Performance Analysis of DWT-Based Epileptic Seizure Detection

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Abstract : Epilepsy is a central nervous system disorder that is well defined by the startling and atypical behavior of seizures and causes loss of consciousness. TheElectroencephalogram (EEG) signal is particularly good for assessing neurogenic activity and is often used in central nervous system interfaces in the human brain, and neuron disease diagnosis. Among the three modules, discrete wavelet transforms(DWT), feature extraction (FE), and the classification of the support vector machine(SVM), the FE unit matches the relevant neurobiological areas of the EEG data using the 9/7th DWT and extracts the required features. Feature extraction classifies the extracted EEG information into four basic sub-bands namely, alpha, beta, gamma, and theta. Feature Extraction utilizes signal analysis methods and computer technologies to extract information from electroencephalography signals. The proposed design consists of medically converted EEG data, DWT, wavelet decomposition, higher-order statistics, a feature extraction (FE) module, and an SVM module unit. Among the various machine-learning techniques, the support vector machine differentiates between healthy and unhealthy illnesses such as epileptic seizures, SVM is deployed due to its high reliability & adaptation to the presence of arbitrary nonlinear decision limits. The posited designed system provides higher accuracy and reliability compared to the conventional methods designed before in time.

Keywords- Electroencephalogram. Discrete wavelet transform Support vector machine, Fast-Fourier transform, look-up table.

I. INTRODUCTION

A neurodegenerative disease, epilepsy results from briefly occurring aberrant neurotransmission in virtually any region of the brain. Seizures are the most common side effect of seizures and are characterized as a transient change in movement, behavior, feelings, or consciousness that lasts from a few seconds to a few minutes.An EEG measures brainwave activity. DWT has gained notoriety as a highly effective signal evaluation method for awide range of practical applications. EEG Feature Extraction uses mathematical signal analysis methodologies and computer technologies to retrieve confessions fromelectroencephalography (EEG) impulses. Because of its excellent accuracy and flexibility to nonlinear decision limits, SVM is widely employed. The SVM is an iterative learning technique that employs a kernel approach to convert raw data into the higher dimensional feature space before segregating the data using a hyper-plan with maximum margins. Medically transformed EEG data, DWT, discrete wavelet transforms (dwt, higher-order statistics, a feature extraction (FE) module, and even anSVM unit are all part of important applications. The FE module fits the neurobiological regions of the electroencephalogram (EEG) signal with the 9/7th Daubechies discrete wavelet transform and extracts the appropriate features. SVM is used to categorize healthy and aberrant or pathological states along with other classificationalgorithms because of its excellent accuracy and flexibility tothe presence of multicollinearity bounds.D. Lasemidis et al.

[1] outlined the topic of seizure prediction is addressed and in this paper's overview and the use of processing techniquesare based on the theory of dynamic behaviour. Advantages includes technologies are used to decode brain signals and enable implantable devices to intervene in time to treat epilepsy. Dis-advantages are broader application of these developments to a variety of systems requiring monitoring, forecasting and control is needed. T. K. Gandhi et al. [2] outlined the ground of EEG signals, , a computerized intelligent model for forecasting epileptic seizures is established. The optimum features that enhances classification accuracy whilst consuming less processing time. Because epileptic signals range in frequency between 6to 80 Hz,the proposed classifier doesn't perform well.

J. Yoo & L. Yan et al. [3] described the construction of an eight-channel system-on-chip for seizure recognition using anon-linear SVM (NLSVM) among patients with epilepsy.Advantages depicts achieve high energy consumption and reduces the area compared to conventionalimplementation and the limitations include less accuracy. Sharmila et al. [4] suggested a pattern recognition approach wherein clinical diagnosis systems require medical information to be analysed with high precision and in less time. Advantages includes proposed pattern recognition technique could attain a higher accuracy. Dis-advantage include only three statistical features derived from EEG signals are vital for outstanding epileptic seizure detection. Z

H. T. Shiao et al. [5] outlined a rudimentary SVM-based approach for iEEG signal-based seizure prediction. The system's architecture is predicated on required standards of clinical factors, which are then formalized into assumptions for data-analytic processing. Advantages includes,this systemhas several novel data-analytic interpretations and improvements. Limitations includes, robust prediction of preictal and interictal iEEG segments.

