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Automated Seizure Detection Using Machine Learning Algorithm in Very Large Scale Integration

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Abstract: The portable automated seizure identification device is so small and portable makes it an especially helpful tool for people who suffer from epilepsy. We propose the use of a VLSI-based automatic seize detection architecture in our proposed system to promote rapid on-chip learning and greater detection rates. The architecture consists of an extractor and an artificial neural network (ANN) module. To produce the time-frequency domain function vector, it first converts the EEG signal into the format of the clinical strip using DWT three-levels, and then it calculates the average absolute value and variance of the four DWT coefficients. Finally, it outputs the function vector in the time-frequency domain. To achieve the highest possible level of productivity from on-chip learning, the classifier is used in conjunction with a Gaussian kernel and a modified version of the sequence minimum optimization method. The results of the study demonstrate that the developed VLSI device reduces the amount of time required to achieve and keep the precision required for detection and recognition.

Keywords: *Seizure detection, Artificial Neural Network, VLSI, Machine Learning*

1. Introduction

Epilepsy, which is the precise neurology word for a seizure that comes on suddenly and without warning, affects around 50 million people all over the world [1]. Epilepsy puts an individual at an increased risk of serious injury or death in seventy-five percent of cases. On the other hand, early detection is key to a successful treatment plan for eighty percent of seizure cases [2]. Electroencephalogram (EEG) signals have been applied in the diagnosis of human brain machinery and neuronal illnesses [3]. These signals have been used to quantify cranial nerve function.

Examination of the patient long-term EEG activity by medical professionals in a hospital setting, which will be covered in more detail below, is one of the methods that is used the most frequently for evaluating seizure activity with an EEG signal. It is unpleasant, and there is no assurance that any seizures will occur during your visit [4]; furthermore, there is no guarantee that any will. In this circumstance, having automatic seizure monitoring and projection technologies would be useful. Furthermore, a successful detection might potentially lead to the development of novel strategies for reducing the frequency of seizures.

A typical use of supervised machine learning is found in the diagnosis and forecasting of seizures. Because of its superior accuracy and adaptability to nonlinear policy constraints, artificial neural networks (ANN) have recently piqued the interest of a significant number of machine learning researchers. ANN is now the most advanced and discriminatory technology that can be utilized.

Both electroencephalography (EEG) and artificial neural networks (ANN) have been utilized to develop a multitude of automated seizure identification and prediction techniques. If an integrated circuit (IC) is going to have an automated seizure detection or prevention device, then the device needs to be both user-friendly and portable at the same time. However, to create robust and accurate predictions, the moving window of the EEG signals is often quite lengthy and resource intensive.

The refinement of the seizure detection technique for implementation in portable integrated circuits consumes

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a significant amount of time and effort. Both the nonlinear ANN on-chip seizure detector and the linear ANN on-chip seizure detector have been presented by Yoo et al. [6]. The linear ANN on-chip seizure detector makes use of the EEG signal. To remove the FD function from the EEG data, each system ran them through seven band-pass filters with bandwidths that were comparable to one another.

However, none of the automatic seizure detection systems for IC adequately addressed the incorporation of the ANN training approach in any of their functionality. The person-to-age variation of seizure patterns is a key issue for the enhancement of the precision of the sensing system [7], as a study indicated that there is a big difference between patients and between the various ages of a patient when it comes to seizure patterns of EEG signals. In addition to this, there does not appear to be a causal link between epilepsy and its occurrence [10]. Because of this, it is rather beneficial that the portable detection system can be taught rapidly to react to oscillations with the assistance of patient-specific and up-to-date EEG data, all owing to the incorporation of the chip training algorithm. This can be done by teaching it to react to oscillations using patient-specific EEG data.

In this paper, a very large-scale integration (VLSI) architecture for an ANN-based nonlinear seizure detection approach is presented. The VLSI architecture integrates the MSMO and db4 DWT algorithms for effective on-chip exercise capacity and excellent detection performance. On an FPGA system, the specification is validated, and then validated once more, making use of both publicly accessible and private data sources.

