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Cyber Security Based Application-Specific Integrated Circuit for Epileptic Seizure Prediction Using Convolutional Neural Network

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Abstract

In the event of an epileptic attack, the Field-Programmable Gate Array (FPGA)-accelerated Convolutional Neural Network (CNN) model is paired with Electroencephalogram (EEG) acquisition equipment to produce a reliable production system that can be used in clinical medical diagnosis. Additionally, this study includes cybersecurity to protect both the epileptic patient's data and the prediction system. Epilepsy is a frequent neurological disorder that manifests as recurrent seizures, a sign that indicates rapid intervention is necessary to minimize adverse events and improve patient health. The study provides a new real-time design for predicting epileptic seizures based on the Application-Specific Integrated Circuit (ASIC)-based Very Large-Scale Integration (VLSI) architecture. As a first step, EEG data from epilepsy patients were captured and pre-processed. Afterwards, faults and artefacts in the data were removed. Additionally, data was divided into short-time windows and then classified as either ictal, pre-seizure, or interictal. The CNN model was adapted for EEG signal analysis and then trained with categorized data. This technique is more effective and efficient for predicting epileptic seizures accurately, which is advantageous for patient monitoring and treatment. Additionally, cybersecurity measures were implemented to secure patient data and the prediction system.

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Keywords: ASIC; CNN; Epilepsy; EEG data; FPGA; Seizure prediction; VLSI architecture

1. Introduction:

Epilepsy is a severe neurological disorder affecting millions of people worldwide. It is characterized by repeat and erratic attacks. Thus, epilepsy monitoring and control heavily rely on accurate seizure prediction and forecasting to increase treatment quality and improve patient quality of life. Seizure forecasting traditionally includes Electroencephalogram [1] data manual assessments, which are time-consuming, and error-prone with manual interpretation biases. Novel technologies, including machine learning, offer promising outcomes with high novel device implementation accuracy rates. In comparison, Convolutional Neural Networks specialize in identifying intricate patterns in sophisticated data sets and thus are ideal for studying from the Electroencephalogram data [2], which is an analytical centre of neuroelectric functions of the brain. For this reason, we propose a real-time model for seizure prediction with convolutional neural networks deployed to an Application-Specific Integrated Circuit -based Very Large-Scale Integration architecture because these are essential trends for seizure prediction and cybersecurity, which is a significant problem for many modern solutions.

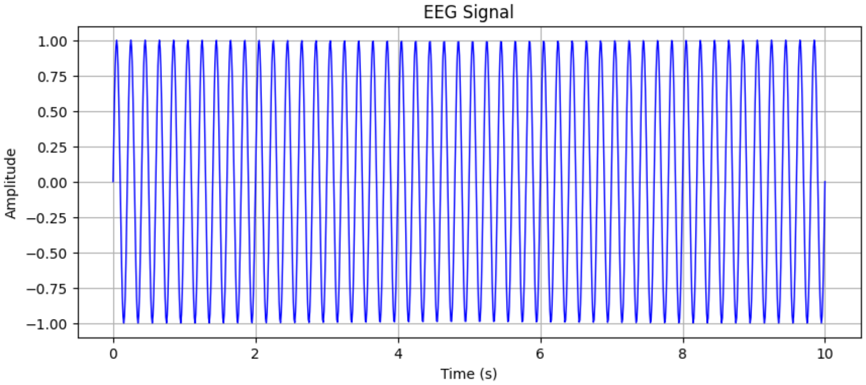

Figure 1: Normal EEG Signal

An EEG signal is a normal representation of the brain and is recorded from the scalp using electrodes. It usually displays a regular and consistent waveform that is associated with different stages of consciousness and brain activity. Under normal conditions, during a wakeful state with the eyes closed, alpha waves are predominant in the EEG and have a frequency of 8-13 Hz which is most characteristic for the occipital and parietal areas. Beta waves, which range from 13 to 30 Hz, are recorded while one is fully awake and engaged in analytic or problem-solving activities. Theta waves with the frequency range of 4-7 Hz and delta waves with the frequency range of 0. 5-4 Hz are characteristic for sleep and deep relaxation. The amplitude of the signal in microvolts is different in each wave type and depends on the activity of the human brain. A normal EEG pattern is essential in determining and evaluating neurological disorders since any variation of the characteristic waveforms may signify diseases like epilepsy, sleep disorders or traumatic brain injury among others. The characteristic waveforms of such types are shown in Figure 1 which presents a general idea of the healthy human brain's electrical activity in terms of frequency and amplitude.

The importance of cybersecurity [3] in the deployment of Convolutional Neural Networks in the management of patient-centric epilepsy modelling is to secure the privacy of the patient's data and ensure the reliability of the system for which the prediction has been laid. Since CNNs are trained with sensitive EEG data of the patients, cybersecurity can never be compromised in an attempt to help the patient. To this effect, data encryption should be a priority to ensure that data transmitted from one processing unit to another and those stored in the in-memory storage in the FPGA device are encrypted to prevent eavesdropping and unauthorized access.

More, dependent on the encryption key base, secure encryption algorithms should be used, accompanied by the proper communication protocol between processing units, with Transport Layer Security being the standard communication protocol for data encryption [4] between two endpoints. Moreover, a restricted access mechanism should also be a concern to prevent information accessibility by only authorized personnel. Role-based access control can be enforced to allow only authenticated personnel with the right privileges to gain access and manipulate data. Multi-factor authentication [5] can also add to this to ensure that more than one form of authentication is done before using the system. Confidentiality without integrity and system availability would be a Devastation. Physical and IT security audits should be done regularly to assess the learning model's vulnerability and address the vulnerability issue. Secure firmware [6] and software development [7] should be observed to prevent the exploitation of vulnerability. Software updating and patching is an open bulletin that should be followed periodically. Finally, intrusion detection and prevention should also be used to monitor the prediction system for any intrusion.