M. Papadonikolakis et al. [6] outlined a potentially adaptable hybrid FPGA architecture for accelerating the SVM training challenge. Merits includes, fully customized processing unit is designed. Limitations includes, theefficiency of the proposed design needs to increase with the precision diversities of the dataset attributes. S. Cadambi et al. [7] outlined an SVM-based algorithm for seizure prediction employing iEEG signals proposed in this research. Advantages includes, proposed FPGA implementation is faster.Limitations includes,this approach is unsuitable for edge analytics which is a growing trend with various IoT applications.B. G. D. Valle et al. [8] subdermal subcutaneous, eight-channel EEG recorder and seizure detector with two operating points and seizure counting is thetarget of this study. Merits include helping determine

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medication efficacy or another clinical endpoint. De-merits are the, need to minimize the system's power and size. J. T. Olkkonen and H. Olkkonen et al. [9] described In noise removal and compaction coding of visuals and information, the discrete wavelet transform (Discrete wavelet transform) has found rapid adoption. Advantages include, The DLWT can be implemented directly to any of the existing DWT algorithms. De-merits include the PR condition that is used to design half-band filters, which effectively eliminate aliasing in decimated tree-structured wavelet transform. T. C.Denk et al. [10] described just it seems there is a technology for inexpensively constructing physiological wavelettransform systems on semiconductors. Merits include the control circuitry that permits sliding them to achieve any correct degree of disintegration without the need for any communication electronics. De-merits are word sizes for material and coefficients differ. H. Peng et al. [11] outlined that an emphasis on the multi-class classification training procedure, this one was advocated to get an analysis of studies that have been focused on the two most often used parallel processing systems: GPU and FPGA.Merits include two parallel processing systems are considered. De-merits include a less accurate system.

M. Ebisawa et al. [12] sketched out a Brain-machine interface (BMI) relies entirely on accurate evaluation of event potentials (ERPs), and its output is significantly reliantjust on proper collection of perceptron requirements and competencies using densely packed brainwave sequences (EEG) inputs. The proposed strategy produced greater classification accuracy than existing methods while simultaneously utilizing fewer channels. It was also discovered that by drastically decreasing the number of channels, exactness may be improved. P. Yun et al. [13] describe the processes mentioned in the patient-specific approach including pre-processing, feature extraction, SVM classification, and post-processing. Pre-processing is appliedto intracranial EEG recordings to remove distortions, and then bipolar and or time-differential pre-processing is used. The spatial frequency properties of unprocessed, bipolar, and/or time-differential intracranial EEG (iEEG) observations are produced from a sliding window that seems to be twenty seconds long & partially replicated in nine bands. E. Osuna et al. [14] describe a detailed look at how the Support Vector Machines (SVMs) are employed in machine learning, but it may be viewed as a novel approach for learning analytics that are using neurons, parametric models, or rectified functions. L. Guo et al. [15] proposed multiwavelets have been making strides in digital signal processing. The auto involuntary spasm detection algorithm discussed in this work doesn't analyzes EEG signals depending on whether a crisis is developing by merging estimated density elements or not.

II. PROPOSED METHODOLOGY

A.ELECTROENCEPHALOGRAM SIGNAL(EEG SIGNAL)

Among both physiologic and pathologic cognitive processes,neural waves are transmitted. EEG has indeed been identifiedto be a tremendously strong instrument in the disciplines of psychiatry and diagnostic neurobiology because it has the capacity to portray all of the mind's functions. Despite the reality fact EEG is an essential idea tool for the detection, monitoring, and therapy of relapsing forms, the main difficulties with EEG analysis and processing remain inhibited in its broad implementation. In acquiring accurate assessments for the treatment of seizures, it is important to evaluate the ECG data that used a systematic and appropriateprocedure. Correlated with greater electrical impulses typically occur from locations apart from the brain in contrast to the brainwaves. The scalp's impulses are heavily contaminated with various undesirable signals, or "relics," that seem to be the result of events unconnected to the physiological event happening. Power supply interruption, termed artifacts, affect research by misrepresenting the impacts of curiosity as a neurogenic effect. The presenceof aberrations introduces spikes that can be misconstrued forbiological cycles, skewing, and confusing the processing of EEG signals and ultimately in erroneous results. For the recognition of anxiety-driving phenomena, θ, alpha, & beta sub-bands are of interest. When an individual is nodding off or resting his eyes, alpha activity prevails. Alpha gradually drops and theta gradually rises, and we go from becoming awake to resting or getting nervous. Electrodes are positioned on a person's scalp to monitor EEG signals.

