this work Parks-McClellan algorithm was used to design the finite impulse response (FIR) filters, which can be used to remove the noise present in the EEG signals. The preprocessed signal is modelled using proposed weighted moving average model. From the modelled signal the features such as mobility feature, Fluctuation index and weighted spectral entropy features are extracted. The K nearest neighbor classifier is used to classify the seizure and normal EEG signal based on the extracted features. The system that has been developed employs the utilization of the Xilinx System Generator methodology on the Zynq-7000 fully programmable SOC (System-on-a-Chip) platform. This approach enables the implementation of a fully customizable and flexible system, utilizing the inherent capabilities of the SOC and the System Generator tool. Furthermore, the use of the Zynq-7000 platform enables integration of both hardware and software components, providing a more efficient and powerful solution.**

Keywords— Epileptic seizure, Parks-McClellan, moving average, Zynq, KNN

I. INTRODUCTION

Epilepsy is the second most common neurological disease after stroke and is a very prevalent neurological condition characterized by seizures [1]. The primary function of electroencephalography (EEG) is to provide information on the brain's neuronal activity and helps to identify epileptic seizures using EEG. The major cause of epileptic seizures is due to inappropriate electrical interference in the brain. Direct examination of EEG signals by an expert is crucial for detecting the disease. Additionally, it requires extensive time and effort, and the final diagnosis may vary among different experts [2]. The rapid identification of seizures can significantly enhance the patient's standard of living. Yao Guo et.al [3] proposed a mixed model classifier to reduce the data labelling task with improved performance. The seizure detection is performed using supervised learning easy ensemble algorithm and produce the accuracy of 92.6%.

To determine the beginning stage of the seizure, jiang-ling song et al. [4] created a system based on a model-driven methodology. The model enables the parameters to be optimized in order to describe the EEG signal. For the analysis of continuous EEG signal and amplitude integrated EEG signal, duanpo wu et al. [5] employed overlapping and morphological filter approach. Using a random forest classifier, the feature is classified with an accuracy of 99.23%. In order to build a multivariate technique for seizure identification, miaolin Fan et al. [6] studied the spatial-temporal synchronization. To track the transient of features in EEG signal, a statistical control chart is made according to the procedure. To identify nonconvulsive seizures in EEG data, aldana et al. [7] presented the Canonical Polyadic Decomposition technique. The accuracy of the experimental method utilising the Hilbert-Huang transform is 98%. A technique was developed by akira furu et al. [8] to explain the non-gaussian that results from random oscillations in EEG recordings. The high frequency band features that are extracted in this strategy produce higher categorization outcomes. A hybrid technique in edge gateway was used by Ali Kadhum et al. [9] to build a strategy for the internet of medical things. When compared to other existing strategies, this strategy improves the performance of compression power. A Poincare plot-based feature from an accelerometer device was used by Ali Kadhum idrees et al. [9]. The best features are chosen using ROC analysis, and classification is carried out using a kernelized support vector. A Hilbert transform-based technique was used by Hisham G. Daoud et al. [10] to diagnose epileptic seizure illness precisely. FPGA is used to analyse the system's real-time performance. A more effective epileptic seizure detection system was developed by prabin jose et al. [11–18] using FPGA and an extreme machine learning classifier.

The matching algorithm for machine learning is discussed by jaffino1 et al. [19-24] for image processing

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applications. A technique based on Kurtosis and correlation coefficient from non-stationary EEG signals was created by mrutyunjaya sahani et al [25]. Using a multi-kernel random vector functional link network, the classification task is carried out with a 99.8% accuracy, and the digital architecture of the approach is created using FPGA. A system based on the extraction of Hjorth descriptor features and classification using KNN classifier is reported by Achmad Rizal et al [25]. The Zynq-700 FPGA device was used for the implementation, and less than 10% of the LUT's available resources were used. The major contribution of this work is explained below

(i)The Parks-McClellan algorithm was designed using design finite impulse response (FIR) filters to preprocess the EEG signal.

(ii) The preprocessed EEG signal is modelled using proposed weighted moving average model.

(iii)The proposed system is implemented using Xilinx system generator tool for real time monitoring of EEG signal and its hardware performance were analyzed.