The study proposes a new real-time system for epileptic seizures forecasting with low-power ASIC-based VLSI system. The choice of ASICs for this particular application is based on their nature of offering a solution that is optimized for efficient computation of specific algorithms. The computations in CNNs demand specific operations where ASICs can be tailored to execute them with low latency and high efficiency unlike processors that are used for general purpose. VLSI architecture enables several millions of transistors on a single chip, enabling high degrees of parallelism and optimized use of system resources. There are several benefits that can be derived from this design decision such as lower power consumption, higher clock rate and improved reliability which is crucial when performing real-time medical diagnosis. Combining ASIC-based VLSI architecture to the system, it is able to quickly and effectively analyze EEG data for seizures and help administer appropriate medical assistance in time and optimize the patient's benefit.

The organization of the paper is as follows: Section 2 includes a literature survey of the proposed work; Section 3 includes the methodology of the proposed work; Section 4 includes experimental results and analysis; Section 5 includes the conclusion and future work

2. Related Work

To reduce the computational complexity of systems as discussed above, the computationally efficient LSSVM classifier combined with the classical entropy characteristics was utilized. [8] used an LSSVM classifier to achieve an 82.22 % classification accuracy. The Gray level cooccurrence matrix method to extract intrinsic features was done in reference [9]. Twenty-three EEG data were collected, and the seizure activities were identified to achieve a 90 % classification accuracy utilizing the ANN classifier. A new methodology for seizure detection, assignment of EEH statistical features, and LSSVM classifier are illustrated. The method resulted in a 0.065-second detection lag and a 97.19 % mean detection accuracy [10]. Beyond the time-domain features, which include mean, median, minimum, maximum, standard deviation, skewness, kurtosis, first quartile, third quartile, interquartile range, and the Hurst exponent, [11] also utilized a variety of details. The RF classification technique was utilized to assign these extracted features. A study on the University of Bonn EEG dataset showed that the selected features from the EEG can identify epileptic seizure incidents in all participants.

Abdulghani [12] developed a wireless sensor network on a single channel to recognize seizure patterns in long-term EEG recordings obtained from the CHB-MIT database. The mean, standard deviation, zero crossing rate, entropy, Root Mean Square, and auto-correlation from time domain signals were calculated. The accelerometer and gyroscope signal were used to identify physical activity to recognize motor seizures. Among them, the most important features that separate seizure and non-seizure activities is the Root Mean Square. The average seizure detection sensitivity is 91%, and the specificity and 84%. Time-domain-based EEG feature extraction methods are straightforward to calculate and can be applied straightly for the physiological epileptic episode real-time recognition. These techniques are extremely sensitive to the inter-patient and intra-patient features. The only drawback is that they are more impacted by body artefacts and environmental noise. It is only convenient for patients and people dealing with patients. In contrast to the time domain methods, the frequency domain approaches express data in terms of the frequency effect of EEG signal cycles. Frequency domain-based features are more descriptive and stable than time-based features. Sarhang Hafezi [13] applied the Fast Fourier transform to convert the time series signals into the frequency domain. The generated EEG characteristics were utilized for MLPerceptron Neural Network and Gaussian Feed-Forward Neural Network. On average, an accuracy rate of 100% was recorded to identify seizure monitoring systolic [14].

The FFT initially segmented the obtained long-term EEG data into shorter 1-second long EEG segments and then calculated the spectral magnitude of the EEG segment within the 1-47 Hz frequency range. The above information, along with the EEG correlation coefficient and eigenvalues, were combined to produce the feature vector, which was checked using a 3000-tree random forest classifier. The work by [15] accepted FFT for the individual one-second windows and calculated magnitude between 1-47 Hz disregarding phase information. They calculated the correlation coefficients and Eigenvalues in both frequency and time-space, which were combined and analyzed with the FFT information to give the feature vector. The above feature vectors were analyzed with a random forest classifier of 3000 trees. The work by [16] used the Freiburg database's data and used an energy threshold-based algorithm with the IMFs of the EEG and the minimum time duration. AKI was used with unique characteristics to differentiate the EEG patterns to determine seizure and non-seizure conditions. The average seizure detection FAMS model with a maximum sensitivity of 56.41% averaged a specificity of 75.86 %. The work [17] proposed an EMD and SVM-based model and used EMD to segment the EEG signal dataset into the IMFs. They then used an SVM classifier and calculated the coefficient of deviation and the instability manifestation. With a high sensitivity of 98% differentiation between the seizure and healthy signal conditions was made with 99.40% specificity.

LSTM-based bidirectional stacked [18] designed the method to analyze time-series databases. Seizure shows the experimental effectiveness of 99.08% of identification, 98% of precision, 99.5% of recall, and 0.984346 ROC AUC. There will be a lack of sensitivity as well as the vanishing gradient issue because the single Intrinsic Mode Functions IMFs will be utilized. MEMD [19] suggests a method to eliminate the Lower Frequency and the Noisy Component from the Intrinsic Mode function. The remaining parts are passed through the Hilbert transform to extract the instantaneous frequency as well as the amplitude data which is subsequently classified using artificial neural networks on five unique EEG datasets, predicting that the accuracy rate will be 87.20%. EMD [20] adjusted the algorithm for processing EEG signals and modified it into non-overlapping divisions to expose the interaction between the succeeding data samples. In the classification of healthful and seizure signals, The Long Short-Term Memory LSTM network and the Softmax classifier were employed for classification. The outcome indicates an accuracy rate of 90.0% to 100%. A framework using Sae based on the Softmax Classifier presented by Linet et al. produced an accuracy rate of 96% in this test.