B.Implementation of DWT

For many real-world applications, the Dwt Transform had established a strong reputation as a very sound-transmitting surfaces analytical tool. The design of the filtering is crucial in the discrete wavelet transform. The Distributive Arithmetic (DA) methodology is used for the utilization, anda multi-phase formation is provided. The design of the filtering is crucial in the discrete wavelet transform. The Distributive Arithmetic (DA) methodology is used for the utilization, and a multi-phase formation is provided.

C. Feature Extraction of EEG signal

The application Feature Extraction Transform (FFT) is based on a butterfly computing unit. The only mathematical units in the butterfly compute unit, that is operated by a finite state machine, are a For BFP calculation, a sixteen- bit signed adder and even a sixteen-bit signed multiplier are used. Figure 3 depicts a butterfly module schematic. To provide a reference to the LUT, any multiplier input was passed through a hash function. The four nibbles of a 16-bit integer were XORed to get a 4-bit hash result in the XOR hash method. The block diagram of a conventional BFP arithmetic butterfly unit is shown in Figure 3. Performance and System Architecture the optimized butterfly module serves as the foundation of the FFT's architecture. Its butterfly processing The module is intended to provide two complicated results, Xi[n] and Xi[n + 1], as well as the largest 16-bit integer included inside Xi[n] and Xi[n +1]. Every butterfly's desired outcome is saved and compared to the preceding value representing the greatest magnitude generated in each FFT step. This circuit illustrates the use of a single butterfly unit over each stage's butterfly operation successively. A classifier uss values for independent variables (features) as input to determine whichcategory a particular predictor variable belongs to. Using data for training, several classifier characteristics must be taught. In this study, we used the classification methodologies outlined below to show the effectiveness of the proposed strategy. The algorithm is an iterative strategy that uses a kernel trick to transform input data to a high- dimensional subspace and then segregates variables using a high energy with optimal margins. And for its ability to handle large datasets, the technique is extensively employedin computer vision for binary classifier tasks.

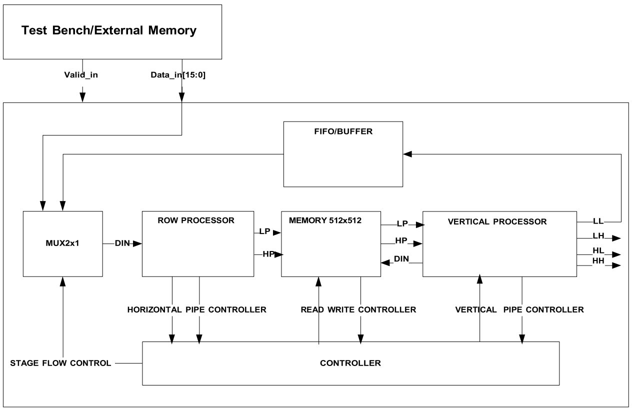


Figure 2. DWT & its communication modules

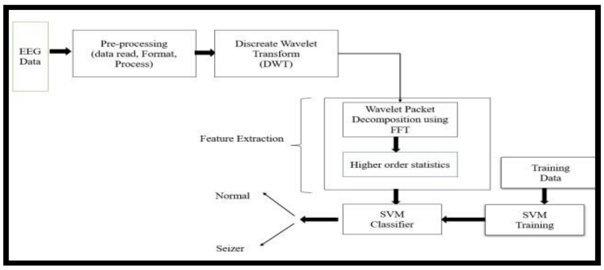
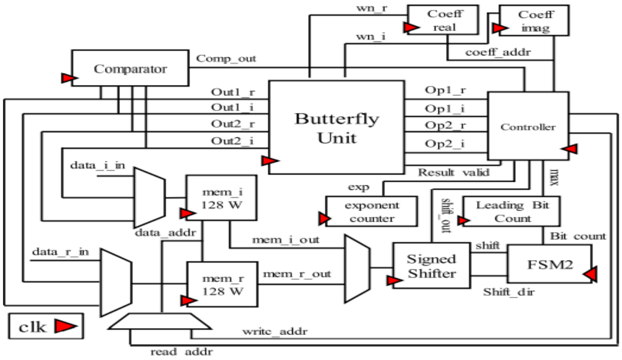