II. MEHTOD USED

The proposed method flowchart for epileptic seizure detection is shown in Fig1. In the initial stage the input EEG signal is filtered using parks- McClellan FIR filter to remove unwanted artifacts present in the EEG signal. The preprocessed EEG signal is modelled using moving average model. In the next stage the statistical features such as mobility feature, Fluctuation index, and spectral entropy were extracted from the modelled signal . The KNN classifier is designed to perform the classification task. The filter design, feature extraction process and KNN classifier is implemented using Xilinx system generator block set. Xilinx system generator was used to construct the suggested method using signals from the Bonn university EEG database. The database includes five sets of EEG signals, each of which is composed of 100 EEG segments and is sampled at a rate of 173.61 Hz.

A. Preprocessing of EEG signal

In order to eliminate the undesired artefacts, present in the EEG signal, a finite impulse response filter is created using the Parks-McClellan algorithm. By specifying filter parameters including filter order, stopband, and pass band frequencies, the Parks-McClellan algorithm creates a linear phase filter. Although the ripple in the passband will rise with a higher filter order, the roll-off will be steeper and the stopband attenuation will be better. Consequently, picking the right filter order is essential for getting the necessary filter performance.

The linear phase FIR filter is expressed as

$$z(e^{j\omega}) = e^{-jN\omega/2} e^{j\beta} \hat{Z}(\omega) \qquad (1)$$

Where $\hat{Z}(\omega)$ is the amplitude response and N is the length of filter coefficient. The weighted error function of the Parks-McClellan algorithm is expressed as

$$\psi(\omega) = M(\omega)[\hat{Z}(\omega) - D(\omega)] \qquad (2)$$

Where $M(\omega)$ is the weighting function and $D(\omega)$ is the desired amplitude response of the filter. The algorithm is iteratively adjusted the coefficients till the error function $\psi(\omega)$ is minimized.

The condition satisfied by the absolute error function is expressed as

$$\left|\hat{Z}(\omega) - D(\omega)\right| \le \frac{\psi_o}{|M(\omega)|} \qquad (3)$$

The desired response of the filter is expressed as

$$D(\omega) = \begin{Bmatrix} 1 \ in\ passband \\ 0 \ in\ stopband \end{Bmatrix} \qquad (4)$$

The weighting error function of the filter is denoted as

$$M(\omega) = \begin{Bmatrix} 1 \ in\ passband \\ \dfrac{\delta_p}{\delta_s} \ in\ stopband \end{Bmatrix} \qquad (5)$$

Where δ_p is the ripple in passband and δ_s is ripple in stop band.

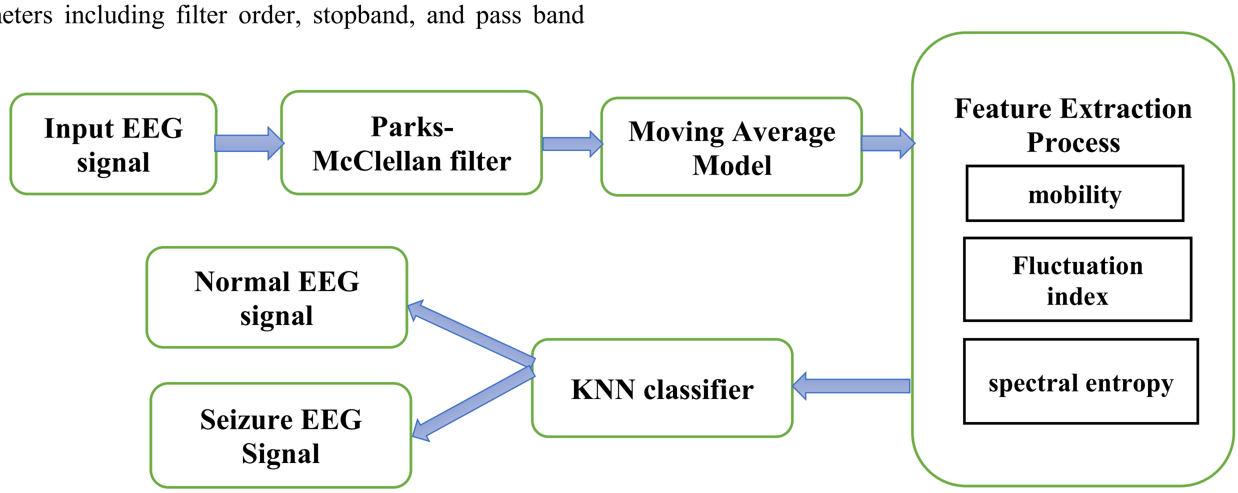

Fig.1. Flow chart of the Proposed method

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B. Weighted Moving Average model