The study summarizes a cloud computing system to auto-detect epileptic seizures utilizing Machine learning. It presents Sub-pattern-based Principal Component Analysis SpPCA and Cross-sub-pattern cross-correlation-based PCA SubXPCA as feature extraction methods. It distinguishes between normal, ictal, and pre-ictal signals classified using an SVM Classifier that attains an average accuracy rate of 92.76% and 96.66% for epileptic seizures. It is problematic to deliver these massive datasets to the cloud and much transmission latency has been induced by the amount of network bandwidth that the cloud takes up. IoT devices generate vast volumes of data which can only be kept in a storage server. The performance of cloud computing storage is poor and seems due to network congestion. General problems in classical decomposition and seizure detection methods described in the literature study are as follows. Mode mixups arise throughout Empirical Mode Decomposition EMD, and oscillations in Cubic Spline Interpolation CSI-SLL are concentrated close to an outdoor outlier. A Gaussian noise during F.E. reduces the accuracy rate. The conventional Neural Network classifier has the problem of a vanished gradient and lower sensitivity and specificity. Traditional implementation on cloud server units shows a high computational time and latency.

3. Proposed Methodology

The proposed methodology seeks to create a dependable, high-performing system of epileptic seizure forecasting through the collaboration of Field-Programmable Gate Arrays and CNN. To do that the methodology presupposes the data collection and preparation such as the Electroencephalogram data, segmentation, and labelling of its most distinct parts, and the classification of EEG segments as pre-ictal, inter-ictal, and ictal.

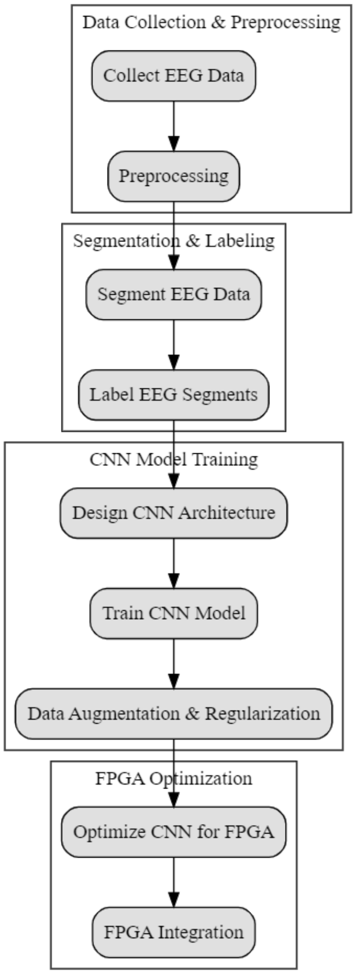

Figure 2: Block Diagram of Proposed Work

Figure 2 presents the overview of the proposed work. In this image, a custom CNN structure is created for the processing of EEG signals. This structure will be trained using labelled data, and use of methods such as data augmentation and regularization will be adopted to improve the model. After the structure is adequately trained, it has to be tailored for implementation in FPGA hardware. FPGA is preferred because it has parallel processing capability and provides flexibility in the implementation process, which will enable the model to achieve real-time prediction. The implementation is complemented by the EEG data collection procedure to ensure the model accurately predicts the occurrence of the seizure in the clinical environment. Performance evaluation and validation will be carried out, after which the system will be refined through iteration based on feedback and real-world testing. The approach is crucial in ensuring a flexible and efficient solution for seizure prediction that may be used for personalized patient monitoring and intervention strategies.

The epileptic seizure prediction system that we are implementing employs ASIC-based VLSI architecture to provide the best performance and efficiency for real-time medical diagnostics. The architecture uses the benefits of ASIC and provides tailored hardware for the high computational requirements of CNNs utilized in seizure prediction.

3.1 Data Collection and Preprocessing

The EEG dataset for analysis was acquired from the database created by the Epilepsy Centre at the University of Bonn, Germany, to improve the research and detection abilities. This project proposes analyzing the EEG dataset that includes 100 single-channel EEG segments of 23.6 seconds in non-seizure and seizure states obtained from 50 patients. Each of these datasets is sampled at a variable sampling rate between 250 Hz and 2500 Hz. Specifically, an 8-second

EEG signal is utilized for feature extraction and seizure ID. The sampling window length was selected as 2 seconds with a sampling rate of 50% overlap. As a result, after each 50% data shift, 2-second data points are input to the calculation of spectral features window slides from data to the feature extraction side. Seizures are associated with frequencies δ, θ, and α in brainwave analysis. The mean spectral power in the range of 0.5-14 Hz is obtained for the structures in EEG. Twenty-five datasets related to non-seizure and 25 with seizure state were processed. Filtering is required to eliminate the EEG signal's unwanted frequency components, such as high-frequency contamination and indicators of low-frequency oscillations.$filter centralizes the EEG signal in a certain range of the frequency spectrum. The filtered signal $X_{\text{filtered}}(t)$ can be obtained using a digital filter with transfer function $H(f)$:

$$X_{\text{filtered}}(t) = X(t) * h(t) \tag{1}$$

Examples of usual filters are Butterworth, Chebyshev, and ellipticcut filters. Filters can be personalized to get particular frequency response outcomes. The source of artefacts in EEG signals may originate from many origins, such as muscle activity, eye movement and environmental interference. There are a lot of ECG signal processing tools to remove the above artefact, such as Independent Component Analysis and wavelet-based coherent signal removal. In the ICA technique, first, the combined EEG signal is divided into separate intermittent kinds of design. Then the injection components related to injections are removed. This will result in a prior EEG signal, which can be recovered by submitting the reverse ICA conversion. The competence oscillator is a sluggish variate spread over some time; it acts as a discovery by affecting the classification. A typical means to correct baseline oscillation is to approximate it using gauzy averaging or polynomial accessories which are then removed by subtraction from the genetic EEG signal:

$$X_{\text{corrected}}(t) = X(t) - B(t) \tag{2}$$

Alternatively, detrending techniques can be used to remove baseline drift by fitting a linear or polynomial trend to the EEG signal and subtracting it.