2. Related Works

To convert the QP issue into a set of linear equations, a variant of the artificial neural network (ANN) with reduced computing cost and good generalization efficiency was constructed [5].

Recent research conducted by the authors of [6] has suggested a parallel, scalable least-square solution as a means of shortening the amount of time required for training. Because of its inequality of form, LSANN calls for a significant increase in the number of supporting vectors, multiplications, and detection operations compared to ordinary ANN. Because it performs better than other learning methods in the detection process [7], which is where the seizure detection strategy is commonly implemented, the classical ANN was selected as the optimal option.

The sample sub-set limits found in [8] are used by the authors of the paper to select optimization instances from the modified SMO method that extend further than the heuristic selection found in the SMO methodology. The presumption that the SMO algorithm would be perfectly satisfied is avoided by frequently employing the limitations to check the sample optimality. This results in fewer iterations and improved performance across the board.

To solve the issue with the FPGA efficiency, the author of suggested that a modified version of the Gilbert algorithm be run in parallel with the computing kernels. This version of the method would have scalable parameters. The SMO technique cuts chunk down to two, which enables problems to be spotted utilizing a large variety of training samples and technology that is quite inexpensive. As a direct consequence of this, the SMO algorithm has two deficiencies. To begin, the fact that the two samples that have been improved likewise fulfill the optimal requirements demonstrates that the remaining samples are ideal in every way.

3. Proposed Method

The massive amounts of raw EEG data are processed using a chip that is specifically designed to work with SDRAM.The DSC standard is an IP-based module that is used throughout the industry to coordinate communication between various devices and SDRAM. Processing raw EEG data is one of the first steps in functional encoding. The EEG signal is divided into three different bands by the db4 DWT algorithm. Using the succeeding MAV and VAR submodules, the 8-dimensional vector is constructed by first estimating the average absolute value of the DWT coefficients across all four subbands and then calculating the variance of those coefficients. After that, data is passed on to the ANN component that can perform detection and learning based on a vector of features that spans 8 dimensions. It is recommended that training samples be utilized to understand the Hyperplane of the ANN classification in opposition to a convulsive edge. The ANN is trained to recognize the warning signs of an approaching seizure and will sound the alarm when it does so. The operation of the ANN module is determined by the signal mode.

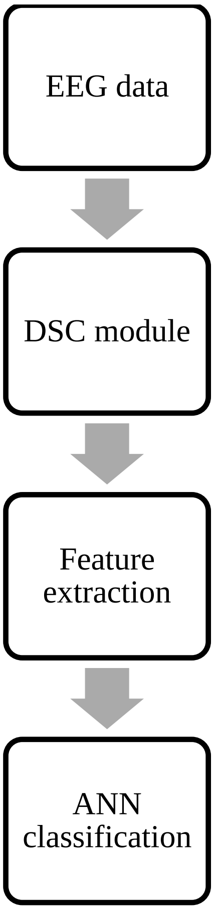

Fig 1: ANN seizure detection

When compared to the modules that are found in the human brain, RNNs are a category of computer models that may be described as both complicated and varied. Their levels of realism also vary. RNNs connect several neurons together through conceptual synapses so that activations can be distributed evenly throughout the network. In contrast to feed-forward neural networks, recurrent neural networks (RNNs) have a linking design that includes a feedback loop. RNNs can be utilized as a universal approximation in continuous processing for the compact field in dynamic system modeling by utilizing a group of static feed-forward networks in conjunction with transverse filters.

