INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 16-09-2023

Accepted: 04-10-2023

Published: 13-11-2023

Citation: Ahamed MZ, Mastani SA (2023) Power and Area Optimized Deep Learning Framework for Accurate Automatic Epileptic Seizure Detection . Indian Journal of Science and Technology 16(43): 3838-3845. https://doi.org/10.17485/IJST/v16i43.2356

* **Corresponding author**.

zaheer.mtech@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Power and Area Optimized Deep Learning Framework for Accurate Automatic Epileptic Seizure Detection

M Zaheer Ahamed[1]*, S Aruna Mastani[2]

1 Research Scholar, Department of ECE, JNTUA, Anantapuramu, Andhra Pradesh, India
2 Assistant Professor, Department of ECE, JNTUCEA, Anantapuramu, Andhra Pradesh, India

Abstract

Objectives: To design Hardware based system for detecting epileptic seizures automatically by processing the EEG signals, which could help the patients in protecting from adverse effects. **Methods:** In this paper, an efficient system for detecting the occurrence of epileptic seizures based on Novel features SCAR (Sum to Cumulative Average Ratio) and RHER (Rescaled Hurst Exponent Range). These features are then used to train a Multi-Layer Perceptron (MLP) network which employs 6 layers with 8 nodes in each layers. The MLP network is then optimized for power and area using Post Trained Quantization (PQT) technique which reduces the memory footprint of the network. Clock Gating and Multiple Operating Frequencies are used for optimizing Power. **Findings:** The classification accuracy in case of seizure detection is 100% for the MLP network. The system is implemented on a Artix7 FPGA for performing real time analysis. The total power consumption of the system is 35.628mW while total number of 1744 LUTS were required for the system. The overall utilization is just 12% of the available resources. The achieved results outperform all the existing works for the case of seizure detection using EEG signal processing. **Improvement:** A Low power, area optimized and highly accurate system is proposed in the proposed work. The power and Device utilization analysis showed the utility of the proposed system for practical applications.

Keywords: SCAR; RHER; MLP; seizure prediction; Artix7 FPGA

1 Introduction

About 1% of people around the world suffer from a very chronic brain disorder named as Epilepsy. The epileptic seizures cause a severe impact on the physical and mental state of a person and even can tend to the death [(1)]. Thus, it's extremely important to predict the occurrence of seizures and also detect the seizures. The human brain activities are significantly captured by the Electroencephalogram (EEG) signals captured from either above or underneath the scalp. So the analysis of these signals exhibits a highly probable case of predicting and detecting the seizures. It's been demonstrated by several neurologists and researchers that the EEG signal patterns of an epileptic seizure differ from a healthy patient and also the patterns show a significant variation for the various stages of seizure. Thus, this information can be utilized in predicting the occurrence of the seizure in its pre-ictal period itself and be used to alert the patient [2].

The traditional way of monitoring the EEG records continuously and looking for the variations manually is a tedious process and also can give way to too many detection errors, specifically if large number of EEG channels is to be monitored. With the advent of artificial intelligence into health sector, this tiring and complicated manual process has been alternated by automatic detection techniques [3].

The brain activity during a seizure can be divided into three stages or states [4]

A. The first stage is the inter ictal or Normal state which refers to the normal condition of a patient.

B. The state of the brain before the occurrence of seizure is referred as the pre-ictal state. The Pre ictal state may last from a few minutes to a few hours depending on the patient.

C. The ictal state is the condition in which the patient undergoes seizure activity.

The patient suffering with epilepsy will be highly benefited and the risk associated can be greatly reduced if the patient is altered about the seizure before its onset. There are several state of art techniques proposed for seizure detection based on concepts of Machine learning and deep learning.

In [5] the authors have implemented a real time epileptic seizure prediction on a System on chip (SoC) FPGA. They have used EPILEPSIAE Database. Frequency domain features were with a Rusboosted Tree Cluster Classifier. They achieved a sensitivity of 77.30 while the False Positive rate is 0.041/h. The proposed model is implemented on FPGA with a LUT utilization of 62%. The system is heavy and may not suitable for portable system implementation.