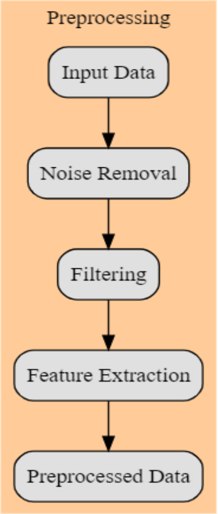

Figure 3: Pre-Processing Proposed Work

Preprocessing EEG data as presented in Figure 3 requires a series of processes triangulated to ensure that it will be clean and artifact-free and be used in later analysis. The objective of these processes is to ensure that the EEG data quality is made better, and its analysis later is more error-free; these processes will be essential in seizure prediction using CNNs.

3.2 Data Segmentation and Labelling

Extract small time windows The preprocessed EEG data is partitioned into short time windows that last several seconds to detect vital patterns about the occurrence of a seizure. Each sub-segment is labelled as either pre-ictal, inter-ictal, or ictal, or based on the clinical annotations or seizure outset. Let represent the preprocessed EEG data, while denoting the EEG signal at time. We divide the EEG data channels, of the EEG signal into segments, with each i th segment of duration length as documented in the equation:

$$X_i = X(t_i : t_i + T) \tag{3}$$

where t_i is the start time of segment i.

After segmentation, each segment X_i is labelled according to its seizure state. The proposed work denotes the label of the segment X_i as Y_i, where Y_i can take one of three values: preictal (1), inter-ictal (0), or ictal (-1). The labelling process can be expressed as follows:

$$\begin{cases} 1 & \text{if segment } X_i \text{ is pre-ictal} \\ 0 & \text{if segment } X_i \text{ is inter-ictal} \\ -1 & \text{if segment } X_i \text{ is ictal} \end{cases} \tag{4}$$

These labelled segments constitute the training samples for the CNN model. The above approach of segmenting and labelling the input data ensures that the CNN model is capable of distinguishing between different epochs of seizures and accurately predicting the time to seizure from real-time EEG data. The input-output pairs supplied are utilized to apply supervised learning to the CNN model and aid it in identifying the features connected with epileptic seizure occurrences. In the later stages of the methodology, the segmented and labelled EEG data is trained on the CNN model and further deployment is optimized concerning real-time seizure prediction on FPGA hardware.

3.3 CNN Architecture Design

Furthermore, the architecture of the Convolutional Neural Network is specifically important in extracting pertinent elements from the pre-processed EEG data that provide accurate forecasting of the seizure. CNN includes multiple layers, including convolutional layers, pooling layers, and fully connected layers, which are structured in hierarchical arrangements to efficiently extract features and process them hierarchically.

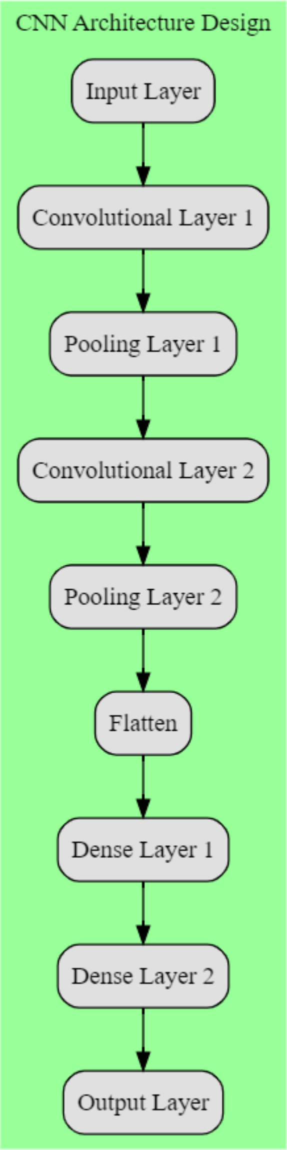

Figure 4: Architecture of Proposed CNN

Figure 4 shows The architecture of the CNN can be represented mathematically as follows: In the l-th convolutional layer, the output feature map Y_l is obtained by convolving the input feature map X_{l-1} with a set of learnable filters W_l followed by a non-linear activation function σ :

$$Y_l = \sigma(W_l * X_{l-1} + b_l) \tag{5}$$

where $*$ denotes the convolution operation, b_l is the bias term, and σ is the activation function (e.g., ReLU, sigmoid, or tanh). Pooling layers are used to reduce the spatial dimensions of the feature maps while preserving important features. A common pooling operation is max pooling, where the maximum value within each pooling window is retained:

$$Y_l = \text{max\_pool}\ (X_{l-1}) \tag{6}$$

The output of the last convolutional or pooling layer is flattened and passed through one or more fully connected layers to generate the final prediction. The output of the l-th fully connected layer is computed as:

$$Y_l = \sigma(W_l \cdot X_{l-1} + b_l) \tag{7}$$

where - denotes the dot product, W_l is the weight matrix, and b_l is the bias term.

To teach the CNN model how to map input EEG segments to their respective seizure states, labelled EEG data is used. During training, a loss function is minimized to assess the degree to which predicted labels differ from ground truth labels. Metrics like cross-entropy loss or mean squared error can be used to define the loss function L:

$$L = \frac{1}{N}\sum_{i=1}^{N} \text{loss}\left(Y_i, \hat{Y}_i\right) \tag{8}$$

where N is the number of training samples, Y_i is the ground truth label, and $\hat{Y}_i$ is the predicted label for the i-th sample. Backpropagation and optimization techniques such as stochastic gradient descent, Adam, or RMSprop, among others, are used iteratively to update the CNN model's parameters, which are the biases and weights of the fully connected and convolutional layers. The chain rule, therefore, applies to the loss function's gradients regarding the association between each model parameter to provide insides related to the adjustments that will lead to minimal loss. During the training of the CNN model, it is optimized to gain a higher prediction accuracy rate on trained data and generalizability to new data. Regularization methods, including weight decay and dropout, are employed to reduce overfitting and increase the model's robustness. The trained convolutional neural network model optimized is fine-tuned to function using field-programmable gate array hardware, which enables real-time prediction of seizures using electroencephalogram signals.