The filtered signal is modeled by using moving average process with white noise of order h is expressed as

$$m(n) = W_t \sum_{k=0}^{h} z_h(k)\gamma(n-k) \quad (6)$$

Where $z_h(k)$ is the filtered signal and $\gamma(n)$ is the unit variance white noise.

The autocorrelation of the filter coefficient is expressed as

$$r_x(k) = z_h(k) * z_h^*(-k)$$

The weighted function to model the EEG signal is represented as

$$W_t = \sum_j (y_i - \mu)P(y_i) \quad (8)$$

Where y_i is the preprocessed EEG signal and μ is the mean intensity value of the EEG signal.

C. Feature Extraction process

The features such as mobility, fluctuation index and spectral entropy were extracted from the moving average modeled signal. The activity determines the EEG signal strength and irregularity in time. The activity of the modelled signal is denoted as

$$\sigma_m^{\ 2} = \frac{\sum_{n=1}^{N-1} (m(n) - \bar{m})^2}{N} \quad (9)$$

Where $m(n)$ is the moving average modeled signal and $\bar{m}$ is the mean of the signal and N is the total number of samples. The mobility of the signal is obtained by dividing the first derivative of the signal and the variance of the signal, which is expressed as

$$Mobility = \frac{\sigma_m'^{\ 2}}{\sigma_m^{\ 2}} \quad (10)$$

The fluctuation index measures the deviation of signal amplitudes in the modelled signal which is expressed as

$$F_I = \frac{1}{N} \sum_{K=1}^{N} |m_{k+1} - m_K| \quad (11)$$

The spectral entropy of the modelled signal is expressed as

$$E_M = -\sum_{K=1}^{N} m_i * \log_2(m_i) \quad (12)$$

D. KNN Classifier

KNN (k-nearest neighbors) is a category of supervised machine learning algorithm utilized for classification and regression. It works by finding the k-number of nearest data points to a given test data point and classifying the test point based on the majority class of its k-nearest neighbors. The value of k is a user-defined parameter, and a larger value of k will result in a smoother decision boundary, while a smaller value of k will result in a more complex decision boundary. It is a simple, effective, and versatile algorithm that can be applied to a wide range of problems. The pseudo code of the KNN classifier is explained below

Step 1 − Load the training feature extracted from the modelled signal

Step 2 – Decide the value of K nearest data points

Step 3 − For each feature of the testing signal do the following

(i) – Determine the distance between test feature and training feature using Euclidean distance measure
(ii) – Using the distance measure value, sort the values in ascending order.
(iii)− select the top K rows from the sorted array.
(iv)− Determine the class to the test feature based on most frequent class

Step 4 − End

III. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, a method for detecting epileptic seizures using EEG signals is presented. The proposed method was implemented using the Xilinx Vivado synthesizer. The EEG signals are obtained from university of born and the sampling rate of the signal is 173.6Hz. In the initial stage the EEG signals were filtered using a finite impulse response filter. The filter coefficients of the filter is designed using Parks-McClellan algorithm. The filtered signal is modelled using weighted moving average models. The features such as mobility, fluctuation index and spectral entropy were extracted from the moving average modeled signal. The System model using Simulink system generator is shown in Fig 2, which includes the FIR filter design, feature extraction process, and KNN classifier. The utilization of resources on the FPGA device for the proposed algorithm is outlined in Table 1, was also investigated. Utilizing the Xilinx System Generator module, the system design was transformed into Verilog code, which was then synthesized and implemented using the Xilinx Vivado design suite. The utilization of resources on the FPGA device is outlined in Table 1.