Ahmed et al [6] demonstrated a real time epileptic seizure detection using an Artificial Neural Network. They have used cross entropy and sparse entropy as the features with TUH EEG Corpus Dataset. The proposed model was implemented on FPGA with total logic elements of 13,014 and achieved an accuracy of 86.7 % for classification.

Jose et al in [7] proposed a compact classification model by using a single hidden layer Extreme Learning Machine (ELM). They used energy, entropy & PSD as the features, utilizing the dataset provided by the Bonn University. They achieved an accuracy of 95.8 % with the total logic units of 2,03,800 and the processor consumes 160mW of power for operation.

In [8], the authors have proposed a seizure detection system using a Deep Learning Neural Network with feature set of 80 parameters. The system was implemented on Xilinx Zynq-7000 series FPGA with a accuracy of 75%. They utilized 58,800 logic elements for the model which consumed around 1.8 Watts.

The authors in [9], have modeled an optimized seizure detection using One way ANOVA and Genetic Algorithm. The features used for these are Average Mean value, kurtosis, Root mean square, zero crossing rate & PSD for the dataset given by Bonn University. They implemented the system on Xilinx Spartan 6 FPGA. They achieved an average accuracy of 92% with 2,774 Logic elements and a power consumption of 38mW.

In the existing literature a tradeoff between the Power & Area vs Accuracy was observed. That is methods which achieve high accuracy consume significantly high power and/or occupy large area. On the other hand, the methods utilizing low power and area have less accuracy making them relatively less applicable in real time. There is no single solution which achieves high accuracy with less area and low power consumption.

This work presents a power and area optimized hardware platform designed specifically for accurate automatic seizure detection using a multilayer perceptron neural network. The proposed platform leverages the inherent parallelism and computation capabilities of neural networks to efficiently process the input data and provide real-time seizure detection and prediction.

The main contributions of the work are listed as follows:

1. Propose two Novel features Namely SCAR and RHER which give High accuracy for seizure detection.
2. Apply the Post Training Weight Quantization (PTQ) Algorithm (an Algorithmic optimization technique) for reducing the memory requirements of the MLP network which in turn reduces the power consumption.
3. Optimize the power consumption of the Hardware Platform with help of Clock Gating and Multiple Operating Frequency (VF) techniques.

The remaining part of this work is arranged as follows: second section gives the methodology used in the paper while the third section presents the results of our work and a discussion about the results is presented. The final section gives the conclusion.

2 Methodology

The block diagram of the proposed system is as shown below. The raw signal is passed through the Discrete Wavelet Transform block which divides the signal into four frequency bands namely Alpha, Beta, Gamma and Delta Bands. Of these the Alpha bands and Delta bands carry significant information needed for doing the seizure detection and prediction and hence the other two bands are neglected, which improves the processing speed of the system significantly.

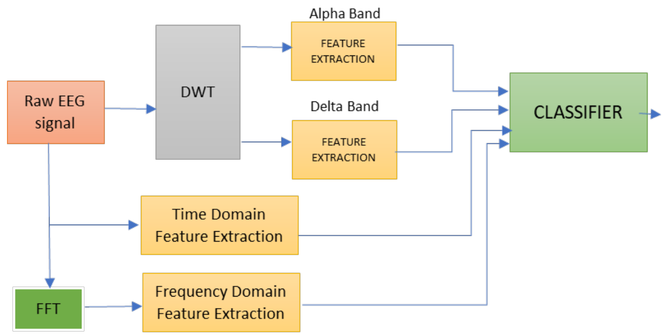

Fig 1. Block Diagram of the Proposed Method

2.1 Dataset

There are several datasets available on EEG signals for seizure analysis. A complete review of all the datasets has been presented in our previous work. The Dataset used for training the model has been taken from Open source data provided by the collaborative contribution of Boston Children Hospital and MIT. This comprises recordings related to 24 patients for duration of around 980 hours. There are around 173 seizure incidents recorded in these 980 hours. The recording was digitized by a sampling rate of 256 and 16 bit resolution. In this work we consider the pre ictal period as the period of 20 minutes before the occurrence of the seizure.