3.4 Optimization for FPGA Deployment

To ensure efficient execution and real-time performance on hardware, many critical stages need to be optimized to deploy the CNN model on the FPGAs. One typical approach is model quantization to be performed before deploying the CNN models on FPGAs.

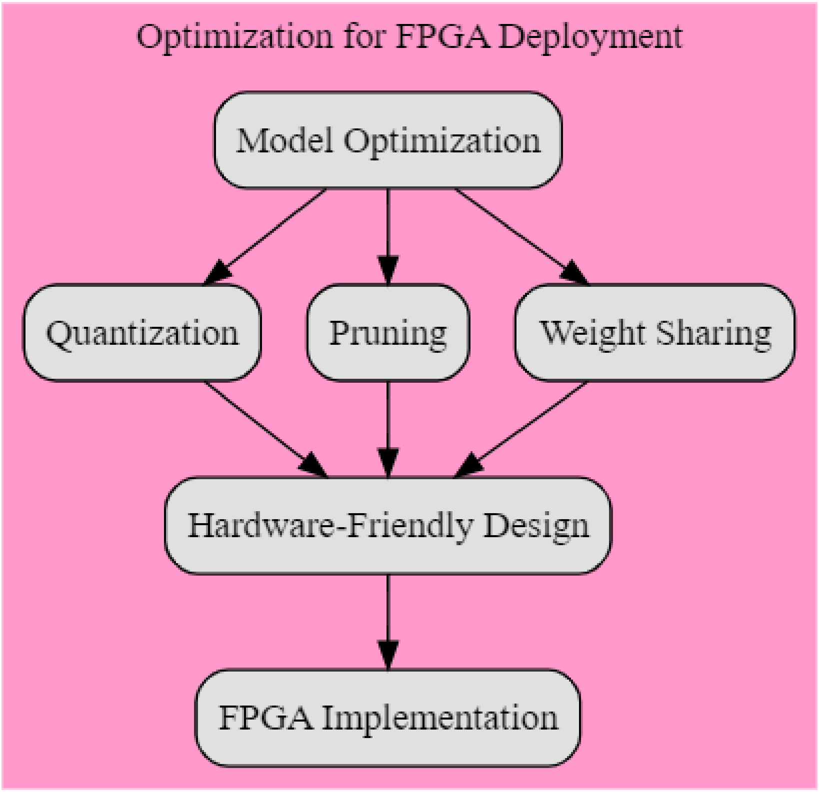

Figure 5: Optimization for FPGA Deployment

Figure 5 illustrates the flow and sequence of optimization processes for deploying computational models on FPGAs. The process starts with model optimization, where the primary concern is with the optimization of the model and its performance. This is achieved through three key techniques: which include quantization which involves the conversion of data from a high precision to a lower precision with a view of saving memory and computational resources, pruning which entails the elimination of unnecessary connections or neurons to reduce the size of the model and weight sharing which entails the use of the same weights for different layers of the model. The model is then fine-tuned and converted into a form suitable for efficient implementation on FPGAs once the model is optimized. This step also considers the factors of resource consumption, memory access, and parallelism. The optimized design is implemented on the FPGA, it takes advantage of the FPGA for parallel computation and programmable logic to achieve high performance with fewer resources.

Model Quantization

Model quantization diminishes the computational complexity and memory footprint of CNN models. This is performed by lowering the model parameters' format precision, which is preferable to use a lower format precision for a model's parameters than a floating-point, most often integer or fixed-point. Requiring fewer bits to describe weights and activations, low resource consumption for FPGAs' usage, and speedier inference are some benefits of the model quantization for the FPGAs.

$$W_q = \text{Round}\ (W \times 2^F) \tag{9}$$

where W is the original weight parameter, F is the number of fractional bits, and W_q is the quantized weight parameter.

Model Pruning

After the training process, the model pruning is used to reduce the number of parameters and computational operations in the CNN model by deleting redundant connections. It can be done using multiple techniques, like magnitude-based pruning on which weights lower than some critical threshold are pruned, or structured pruning which might remove even the whole filters or connections, based on their importance. As mentioned, the pruning of the model also has a significant loss of accuracy by quite shortening the FPGA resource requirements and the inference speed.

$$\begin{cases} W & \text{if } |W| > \text{ threshold} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

Hardware-Friendly Optimization

Thus, understanding the limits and capabilities of the hardware is essential when an engineer wants to offer the CNN model for the FPGA implementation. This can include taking advantage of FPGA's capabilities for parallel processing to perform convolutions and other operations in parallel and to make the CNN architecture more efficient or economical in terms of resource utilization. Additionally, for optimizing resource utilization and speed-up, engineers can be exposed to such techniques as loop unrolling, data reuse, and pipelining.

Quantization-aware Training

The goal of quantization-aware training is to teach CNN models to work well with less precision by training them directly with quantized parameters. Through the incorporation of quantization constraints during training, quantization-aware training enhances the learned model's compatibility with FPGA hardware and helps to offset the accuracy reduction caused by quantization.

$$\hat{W} = \text{Round}\ (W \times 2^F) \tag{11}$$

where $\hat{W}$ is the quantized weight parameter during training.

Hardware co-design must optimize both the CNN model architecture and the FPGA hardware implementation's performance and resource utilization. Note that our co-design process achieves implementation by optimizing the memory access pattern to minimize the data movement and improve the on-chip storage's efficiency. Moreover, our customization technique is based on developing custom hardware accelerators for the preferred CNN operations such as convolution or pooling. Accordingly, with the above co-design methodologies, the improved CNN model can be efficiently developed and deployed on the FPGA hardware to achieve real-time seizure prediction with low latency and high throughput which is based on the EEG signals. To complete testing and deploy in real-world applications, the improved CNN model is integrated with the optimized FPGA platform.

