Implementation of Classified EEG signals Using Deep Machine Learning on FPGA

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***Abstract*—This paper presents the classification of EEG signal using the deep machine learning and implementing the application on the FPGA.EEG signal analysis is such an important thing for disease analysis and brain–computer analysis. Electroencephalography (EEG) monitoring the state of the user's brain functioning and treatment for any psychological disorder. Using this way we will be able to find the accurate outputs of the expected results. This is achieved by training the artificial neural network in MATLAB application. This algorithm uses wavelet transform and neural network for training the artificial neurons.Deep machine learning algorithm will require massive data for feeding into our models.**

Keywords :- *Brain comuting interface,Deep learning,wavelet transform,field programmable gated array, Electroencephalography,artifical neurons.*

I. Introduction

EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of these signals are limited. Since there is no definite criterion evaluated by the experts, visual analysis of EEG signals is insufficient. Since routine clinical diagnosis needs to analysis of EEG signals, some automation and computer techniques have been used for this aim. Since the early days of automatic EEG processing, representations based on a Fourier transform have been most commonly applied. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands— delta (< 4 Hz), theta (4–8 Hz), alpha (8–14 Hz), and beta (14–30 Hz). Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Numerous other techniques from the theory of signal analysis have been used to obtain representations and extract the features of interest for classification purposes. Neural networks and deep learning methods have been applied to EEG analysis.

All the rest of the neurons are hidden from view. We will decide the number of neurons and the number of hidden layers. We train the neural network in MATLAB.So, train the network for the expected outcome.because the learning algorithms for recurrent nets are (at least to date) less powerful Other neurons provide the real world with the network's outputs. This output might be the particular character that the network thinks that it has scanned or the particular image itthinks is being viewed.

systems have been proposed by a number of researchers. Various feature based on this model was classified with a multilayer, feedforward, neural network using the error back-propagation training algorithm.A Neural Network, or NN, is a generic architecture used in machine learning that can map different types of information. Given an input, a trained NN can give the desired output. However, NNs cannot learn from sequences. Recurrent Neural Networks, or RNNs, address this issue by adding feed-back to standard neural networks. Thus, previous outputs are taken into account for the prediction of the next output. RNNs has been shown to be successful in various applications, such as speech recognition , machine translation and scene analysis . A combination of a Convolutional Neural Network (CNN) with a RNN can lead to fascinating results such as image caption generation

II.PROCCESS FLOW

A. FEATURE EXRACTION

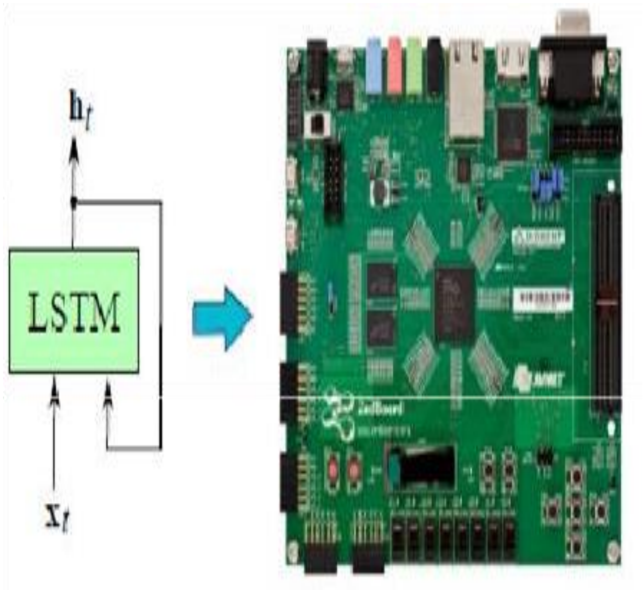
Wavelet Transform (WT) is mathematical technique extensively used for extracting information from various types of continuous data such as image and speech data. This approach is suitable for non-stationary signals due to flexible method of representing the time-frequency domain of signal However, the disadvantage is lack of specific methodology for apply to the pervasive noise. Using this method we extract the features of the obtained EEG signals i.e Alpha, Beta, Gamma, Theta, Delta. After feature extraction we find the energy of each signal and compute it in a single data. This enables us to classify the EEG signals in the future steps.

B. Classification of EEG signal

The design of the input and output layers in a network is often straightforward.Recurrent neural nets have been less influential than feedforward networks, in part .

C. Implementation on FPGA

The implemented module uses Direct Memory Access (DMA) ports to stream data in and out. The DMA ports use valid and ready handshake. Because the DMA ports are independent, the input streams are not synchronized even when the module activates the ports at same the time. This ensures that vector and matrix row elements that goes to MAC units are aligned. It considers the control and testing software was implemented with C code. The software populates the main memory with weight values and input vectors, and it controls the hardware module with a set of configuration registers. The weight matrix has an extra element containing the bias value in the end of each row. The input vector contains an extra unity value so that the matrix-vector multiplication will only add the last element of the matrix row (bias addition)



III. BLOCK DIAGRAM

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The flow of this project is shown in the figure 1.The signals are extracted and the preprocessing and the feature extraction using wavelet transform is performed in the MATLAB.Which is followed by the Classification of signals using the deep learning technique and implementing the same with the help of Xilinx on the FPGA

IV.FORMULAE

The set of wavelet functions is usually derived from the initial (mother) wavelet h(t) which is dilated by value a =2m, translated by constant b = k 2m and normalized so that

hm,k(t)= 1 √a h(t−b a)= 1 √2m h(2−m t−k) (1)

In case of a sequence {x(n)}N−1 n=0 having N =2 s values it is possible to evaluate its expansion
x(n)=a0 +s−1 m=0
2s−m−1−1 k=0
a2s−m−1+k h(2−m n−k)
The following are few equations we use to compute the hardware implementation on the FPGA board.