Table1: Device utilization Summary

Resource	Utilization	Available	Utilization %
Slice LUTS	273	203800	1
Slice register	1284	407600	1
DSP	24	840	2.8
IO	38	442	8.5

The power consumption of the proposed method is tabulated in table2.

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Table 2. Power consumption analysis

Sl No	Utilization	Value
1	Total On-Chip Power	0.18
2	Dynamic power	0.0014
3	Device Static	0.162
4	Junction Temperature	25.3
5	Confidence Level	high

The utilization of the resources such as slices, slice registers, DSPs, and Ios are tabulated in table1. The specific numbers provided indicate that out of the total available resources, a certain portion is being used. In this work 273 slices out of 203800 are being utilized, and 1284 slice registers out of 407600 are being utilized. Similarly, 24 DSPs out of 840 and 38 IOs out of 442 are being utilized. These numbers are used to evaluate the efficiency of the design.

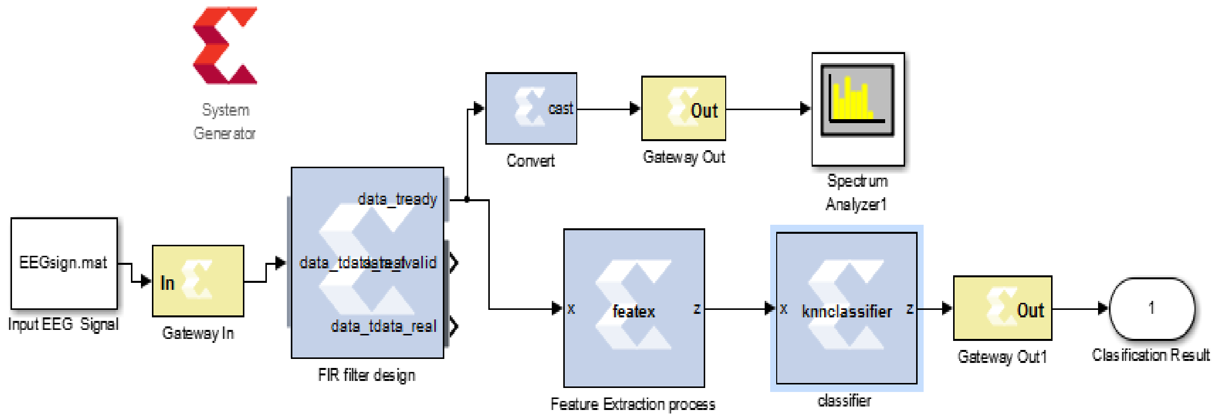

Figure 2. System model using Simulink system generator

The results being discussed pertain to the power consumption of a device. The total on-chip power used is 0.18 watts, and it is broken down into two main components: dynamic power and static power. Dynamic power is the power consumed by the device while it is actively performing operations, and in this case, it is 0.0014 watts. Static power is the power consumed by the device even when it is not performing any operations, and in this case, it is 0.162 watts. The static power consumption is much higher than the dynamic power consumption, this could mean that the device is consuming a lot of power even when it is idle. The power consumption is an important factor in the design of electronic devices, as it directly affects the device's battery life, heat dissipation, and overall energy efficiency

The performance of the system is analysed in terms of accuracy which is expressed as

$$Accuracy = \frac{Correctly\ classified\ signal}{Total\ number\ of\ signals}$$

In this work 500 EEG signals are utilized for testing the performance of KNN classifier. The KNN classifier correctly classified 470 signals and the accuracy obtained by this method is 94%.

IV. CONCLUSION

In this work xilinx vivado design suite is used to create the epileptic seizure detection method using signal modelling and KNN classifier. The performance of the system is measured in terms of accuracy. The utilization of the resources such as DSP, IO, Slice registers, slice LUts are analyzed in terms of complexity and efficiency of the circuit design. The proposed method utilizes the hardware resources effectively based on cost and power consumption. Power consumption of the proposed method is analyzed The total on-chip power used was 0.18 watts, which is broken down into dynamic power and static power. The system provides an accuracy of 94% which is a crucial factor in the design of detection system. In future more advanced machine learning algorithms can be implemented using Xilinx system generator tool.

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