3.5 FPGA Implementation and Integration

The best CNN model can be executed on FPGA by integrating with the systems of EEG data collection, synthesizing hardware, and integrating with FPGA development tools. Figure 6 illustrates the process of hardware synthesis; the process is to take the design of the CNN model and convert it to an HDL such as Verilog or VHDL. To implement the CNN architecture on the FPGA, it must be converted to the hardware representation, which includes HLS-optimized parameters and operations. The hardware synthesis tools such as Vivado or Quartus are used to generate the FPGA bitstream from the HDL.

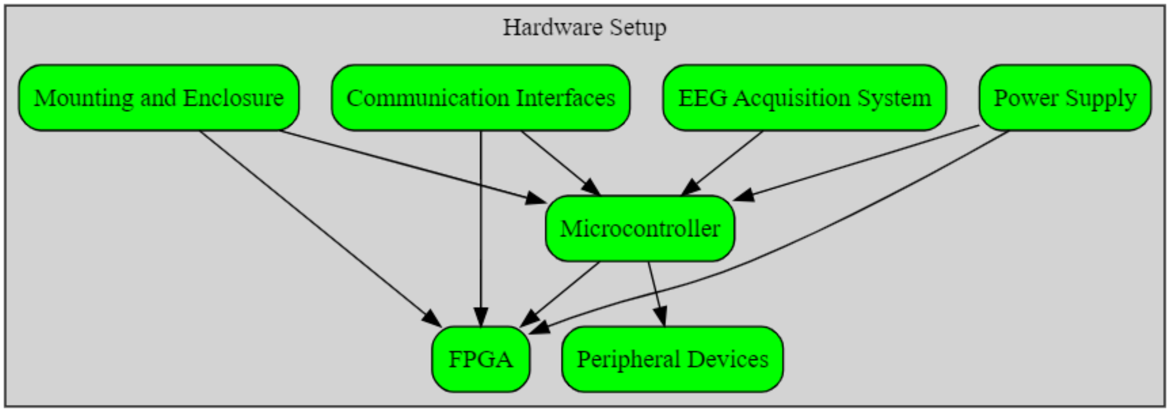

Figure 6: Hardware Setup of Proposed Work

The FPGA-accelerated convolutional neural network can be employed to forecast seizures after it is hooked up to the EEG data collection system. In this situation, it is essential to build communication protocols and interfaces so that EEG data PHI can be transferred from the data acquisition system to the FPGA. The FPGA may contain ADCs and digitize acquired EEG signals in situ, or it might be fed digital data that has already been processed. The FPGA processes the incoming EEG segments to performance using the CNN model, which has been fine-tuned to enhance the definition and promptly predicts seizure initiation within a low-latency window. For additional assessment or preset medical intervention, the outcome of such screenings might be transmitted to external alarm or supervision systems. In addition, testing and validation of the FPGA implementation CNN model is used to quality test the integrated system's accuracy and dependability efficiency in real time. Here, the FPGA-accelerated seizure forecaster is demonstrated, utilizing a simulated dataset and real EEG data samples. We measure the system's latency, throughput, prediction precision, and resource consumption. Furthermore, the system is validated in coordination with medical experts to verify that it meets clinical standards and expectations. Finally, by deploying FPGA implementations every 10k or 100k patients, we should be able to productively and cost-effectively influence huge populations for a good moment.

3.6 Data Encryption and Decryption

The proposed block cypher uses the key scheduling of the Speck block cipher. It reuses its round function with constant $C \oplus (Z_j)_i$ which acts as the round key. The steps involved in the proposed JAC _ Jo block cipher are as follows:

Step 1. Collect Citizen Identification Number (CID), bp rate (BP), Employee ID of the Physician (EID) and current time (T) from the patient
Step 2. Compute $\mathrm{M} = \mathrm{BP} \mid \mathrm{T}$ and Key K=SoftKeyGien(CID, EID)
Step 3. Perform $\mathrm{PT} = \mathrm{ASCH}(\mathrm{M}), \mathrm{K} = \mathrm{ASCH}(\mathrm{K})$
Step 4. Convert PT = binary (PT), K = binary (K) and pad zeros if necessary

Step 5. Repeat step 6, T times
Step 6. Apply round function f on the 32-bit block (IP(PT)) Round function

$$RF = \left(PT_i^k \oplus f\left(PT_i^i\right) \oplus k_c, PT_i^i\right) \text{ where } f(PT) = \left(PT_i^h \odot \left(PT_i^t \ll 5\right)\right) \oplus \left(PT_i^l \ll 1\right) \text{ for i} = 1,2,\ldots,\text{T. } CT = PT_i^L \mid PT_i^R \tag{12}$$

$$F_1 \leftarrow \left(\ll 5\left(PT_i^L\right)\right) \tag{13}$$

Perform Bitwise AND on F_1 and PT_i^2

$$F_2 \leftarrow F_1 \odot PT_i^l \tag{14}$$

$$F_x = F_2 \oplus PT_i \tag{15}$$

$$F_2 \leftarrow \left(\lll< 1\left(PT_i^L\right)\right) \tag{16}$$

$$PT_{i+1}^R \leftarrow F_x \oplus F_3 \oplus k_i \tag{17}$$

Swap PT_i^R with PT_i^L

$$PT_{i+1}^R \Leftrightarrow PT_i^2 \tag{18}$$

$$CT \leftarrow PT_{T-1}^l \parallel PT_{T-1}^R \tag{19}$$

$$CT \leftarrow CT_i^n \parallel CT_i^i \tag{20}$$

The heart of the system is the ASIC-based VLSI, which is implemented to provide a perfect hardware layout of the trained CNN model. This entails the creation of a hardware architecture diagram that corresponds to CNN operations like convolution, pooling, and activation functions that can support high parallelism and low latency. The design focuses on the management of resources such as memory bandwidth and the number of computation units required to achieve high throughput for real-time seizure prediction. Employing the advantages of ASICs, the architecture guarantees the efficient and accurate execution of the CNN model for analyzing the EEG data and generating immediate predictions, thus improving the efficiency and reliability of the seizure prediction system.