At regular intervals, make changes to the latent states of the basic network (after training, these latent states can be interpreted as learned representations that are pertinent to our job). To begin, let adjust our nomenclature such that we may conduct an experiment consisting of a single sequence.

$$h_1 = \tanh\left(W_{xh}x_1 + b_h\right)$$

$$p\left(\gamma_1 \mid x_1\right) = \sigma\left(W_{h\gamma}x_1 + b_\gamma\right)$$

Then, let modify the linear development of the equation that describes the secret state depending not only on our input x, but also on the facts on the secret state that we already possess. The revelation that our top-secret condition is actually 0 has the potential to be interpreted as an absence of historical awareness.

$$h_0 = 0$$

$$h_1 = \tanh\left(W_{hh}h_0 + W_{xh}x_1 + b_h\right)$$

$$p\left(\gamma_1 \mid x_1\right) = \sigma\left(W_{h\gamma}x_1 + b_\gamma\right)$$

The different network modeled in the beginning are the operational number (vector multiplication matrix with h0 = 0). However, it seemed inevitable that our network would grow to include others who were participating in other tests.

$$h_0 = 0$$

$$h_1 = \tanh\left(W_{hh}h_0 + W_{xh}x_1 + b_h\right)$$

$$h_2 = \tanh\left(W_{hh}h_1 + W_{xh}x_2 + b_h\right)$$

$$\ldots$$

$$h_T = \tanh\left(W_{hh}h_{T-1} + W_{xh}x_T + b_h\right)$$

This RNN processes sequences of each length, for instance, given that, over the course of the years, the transformation function and its parameters have been divided into one T=1 and one T=8 over a length.In the event that the network has already been constructed, the technique for feeding up is essentially the same.

Every patient is now given the option to select from a variety of assessments, such as the x1,..., x, and yT score. At the moment, we are in the process of constructing a prediction map by unrolling the RNN and using the processes to determine the likelihood of developing cancer and suffering loss. After that, we invert the gradients by employing a method called stochastic optimization.

$$p\left(\gamma_1 \mid x_1,\ldots,x_T\right)=\sigma\left(W_{h\gamma}x_T+b_\gamma\right)$$

$$h_t=\tanh\left(W_{hh}h_{t-1}+W_{xh}x_t+b_h\right)$$

In hidden situations like these, the initial state that is assumed to be h0 = 0 until anything otherwise is provided.

4. Results and Discussions

The identification rate and the proportion of false positives are two statistical indicators that can be utilized in the process of performing a quality check on the work that was completed. Figures 2 and 5 give the impression of demonstrating that the suggested strategy improves the rate at which on-chip seizures are discovered while simultaneously reducing the number of occasions on which false alarms are triggered.

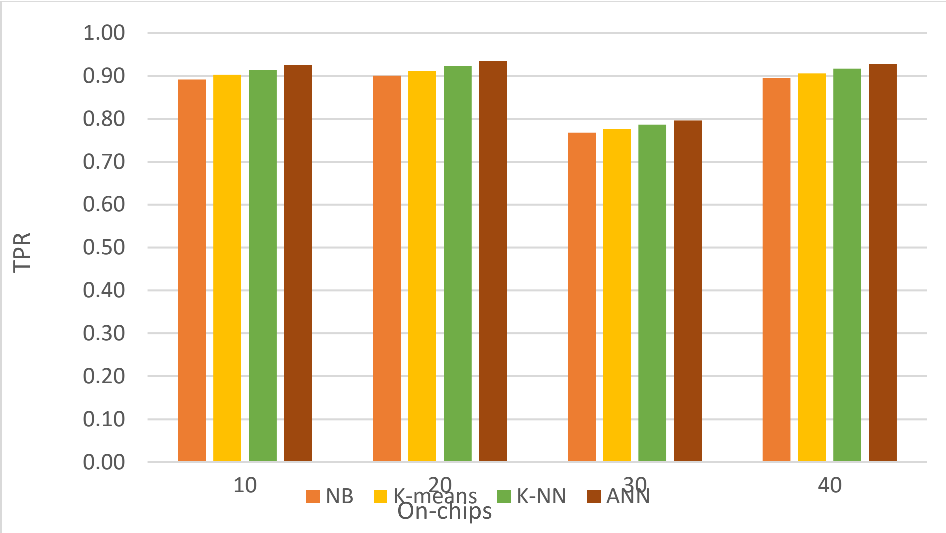

Fig.2. True Positive Rate

The true positive rate is higher for the approach that was suggested, as can be shown in Figure 2. This is in comparison to the k-NN, k-means, and NB classification methods that are currently being used. As can be seen, the suggested method performs far better than the alternatives when it comes to determining which samples are authentic.