It=WxiXt+Whi Ht-1+ bi (2)

ft=Wxfxt+Whf h t-1+b f (3)

0t=wxoxt+wh oht-1+b0 (4)

ct=tanh(wxcxt+whc ht-1 +bc) (5)

ct=ft*ct-1+it*ct (6)

ht=ot-*tanh(ct) (7)

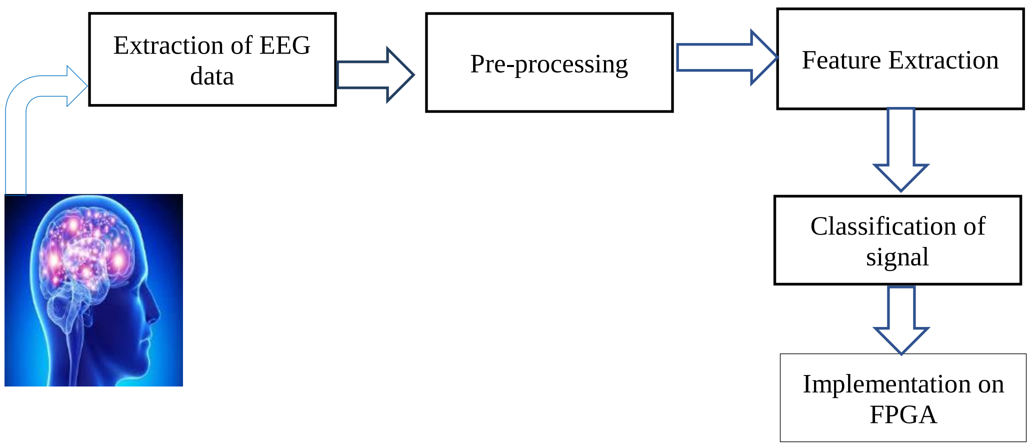


Fig 1: Block Diagram of Classification of signal

Disadvantages by existing device:

- EEG poorly measures neural activity that occurs below the upper layers of the brain
- Signal-to-noise ratio is poor
- EEG poorly measures neural activity that occurs below the upper layers of the brain

Advantages:

- Hardware costs are significantly lower than those of most other techniques
- EEG can detect covert processing
- EEG is silent, which allows for better study of the responses to auditory stimuli.
- EEG is a powerful tool for tracking brain changes during different phases of life

Applications:

- to monitor the depth of anesthesia
- to prognosticate, in certain instances, in patients with coma
- to determine whether to wean anti-epileptic medications
- to monitor for secondary brain damage in conditions such as subnormal analysis
- EEG, and the related study of ERP s are used extensivelyin neurosciences ,cognitive science, cognitive,neurolinguistics and psychological research.

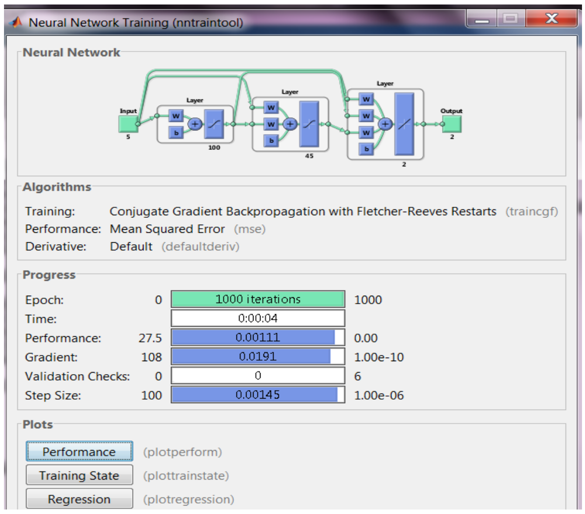
V.RESULT AND DISCUSSION

The following table shows the outcomes of the trials that were performed. The results are accurately obtained as the excepted from the code. Later this is implemented on the FPGA that is the final result of this paper.

Input	Target	Output
Set 1	0.2	0.2
Set 2	0.6	0.6

Table 1: Outcomes of neural network

The graph shows the graphical output of the trained neural network. This is the target to the output results after the network is trained to may layer that enables us to find the exact outputs since it is deep learning method.In the deep learning method the process is training the network for many layers and many neurons at a time. The accurate output is obtained for different sets of the input and this verified with formulae that is mentioned above



VI. CONCLUSION

This paper has addressed the appropriate technique applied for BCI at pre-processing, feature extraction and classification stage. This paper also discussed the advantages, disadvantages and current trends of BCI at every stage. Furthermore, the implemented hardware showed to be significantly faster than other mobile platforms. This work can potentially evolve to a RNN co-processor for future devices, although further work needs to be done. While EEG data is by nature sequences of vectors, as words are, the relationship from one element in the sequence to the next must be different, to some impactful degree, in EEG from Natural Language Processing. The main future work is to optimize the design to allow parallel computation of the gates. This involves designing a parallel MAC unit configuration to perform the matrix-vector multiplication.

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