2.2 Feature Extraction

Two novel features namely Sum to Combined Average Ratio (SCAR) and Rescaled Hurst Exponent Range (RHER) are proposed. The procedure for calculating these features is given below.

2.2.1 Sum to Cumulative Average Ratio (SCAR)

Let x be the raw EEG signal, which is a one-dimensional array of length N=4096 samples

i. Calculate the RMS value (RM), Mean (M) & Hjorth activity (H) of the signal

RMS value, RM=

Mean, M = $\frac{x1+x2+x3+\cdots+xn}{N}$

Hjorth Activity or variance H = $\frac{\sum_{i=0}^{N-1}(xi-M)^2}{N}$

ii. Calculate the Range factor of a series as R= max(x)- min(x)

iii. Add mean, Hjorth activity, RMS and R to calculate Combined average coefficient T

T= M + H + RM + R

iv. Convert the signal into a positive array. By calculating the magnitude of it. x= |x|

v. determine the sum of all elements in the array of x S= sum(x)

vi. Now the SCAR (Sum to combined average Ratio) is calculated as

SCAR = S / T.

2.2.2 Rescaled Hurst Exponent Range (RHER)

Hurst Exponent is a widely used statistical feature for Linear Discriminant Analysis of Non stationary signals. But the Hurst exponent is evaluated by taking Logarithmic scale and thus the Hurst exponent ranges between 0 and 1. But the Hurst exponent is difficult to be implemented on hardware. Therefore, the Hurst exponent is reformulated as follows

Let x be the raw EEG signal, which is a one-dimensional array of length N=4096 samples

i. Calculate the mean of the signal m= $\frac{x1+x2+x3+\cdots+xn}{N}$

ii. Create a mean adjusted series $Y_t = X_t - m$

iii. Calculate the cumulative deviate series Z_t as

iv. Compute the range R as
R(n) = max (z1, z2, z3….)- min (z1, z2, z3…….)
v. Compute the standard deviation S(n) =
vi. Calculate the re scaled range as RHER = R(n) / S(n).

2.3 Classification

All the features computed in the earlier section are applied to a neural network which performs the classification. In this work we use a Multi-Layer Perceptron with Back Propagation have been used for performing seizure detection and prediction. The architecture of the Multilayer Perceptron is as shown below. The MLP network used in the work has 5 hidden layers each layer comprising 6 nodes. The network is trained by the Levenberg–Marquardt[10] function. It is the fastest back propagation algorithm that optimizes and updates the bias and weights of each node automatically. The 'Hyperbolic tangent sigmoid'[11] function as the transfer function for training.

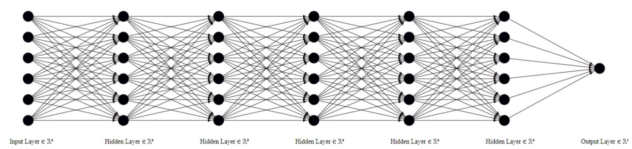

Fig 2. Structure for MLP Network

The Network is then optimized using PTQ Algorithm. PTQ begins with training a neural network using standard techniques. This involves forward and backward passes with full-precision (typically 32-bit or 64-bit) floating-point numbers for weights and activations. Once the training is complete, the neural network is evaluated to ensure that it meets the desired performance metrics. After training and evaluation, the next step is to quantize the model. This involves converting the weights and, optionally, the activations from their original high-precision format (e.g., 32-bit floating-point) to a lower-precision fixed-point or integer format (e.g., 8-bit or 16-bit integers).