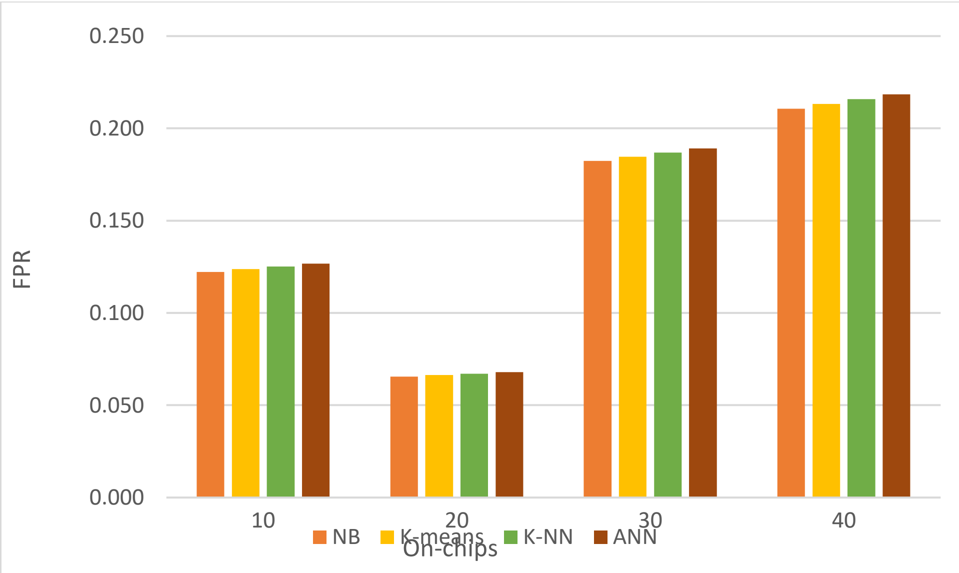

Fig.3. False Positive Rate

The results of the simulation demonstrate that the suggested strategy has a higher false positive rate than other existing approaches such as k-NN, k-means, and NB classification. Figure 3 presents the findings of the false positive rate, and the results of the simulation reveal the same thing. As can be seen, the suggested method performs far better than the alternatives when it comes to determining which samples are authentic.