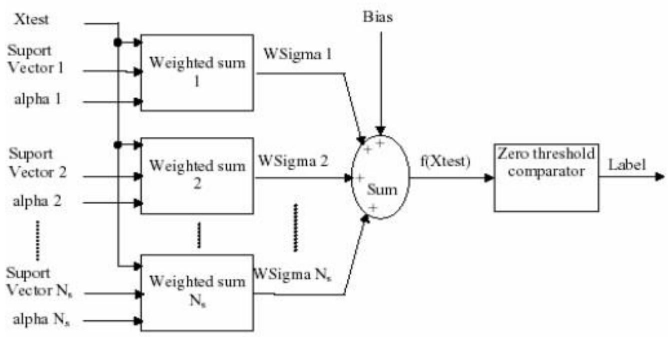
Figure 1. Block Diagram of the proposed seizuredetection system

D.Support Vector machine Classification

To identify what group given independent variable belongs to, a classifier utilizes values for independent factors (features) as input. Several classifier parameters must be learned using data for training. We employed the categorization approaches described below to demonstrate the efficacy of the recommended strategy in this investigation. The algorithm is an iterative technique that employs a kernel function to transform input data into a multidimensional feature space, whereby it segregates the variables using a hyper-plan with optimal margins. The approach is commonly used in machine learning for binary classifier tasks due to its capacity to manage big datasets.



(a) Feature extraction using butterfly unit



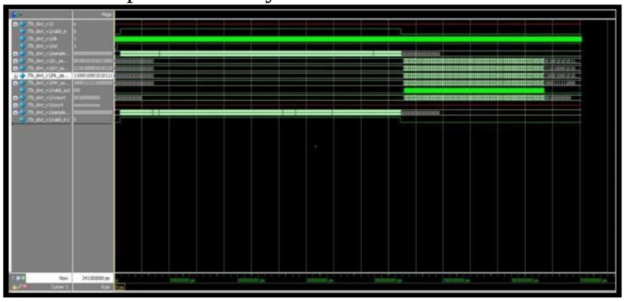
(b) SVM classifier

Figure 3. Feature extraction and SVM classification, (a) Feature extraction using butterfly unit

(b) SVM classifier

III. RESULTS

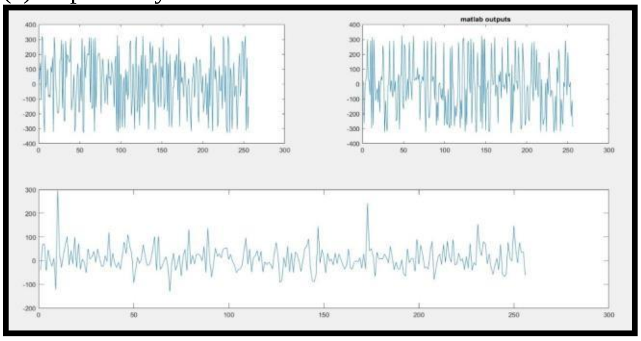
I used the best of the classifier among the different machine learning algorithms,i.e, the Support Vector Machine. The SVM gives the most accurate result during classification. Overall, the DWT is implemented in Verilog and compared with the MATLAB plot. The DWT simulation result is shown in Figure 4. In this plot, the DWT gives four differentoutputs. The output of DWT is then compared to a MATLAB plot and analyzed with values.



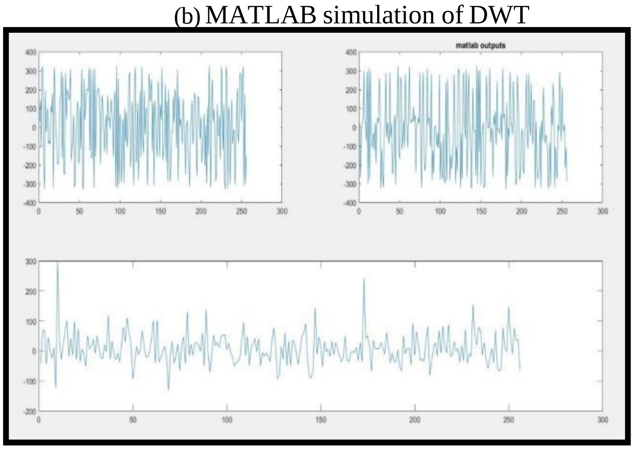
(a) Simulation of DWT

The simulation of DWT is shown in Figure 4(a). The comparison of the DWT in EEG data and DWT using EEG data is shown in Figure 4

(b) and 4(c) respectively. The data is read from a text file to MATLAB.