2.4 Hardware Implementation

The major blocks of the systems are DWT, Feature Extraction Block, FFT and Classification Networks. All these modules are implemented using Verilog HDL. The schematics of these are shown in the figure below.

The first module in the system is a Discrete Wavelet Transform.

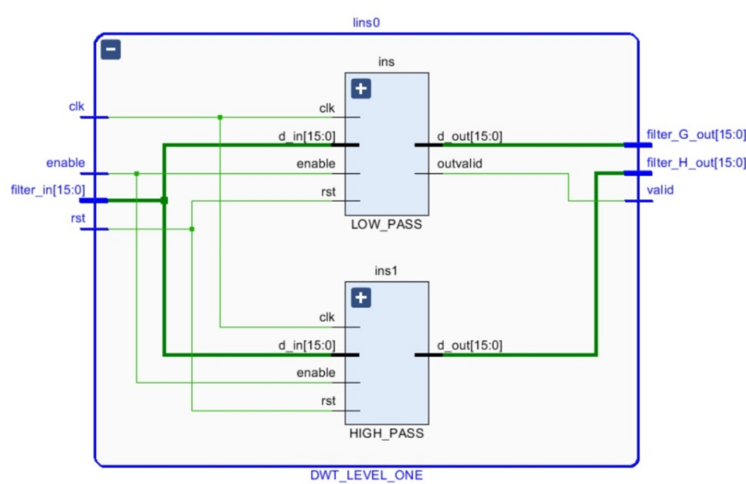

Fig 3. DWT block at the Level 1

The implementation of a Discrete Wavelet Transform for three level is shown below.

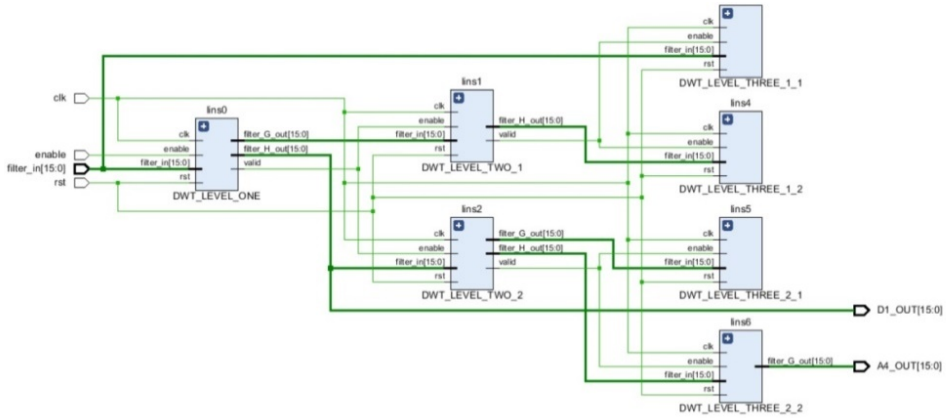

Fig 4. Complete DWT structure

The feature extraction module comprises a Multiplier, Floating Point Divider and Adders for computing the two novel features namely RHER and SCAR.

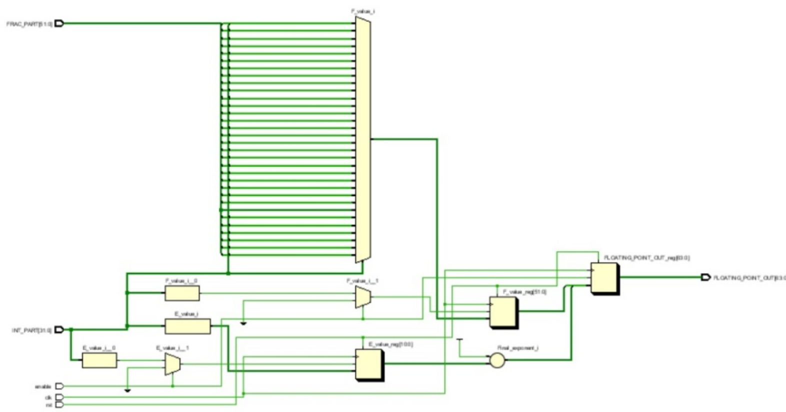

Fig 5. Feature Extraction Block

The Multilayer Perceptron is a neural network comprising an input layer, three hidden layers and output layers. The structure of the network is shown figure below.