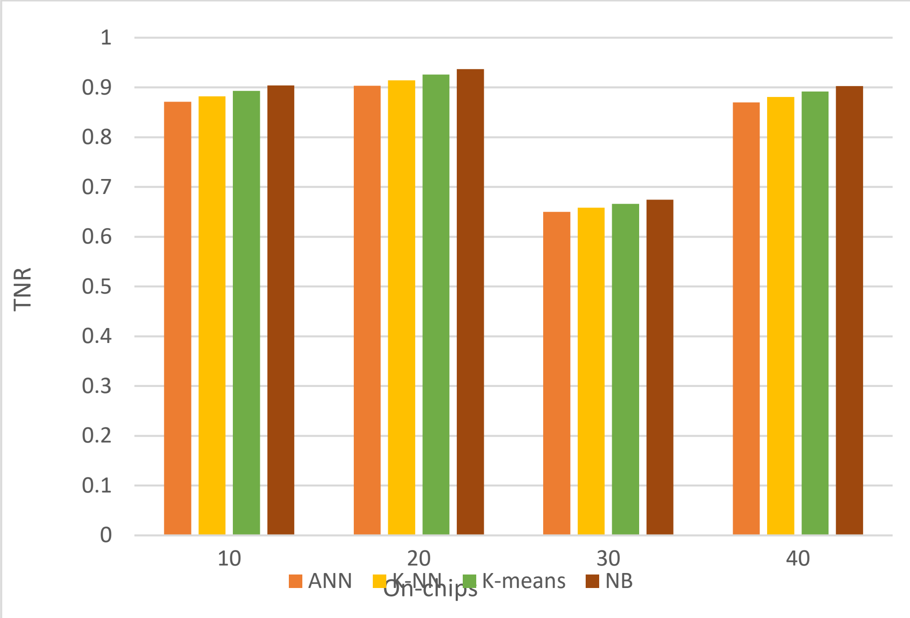

Fig.4. True Negative Rate

The true negative rate is lower for the approach that was suggested, as can be shown in Figure 4. This is in comparison to the k-NN, k-means, and NB classification methods that are currently being used. As can be seen, the suggested method performs far better than the alternatives when it comes to determining which samples are authentic.

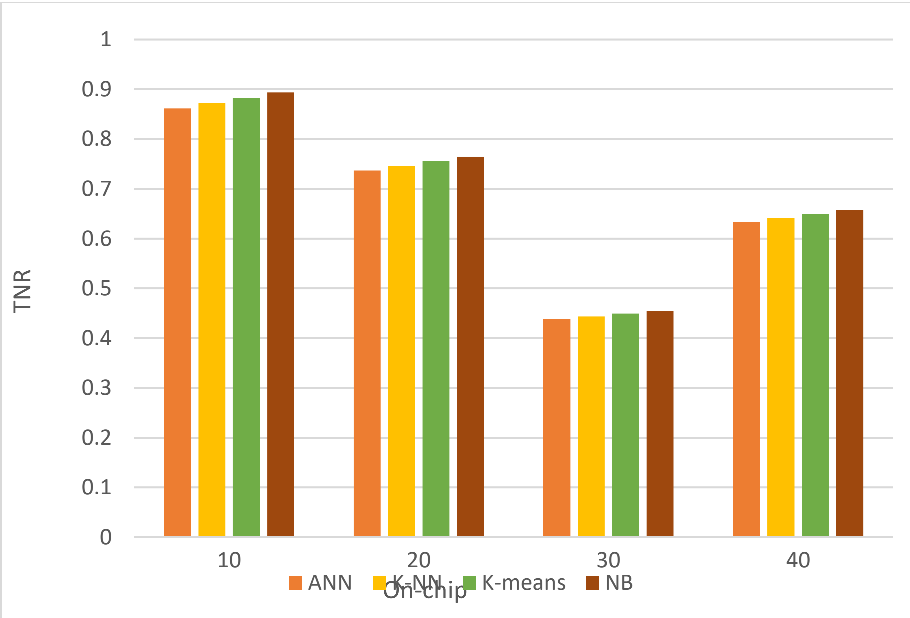

Fig.5. False Negative Rate

The results of the simulation reveal that the suggested technique has a lower false negative rate than existing methods such as k-NN, k-means, and NB classification (for more information regarding this topic, please refer to Figure 5). As can be seen, the suggested method performs far better than the alternatives when it comes to determining which samples are authentic.

By utilizing the ANN, it is possible to make comparisons between the current strategy and earlier iterations of the IC program. As a result of the TFD and nonlinear ANN capabilities of our system, not only are we able to provide on-chip instruction for patients who suffer from epilepsy, but we can also achieve superior DR, which makes our system an excellent choice for implementation in mobile devices.

5. Conclusions

A VLSI architecture for autonomous seizure detection is being developed in order to enhance detection rates and enable quick on-chip learning. Both goals are being pursued simultaneously. The architecture consists of an extractor and an artificial neural network (ANN) module. It first converts the EEG signal into the format of the clinical strip by using DWT, and then it calculates the average absolute value and variance of the four DWT coefficients to produce the time-frequency domain function vector. Because the ANN module uses a modified sequential minimum optimization technique, on-chip training with a table-driven Gaussian kernel is feasible. This is since the technique is implemented. It appears from the results of the trials that the newly designed device not only enhances the participant detection rate but also their performance during the training sessions. The implementation of cutting-edge parallel and flexible research methods in forthcoming studies has the potential to significantly boost the quality of ANN training.

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