(b) MATLAB simulation of DWT



(c) MATLAB simulation of DWT using EEG data

Figure 4. (a)Simulation of DWT(b))MATLAB simulation ofDWT ,(c) MATLAB simulation of DWT using EEG data

The feature extraction is done after the computation of N- point FFT, here N=8 and N=1024. The 8-point FFT is computed via Verilog and is shown in Figure 5.

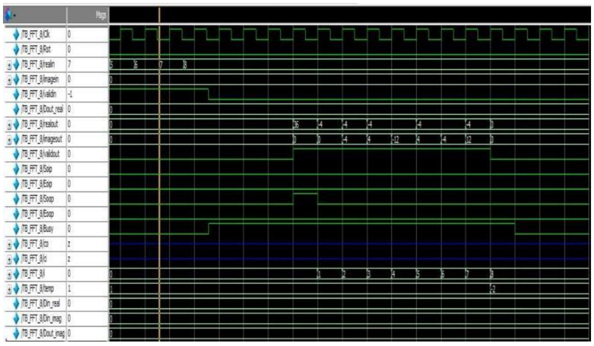


Figure 5. Simulation of 8-point FFT

After the FFT computation, the output is matched with the MATLAB plot for further verification. The matched output plot is shown in Figure 6.

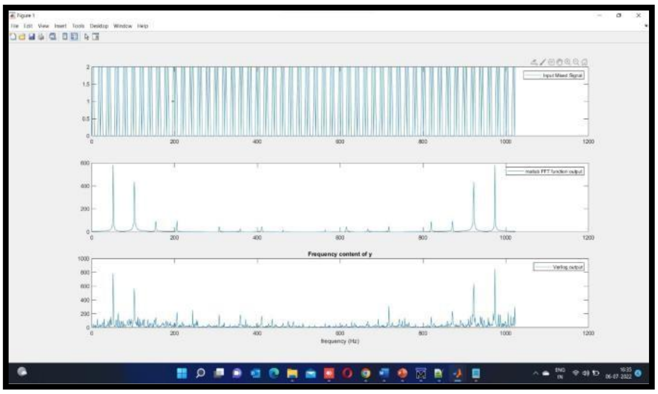
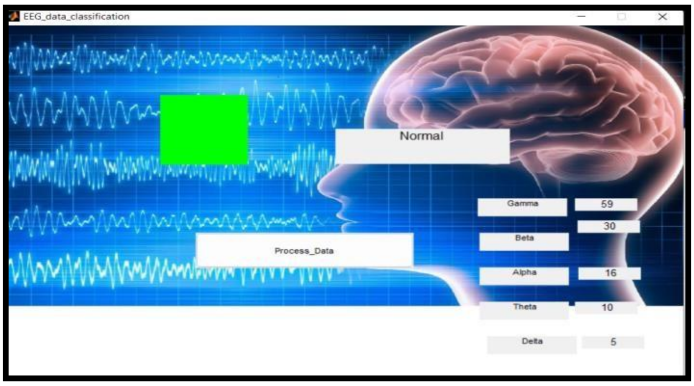
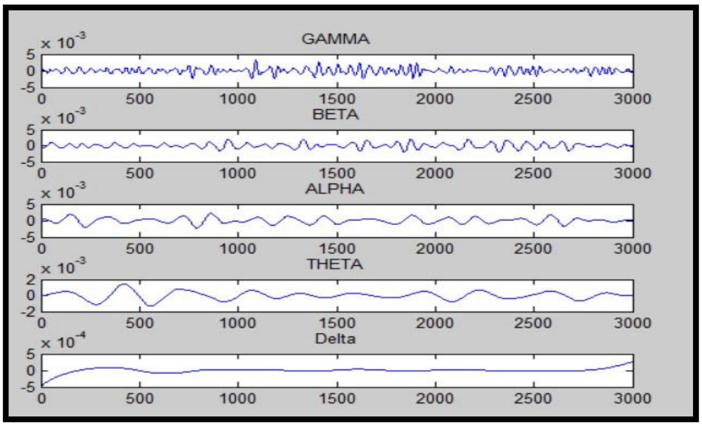


Figure 6.1024-point FFT verified using the MATLAB

After the feature extractions classification is done using MATLAB, a graphical user interface(GUI) is proposed for the classification of normal or stage-1conditon for non- epileptic patients. The data is processed, as it performs the entire procedure from EEG signal as input then DWT, extraction of the required features, and finally, classified into normal and abnormal conditions. Figure 6(a) depicts theclassification result for normal/non-epileptic conditionsusing a MATLAB plot. Figure 6(b) depicts EEG wavelets classification for non-epileptic conditions where it showsthe four wavelets, gamma, theta, alpha, beta, and delta.