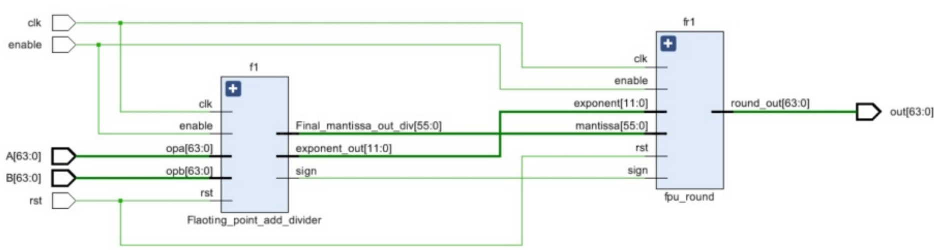

Fig 6. Top level Block of MLP

3 Results and Discussion

The Proposed system has been implemented on the Artix 7 FPGA and the results are presented below.

The proposed system is validated for accuracy, sensitivity and specificity by considering 100 test samples selected randomly. The confusion matrix for the case of (Normal vs Ictal) is as shown below.

Test Dataset			
TARGET / OUTPUT	Class0	Class1	SUM
Class0	50 50.00%	0 0.00%	50 100.00% 0.00%
Class1	0 0.00%	50 50.00%	50 100.00% 0.00%
SUM	50 100.00% 0.00%	50 100.00% 0.00%	100 / 100 100.00% 0.00%

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Class0	1.00	0.00	1.00	0.00	1.00
Class1	1.00	0.00	1.00	0.00	1.00
Accuracy	1.00				
Misclassification Rate	0.00				
Macro-F1	1.00				
Weighted-F1	1.00				

Fig 7. Simulation Results for seizure detection

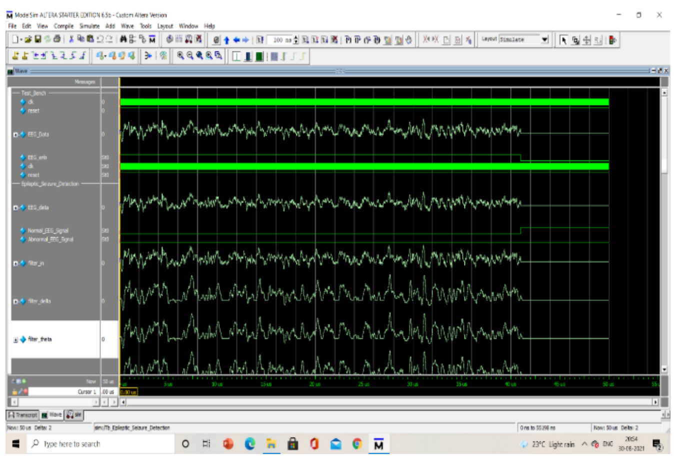

Fig 8. Simulation Output

3.1 Power & Utilization Report

The power report of the proposed system for evaluation of a single sample is shown as below.

Table 1. Power and Utilization Reports

	Metric	Value	
	Dynamic Power	35.143 mW	
	Static power	0.485 mW	
	Total power	35.628 mW	
Resource	**Utilization**	**Available**	**Utilization %**
LUT	629	20800	3.02
LUTRAM	88	9600	0.92
FF	983	41600	2.35
DSP	23	90	25.56
IO	21	170	12.35

3.2 Comparison with Previous Works

There any many other methods proposed in the Literature of seizure detection & Prediction. The proposed system is compared with the state of the art methods in the literature.