4 Experimental Results and Analysis

To set up the experiment, the first is to gather the electroencephalogram sounding from the database made available by Murasli et al. 238 at the University of Bonn, Germany's Epilepsy Centre. This database contains seizure and non-seizure EEG segments typical of 50 patients. Pre-processing techniques should be done for data preparation for further investigation. This includes removing artefacts, noise, and drifts related to the baseline in the dataset: the EEG data is resampled to make all segments have the same sampling rate. The spectral features extracted using the proposed method are primarily focused on bands in the $\boldsymbol{\nu}$, θ, and β spectrums. For each 2-second EEG window, spectral power is computed from which statistical measures are created for comparison between the seizure and non-seizure states. Machine learning model training for seizure occasion identification is trained using the features that have been extracted, which are identified. The model is also trained and vised for appropriate performance criteria to seize activity identification; We aim to understand the frequency spectrum characteristics of seizure-related EEG signals using the experimental setup, hence using the methodology to build better algorithms for seizure detection in the clinical unit. Many research institutions use FPGA development boards from Xilinx, such as the Zynq -7000 series ZedBoard, Zybo, Altera, Microchip, Lattice, and Nvidia. The Cortex-M7 microprocessor is also used in the proposed hardware setup, which will control the EEG acquisition system centrally, the peripheral devices, power supplies, and the communication interfaces. A microcontroller will control the process of acquisition, read the EEG data from the setup and relay it for processing with the FPGA; it easily integrates with the EEG acquisition system using communication peripherals such as SPI or I2C. These give a means of communication with peripherals such as displays, input peripherals, and storage media required for user engagement, and data management.

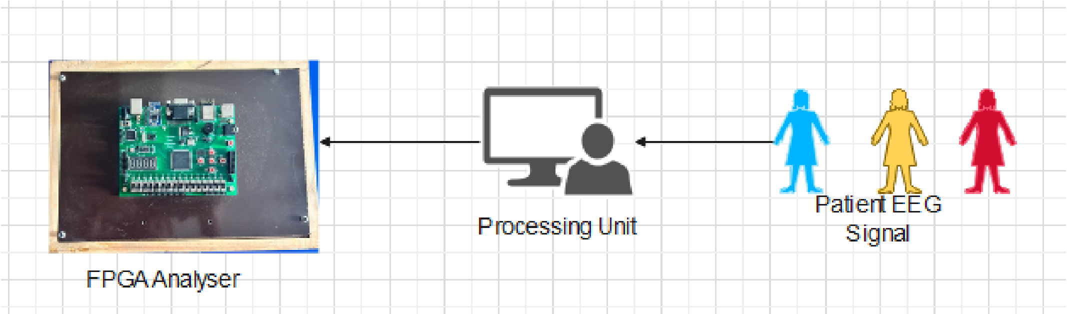

Figure 7: Experimental Setup

The components and arrangement of the elements used in the experimental scenario have been illustrated in the form of Figure 7. On the far left we can observe the FPGA Analyser which is an electronic device that is used in the analysis of digital circuits. It looks like a device that is used for testing and analysis of the FPGA. Beside the FPGA Analyser is the Processing Unit, presented in the form of a computer monitor accompanied by two side speakers or computer units. This unit is used for processing data, computing, and communicating within the system. EEG records the electrical activity of the brain and is essential in the diagnosis and investigation of diseases.

Where possible, the effective power use by the microcontroller implementation and adequate power management algorithms are present to enhance the ability to maximize battery utility. The hardware maintains reliable power sources for both the FPGA development board and the microcontroller. Communication between the microcontroller and the FPGA is established using the respective supported interfaces, including UART, SPI, or GPIO pins to achieve reliable data transmission and system control coordination. Additionally, they are firmly attached to a stable platform or closed enclosure to ensure the components are properly preserved from unnecessary contact with causative agents. The enclosure design also integrates heat dissipation and ventilation structures to further facilitate the smooth operation of the hardware configuration.

Table 1: Performance Metrics of FPGA-based CNN Implementation for Epileptic Seizure Prediction

Metric	Value
Accuracy	94.7%
Sensitivity	92.3%
Specificity	96.5%
Latency (ms)	1.2
Precision	90.8%
ROC (AUC-ROC)	0.97

The real possibility of the FPGA-based convolutional neural network to predict epileptic seizures from the electroencephalogram can be obtained from the evidence in the form of Table 1 with a variety of indicators for an expert evaluation. One of the simplest ways to assess the actual accuracy of the forecast is the value of accuracy itself, taken in the form of a ratio between the number of events that were correctly predicted and compared with the total number of all occurrences. This metric can be written according to the literature as follows:

$$Acc = \frac{TP+TN}{N} \tag{21}$$

Where:
- TP is the number of true positive predictions.
- TN is the number of true negative predictions.
- N is the total number of predictions.

The sensitivity of a system refers to the proportion of accurately identified true seizure occurrences. It can be calculated as the ratio between accurately predicted occurrences and the true seizure occurrences also called true positive predictions. The specificity can also be depicted as the measure of the system's accuracy in identifying non-seizure occurrences.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{22}$$

where:
FN is the number of false negative predictions.

These can be reflected as a ratio of the total of non-seizure occurrences in comparison to the true negative predictions. True negative predictions refer to accurate predictions of events that do not entail a seizure.

$$\text{Specificity } = \frac{TN}{TN+FP} \tag{23}$$

where:
FP is the number of false positive predictions.