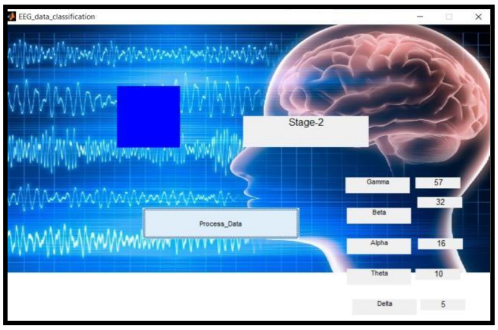


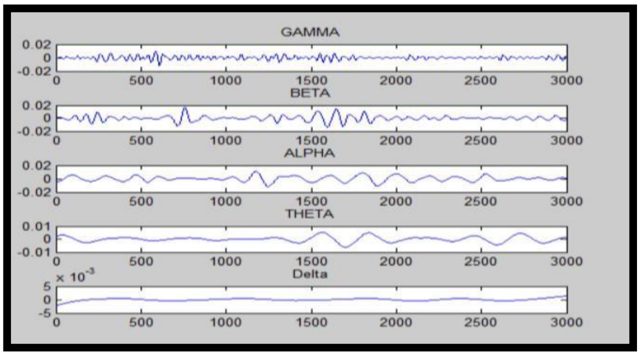
(a) Classification result for normal/non-epileptic condition



EEG wavelets classification for non-epileptic condition Figure 6.(a) Classification result for normal/non-epilepticcondition(b) EEG wavelets classification for non-epilepticcondition.

Figure 7(a) depicts the classification result for ab- normal/epileptic conditions using a MATLAB plot. Figure 7(b) depicts EEG wavelets classification for epileptic/stage-
2 condition where it classification shows the four wavelets,gamma,thetha,alpha,beta and delta.





(a) EEG wavelets classification result for Abnormal/ epilepticcondition Figure 7.(a) Classification result for Epileptic/stage-2 condition (b) EEG wavelets classification result for Abnormal/ epilepticcondition.

Table 1: Performance Comparison:

Performance	**FENG et al.[16]**	**Proposed System**
Delay	9.435ns	5.295ns
Maximum Frequency	105.9878Mhz	188.872MHz
Slices (Slices+ Slice Flip Flops)	7,290	6,190
LUTs	1305	1705
Power	112uw	56uw

The comparison of the performance of the EEG data in termsof delay, LUTs used, and power consumption is shown in Table 1. The overall accuracy is increased for the proposed model and the calculation of each model is shown.

IV.CONCLUSION

Epilepsy is a central nervous system disorder that is well definedby the startling and atypical behavior of seizures and causes loss ofconsciousness. The proposed design consists of medically converted EEG data, DWT, wavelet decomposition, higher-order statistics, a feature extraction (FE) module, and an SVM module unit. Among the various machine-learning techniques, the support vector machine differentiates between healthy and unhealthy illnesses such as epileptic seizures, SVM is deployed due to its high reliability & adaptation to the presence of arbitrary nonlinear decision limits. The posited designed system provides higher accuracy and reliability compared to the conventional methods designed before in time.