In the previous literature the best achieved accuracy was 96% while the proposed method achieves an accuracy of 100% which outperforms all the existing techniques. The hardware implementations proposed in the literature achieve a minimum of 160mW, while the proposed achieves a power consumption of 35.6mW due to the various power optimization techniques used. Hence, the proposed method is 400 times efficient compared to the existing methods. Also, the proposed method achieves area efficiency of around 200 times in comparison with the existing methods.

Table 2. Comparison of Existing Techniques with Proposed Method

Reference	Algorithm Used	Parameter	Number of LUTS	Power
Ercan Cosgun et al [5]	Rusboosted Tree Classifier	Specificity – 77.30	44,801	332.3mW
A. Ahmad et al [6]	MLP Network	Sensitivity – 95.14	13,014	234.6mw
Tahar et al [8]	Deep Neural Network with 80 features	Accuracy - 75	58,800	1800mW
Jose et al [7]	Energy, Entropy & PSD with ELM network	Accuracy - 95.8 %	2,03,800	160 mW
Proposed Method	SCAR, RHER with MLP network	Accuracy - 100 %	1,744	35.6 mW

The comparison is made in terms of Accuracy, Logic utilization and power consumption. The comparison results indicate that the proposed technique outperforms the existing methods in terms of all the parameters.

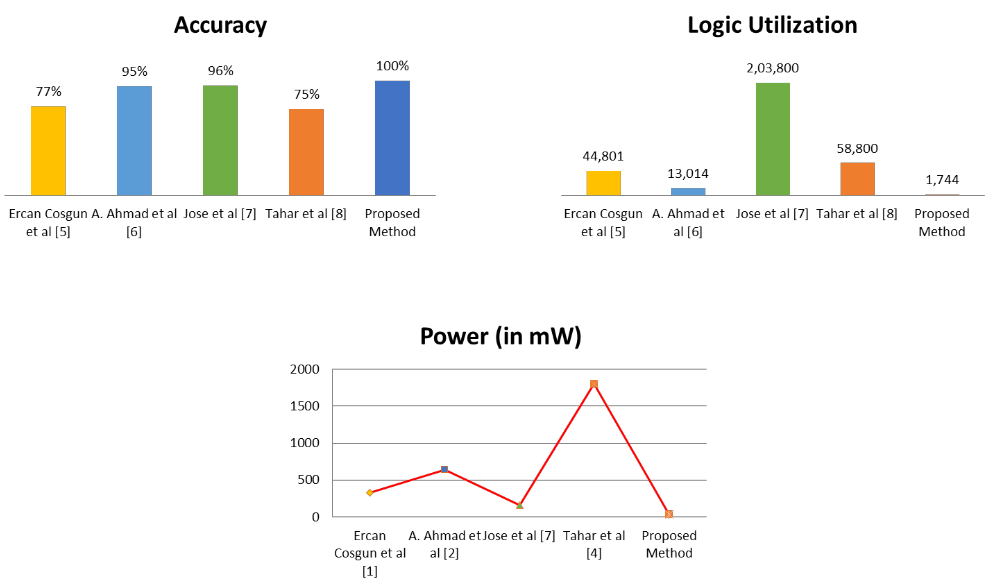

Fig 9. Accuracy, Logic and Power Comparison Analysis

4 Conclusion

In this work, a low power and area efficient hardware platform for epileptic seizure detection system which achieves a very high accuracy has been proposed. The method uses two novel statistical features utilizing the non-stationary properties of EEG signals on selective bands of frequencies. The Multilayer perceptron Network utilized is made Memory efficient using the Weight Optimization Algorithm, which resulted in a significant reduction in power and Area efficiency. Further, at the architecture level, Clock gating and Multiple Operating Frequency techniques were used to make the hardware power efficient. The proposed system achieved an accuracy of 100% and precision of 99%. The system is implemented on Artix 7 FPGA which consumes a power of 35 mill watts and utilizes 1744 logic elements in total. This outperforms all the existing techniques for seizure detection in terms of accuracy, Power consumption and Area. Thus, a feasible hardware solution for implementing the seizure detection system in real time was achieved.