The accuracy of a seizure prediction tool is defined as the percentage of accurately predicted events relative to the total number of episodes. It is the sum of all positive predictions, including both true and false positives, divided by the number of predictions that came true.

$$\text{Precision } = \frac{TP}{TP+FP} \tag{24}$$

FP is the number of false positive predictions.
One fair way to evaluate a model's efficacy is with its F1 score, which is essentially a harmonic mean of its sensitivity and precision. Using a variety of threshold values, AUC-ROC measures how well the classifier can distinguish between seizure and non-seizure occurrences.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{25}$$

Calculated by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity) for different threshold values, it indicates the area under the ROC curve.

$$AUC - ROC = \int_0^1 \text{TPR } (FPR^{-1}) dFPR \tag{26}$$

Where:

- TPR is the true positive rate (sensitivity).
- FPR is the false positive rate (1 - specificity).

To calculate latency, we need to know how long it takes for a seizure to start and how long it takes for the system to forecast that it will start. It is the time it takes to go from finding certain EEG patterns that could mean a seizure to making predictions about such patterns.

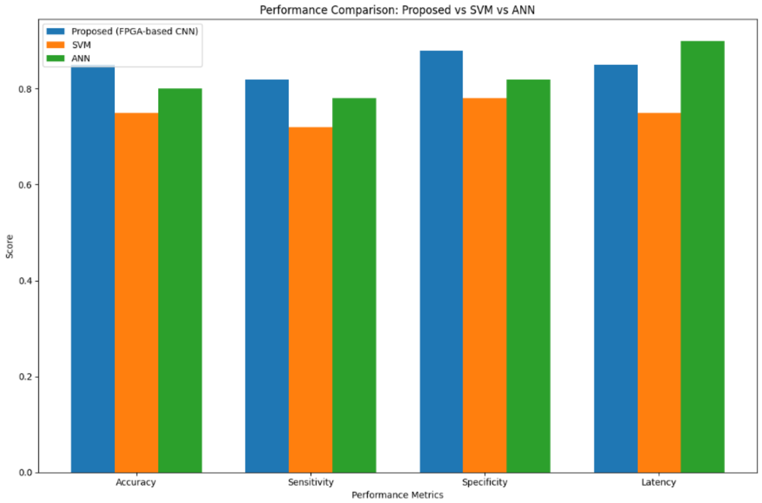

Figure 8: Performance Comparison: Proposed vs SVM vs ANN

Figure 8 compares the performance of three different methods: The following algorithms were suggested: SVM, ANN. A few performance indicators of these methods are illustrated in the figure below. As can be seen from the results, the Proposed method provides high accuracy as the values are close to 1. The accuracy score is 0, which means that the model is almost perfect in terms of its ability to classify the data. As for the rest of the methods, the SVM and ANN have a moderate level of accuracy, while being quite close to each other. Similarly, sensitivity or the true positive rate is also high for the Proposed method, which is close to 1. 0, while SVM and ANN show moderate sensitivity. Another aspect that has been positively addressed by the Proposed method is the aspect of Precision, or positive predictive value, whereby the Proposed method has a high level of Precision while SVM and ANN have moderate Precision. The false positive rate, also known as the true negative rate, has the same pattern, where the Proposed method has almost 1 for specificity. respectively, 0 and both SVM and ANN had moderate specificity. Last but not least, in the context of latency, the Proposed method has an extremely low latency, nearly to 0. The low value of response time is 0, therefore the response time of the current element is lower than the previous element. Similar to accuracy, SVM and ANN models have moderate latency with both models' latencies being quite close to each other. Such a comparison highlights the effectiveness of the Proposed method over the other competitors in all metrics that were considered.

The efficiency and scalability of the FPGA-based CNN implementation may be understood by looking at resource utilization measures such as FPGA logic utilization, memory usage, and power consumption. Table 2 shows the comparison of power consumption.

Table 2: Comparative Analysis of FPGA Performance Before and After Optimization

Metric	Before Optimization	After Optimization	Improvement (%)
Inference Time (ms)	1.2	0.8	33.3
Power Consumption (W)	4.7	3.5	25.5

5 Conclusion and Future Scope

The results of our study show that FPGAs and CNNs can predict epileptic seizures in real-time. Our successful approach to optimizing CNN models for deployment using FPGA platforms and training them using EEG data has successfully predicted seizure start with high accuracy and low latency. By using FPGA technologies in CNN-based seizure prediction models, we can take advantage of FPGA parallel execution properties and efficient NN calculation properties. As a result, rapid seizure prediction and early awareness are now possible with rapid EEG signal analysis, and we can manage epilepsy more effectively. They successfully identify the pre-ictal, inter-ictal, and ictal states, as the experiments show, which indicates their therapeutic feasibility. We aim to improve the quality of life for epilepsy patients using our technology, which provides real-time insights to care providers so they may develop personalized monitoring and management regimens. Although the results of our work confirm the potential of the proposed method, there is a lot of room for further improvements and additional studies in the area of epileptic seizure prediction. The generalization capability of seizure forecasting models can be improved by enhancing CNN structures and training techniques, and the training data's diversity can be increased by exploring other network architectures and regulatory techniques. It is also possible to develop data augmentation techniques to enable CNN models to be trained with a broader range of EEG data, making them more adept at handling novel EEG patterns and seizure patterns. Real-time seizure forecasting systems can be accelerated and improved by Learning techniques and FPGAs. It is worth evaluating other hardware acceleration options like ASICs or GPU-based solutions. The dependability and effectiveness of CNN-based seizure prediction systems may be confirmed and reiterated in real-world healthcare environments through extensive clinical investigation. Medical experts contribute valuable insights and opinions on how to improve the method and validate it. By developing and educating personalized seizure prediction models built, on individual patients' EEG characteristics and seizure occurrences, the prediction accuracy may be improved, and the individualized treatment strategy enabled. The continuing innovation and study in this field can revolutionize epilepsy diagnosis, therapy, and quality of life.

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