V.REFERENCES

1. Lasemidis, Author, “Epileptic Seizure Prediction and Control”, IEEE Trans. Biomed. Eng., vol.50, no. 5, pp. 549558, May (2019).
2. T. K. Gandhi, P. Chakraborty, G. G. Roy, and B. K. Panigrahi, Authors, “Discrete harmony search based expertmodel for epileptic seizure detection in electroencephalography”,IEEE Transactions OnBiomedical Circuits and systems, Vol. 12, No. 1,February 2019.
3. . Yoo, L. Yan, D. El-Damak, M. A. Altaf, A. Shoeb, and A. P. ChanDrakasan,, “An 8-channelscalable EEG acquisition SoC with patient- specific seizure classification and recording processor,” IEEE J. Solid-State Circuits, vol. 48, no. 1, pp. 214–228, Jan. 2018.
4. Sharmila and P. Geethanjali, “DWT based detection of epileptic seizure from EEG signals using naive Bayes and k-NN classifiers,” IEEE Access, vol. 4, pp. 7716–7727, 2018.
5. H. T. Shiao et al.SVM-based system for prediction of epileptic seizures from iEEG signal,” ,IEEE Trans. Biomed. Eng., vol. 64, no. 5, pp. 1011-1022, May 2017.
6. M. Papadonikolakis and C. S. Bouganis, , “A heterogeneous FPGA architecture for support vector machine training,” in Proc. 18th IEEE Annu. Int. Symp. Field-Program.Custom Comput. Mach., May 2017.
7. S. Cadambi et al., “A massively parallel FPGA-based coprocessor for support vector machines,” in Proc. 17th Annu. IEEE Symp. Field Programmable Custom Comput. Mach., 2016, pp. 115–122.
8. C.-H. Peng, B. W. Chen, T. W. Kuan, P. C. Lin, J. F. Wang, and N. S. Shih, “REC- STA: Reconfigurable and efficient chip design with SMO based training accelerator,” IEEE Trans. Very Large Scale Integr. Syst., vol. 22, no. 8, pp. 1791–1802, Aug.
9. G. D. Valle, S. S. Cash, and C. G. Sodini, “Low- power, 8-channel EEG recorder and seizure detector ASIC for a subdermal implantable system,” IEEE Trans. Biomed. Circuits Syst., vol. 10, no. 6, pp. 1058–1067, Dec. 2015.
10. J. T. Olkkonen, “Discrete lattice wavelet transform," IEEE Trans. Circuits Syst. II, Express Briefs, vol. 54, no. 1, pp. 71-75, Jan. 2015.

11. H. Huang and H. Yu, “Least-squares-solver based machine learning accelerator for real-time data analytics in smart buildings,” in Emerging Technology and Architecture for Big-data Analytics, A. Chattopadhyay et al., Eds. Berlin, Germany: Springer, 2017, pp. 51–76.
12. M. Fernandes, “Use of support vector machines to automatically detect epileptic activity in EEG data,” M.S. thesis, Dept. Eng., Univ. Witwatersrand, Johannesburg, South Africa, 2011.
13. A. M. Lima and A. L. V. Coelho, “Kernel machines for epilepsy diagnosis via EEG signal classification: A comparative study,” Artif. Intell. Med., vol. 53, no. 2, pp. 83–95, Oct. 2011.
14. U. R. Acharya, S. V. Sree, G. Swapna, R. J. Martis, and J. S. Suri, “Automated EEG analysis of epilepsy: A review,” Knowl.-Based Syst., vol. 45, pp. 147–165, Jun. 2013.
15. P. Yun, L. Luo, K. K. Parhi, and T. Netoff, “Seizure prediction with spectral power of EEG using cost- sensitive support vector machines,” Epilepsia, vol. 52, no. 10, pp. 1761–1770, 2011.
16. Lichen Feng, Zunchao Li, and Yuanfa Wang “VLSI Design of SVM-Based Seizure Detection System With On-Chip Learning Capability” IEEE TRANSACTIONS ON BIOMEDICAL CIRCUITS AND SYSTEMS,2018
17. P. Yun, L. Luo, K. K. Parhi, and T. Netoff, “Seizure prediction with spectral power of EEG using cost- sensitive support vector machines,” Epilepsia, vol. 52, no. 10, pp. 1761–1770, 2011.
18. H. T. Shiao et al., “SVM-based system for prediction ofepileptic seizures from iEEG signal,” IEEE Trans. Biomed. Eng., vol. 64, no. 5, pp. 1011–1022, May 2017.
19. R. Hussein, A. Mohamed, K. Shahan, and A. A. Mohamed, “EEG feature extraction and selection techniques for epileptic detection: A comparative study,” in Proc. IEEE Symp. Comput. Informat., 2013, pp. 170– 175.
20. D. Chen, S. Wan, and F. S. Bao, “EEG-based seizure detection using discrete wavelet transform through full- level decomposition,” in Proc. IEEE Int. Conf. Bioinformat. Biomed., 2015, pp. 1596–1602.
21. A. Subasi, “EEG signal classification using wavelet feature extraction and a mixture of expert model,” Expert Syst. Appl., vol. 32, no. 4, pp. 1084–1093, May 2007.