The proposed work addresses the problem of seizure detection, while it can be extended to seizure prediction as well in the future. Also, the practical applicability of the proposed system can be further verified by implementing the system on ASIC platform which can be explored in further studies.

References

1) Wieczorek JŁ, Zabolotny WM, Schmid A. Epileptic Seizure Detection Using FPGA-Accelerated Neural Networks and EEG Signals. *SSRN*. 2023;p. 1–26. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4414752.
2) Ahamed MZ, Mastani SA. Comparative Analysis on Factors Affecting Accuracy of Seizure Detection Using EEG Signal Processing. In: Proceedings of the 2nd International Conference on Computational and Bio Engineering;vol. 215 of Lecture Notes in Networks and Systems. Springer, Singapore. 2021;p. 33–41. Available from: https://doi.org/10.1007/978-981-16-1941-0_5.
3) Harpale V, Bairagi V. FPGA Based Architecture Implementation for Epileptic Seizure Detection Using One Way ANOVA and Genetic Algorithm. *Biomedical & Pharmacology Journal*. 2019;12(3):1543–1553. Available from: https://dx.doi.org/10.13005/bpj/1785.
4) Cui X, Wang T, Lai X, Jiang T, Gao F, Cao J. Cross-Subject Seizure Detection by Joint-Probability-Discrepancy-Based Domain Adaptation. *IEEE Transactions on Instrumentation and Measurement*. 2023;72:1–13. Available from: https://ieeexplore.ieee.org/document/10050518.
5) Coşgun E, Çelebi A. FPGA based real-time epileptic seizure prediction system. *Biocybernetics and Biomedical Engineering*. 2021;41(1):278–292. Available from: https://doi.org/10.1016/j.bbe.2021.01.006.
6) Ahmad AA, Massoud YM, Kuhlmann L, Ghany MAAE. FPGA Implementation of Epileptic Seizure Detection using Artificial Neural Network. In: 2022 4th Novel Intelligent and Leading Emerging Sciences Conference (NILES). IEEE. 2022;p. 340–344. Available from: https://ieeexplore.ieee.org/document/9942397.
7) Jose JP, Sundaram M, Jaffino G. FPGA Implementation of Epileptic Seizure Detection Using ELM Classifier. In: 2020 Sixth International Conference on Bio Signals, Images, and Instrumentation (ICBSII). IEEE. 2020;p. 1–5. Available from: https://ieeexplore.ieee.org/document/9167598.
8) Dissanayake T, Fernando T, Denman S, Sridharan S, Fookes C. Geometric Deep Learning for Subject Independent Epileptic Seizure Prediction Using Scalp EEG Signals. *IEEE Journal of Biomedical and Health Informatics*. 2022;26(2):527–538. Available from: https://ieeexplore.ieee.org/document/9497714.
9) Sarić R, Jokić D, Beganović N, Pokvić LG, Badnjević A. FPGA-based real-time epileptic seizure classification using Artificial Neural Network. *Biomedical Signal Processing and Control*. 2020;62:102106. Available from: https://doi.org/10.1016/j.bspc.2020.102106.
10) Samanta A, Hatai I, Mal AK. Design an Efficient FPGA Based Hardware Implementation for Real-Time Mobile Epileptic Seizure Prediction Using Deep Neural Network. 2023;p. 2–25. Available from: https://doi.org/10.21203/rs.3.rs-1819772/v1.
11) Roy SK, Manna S, Dubey SR, Chaudhuri BB. LiSHT: Non-parametric Linearly Scaled Hyperbolic Tangent Activation Function for Neural Networks. In: International Conference on Computer Vision and Image Processing, CVIP 2022: Computer Vision and Image Processing;vol. 1776 of Communications in Computer and Information Science. Springer, Cham. 2023;p. 462–476. Available from: https://doi.org/10.1007/978-3-031-31407-0_35.