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Seizure Detection from EEG Signals Using Low Dimensional Convolutional Neural Network

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***Abstract*—Seizure is a neurological disorder and electroencephalography (EEG) is a commonly employed clinical technique for its diagnosis. However, neurologists are heavily burdened by the time-consuming and tedious procedure of manually inspecting EEG readings. Many automated approaches have been put out to identify seizure using traditional methods in order to overcome this issue. In this work, a deep learning-based method for automated seizure detection from EEG signals using a low dimensional convolutional neural network (LD-CNN) is presented. The suggested model differentiates between ictal (seizure) and preictal (non-seizure) states using the CHB-MIT dataset, which consists of EEG recordings from 24 individuals. To improve the data, a thorough preprocessing step was carried out which included signal normalization and noise reduction. The model exhibited outstanding performance, attaining an accuracy of 99.91%, a precision of 99.81%, a recall of 100%, and an F1-score of 99.90%. The suggested strategy also outperforms current deep learning architectures and conventional machine learning techniques, demonstrating its superiority in seizure detection according to a comparison analysis.**

***Index Terms*—Electroencephalography, LD-CNN, CHB-MIT Dataset, Seizure**

I. Introduction

Epilepsy is a serious neurological condition that affects over 60 million individuals worldwide and is marked by recurring seizures caused on by abnormal electrical brain activity [1]. In addition to creating immediate physical symptoms like muscular jerks and convulsions, epilepsy has far-reaching effects that include cognitive deficits, emotional discomfort, and social judgement. For patients and their families, the unpredictable nature of seizures exacerbates their difficulties by causing worry and anxiety. Early diagnosis and efficient care are crucial for addressing these problems [2]. Recent developments in seizure detection, especially via machine learning and electroencephalography (EEG), have demonstrated significant potential in enhancing the diagnosis and treatment of epilepsy. This research presents an automated seizure detection system utilizing a LD-CNN and the CHB-MIT EEG dataset, comprising recordings from 24 subjects. The suggested method proficiently differentiates between seizure (ictal) and non-seizure (preictal) phases, overcoming the constraints of conventional machine learning, including extensive feature engineering and challenges in adapting to varied patient datasets. The methodology emphasises rigorous preprocessing to extract relevant EEG features, hence improving model accuracy and diminishing dependence on manual EEG interpretation. The automation of seizure diagnosis guarantees expedited and more dependable outcomes, facilitating prompt clinical actions. Deep learning models such as LD-CNNs enhance scalability, reliability, and diagnostic accuracy, rendering them a feasible substitute for traditional methods. This innovation enhances seizure detection systems and improves patient care by minimising labour-intensive processes and increasing accessibility. Deep learning methods, exemplified by the proposed LD-CNN, represent a substantial advancement in addressing the constraints of traditional machine learning. This research illustrates the capability of these models to provide precise, dependable, and scalable seizure detection systems. The automation of this crucial diagnostic procedure enhances epilepsy care and facilitates prompt action. Furthermore, it aids in the formulation of economical and successful treatment options. The research highlights the capacity of deep learning to transform epilepsy management, providing scalable, precise, and effective treatments for this widely prevalent disorder.

II. Literature Review

The differentiation of seizure from non-seizure EEG signals need effective techniques for feature extraction and classification [3]. Conventional methods, including manual analysis by neurologists, are effective although time-consuming and impractical for real-time use [4]. Rule-based algorithms, spectral analysis, and statistical classifiers have been employed. However, they frequently encounter difficulties with the complexity of EEG patterns [5]. Methods such as discrete wavelet transform (DWT) in conjunction with support vector machines (SVM) have shown enhancements in precision [6]. Deep learning (DL) has markedly advanced medical image processing and enhanced its application in EEG-based epilepsy detection [7]. Convolutional neural networks (CNNs) have become popular owing to their proven efficacy across diverse research domains [8]. More recently, the fourier synchrosqueezed transform (FSST) has been applied to classify epileptic phases with feature selection algorithms and classifiers like SVM and k-nearest neighbors (KNN) [9].

The paper highlights the capacity of deep learning to address these difficulties by eliminating manual feature engineering, thus enhancing the accuracy and scalability of seizure detection systems. Leveraging from the reviewed papers, the suggested methodology aims to establish a flexible deep learning model that proficiently classifies EEG signals as either seizure or non-seizure, even in the presence of constrained data, thereby establishing a standard in epilepsy diagnosis.

III. Data Description and Preprocessing

A. Dataset

The CHB-MIT dataset is a publicly accessible EEG dataset obtained from 23 paediatric patients (24 subjects, as one subject was recorded twice) suffering from intractable epilepsy at Children's Hospital Boston. The dataset comprises more than 950 hours of EEG recordings across 686 files, collected to assess the participants eligibility for surgical procedures following the cessation of anti-seizure medication. The dataset comprises 23 standard EEG channels captured via the International 10–20 system at a sampling rate of 256 Hz with 16-bit resolution. All recordings are preserved in the .edf format, featuring continuous data collection over several days. In seizure detection studies, EEG data is classified into ictal (seizure) and preictal (non-seizure) stages. The ictal phase displays elevated, synchronized electrical activity, whereas the preictal phase reveals stable, low-amplitude waves. Exclusive dependence on the CHB-MIT dataset constrains the generalizability of an LD CNN model due to factors such as restricted patient diversity, dataset imbalance, and variations in electrode configurations. The model may encounter difficulties in adapting to alternative datasets characterized by differing seizure types, signal quality, or equipment, thereby impacting its robustness and performance.

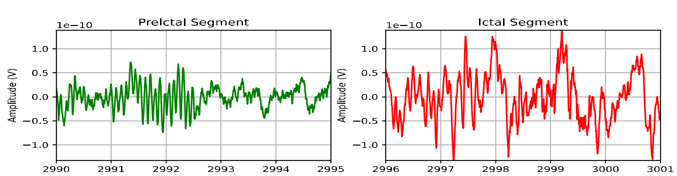

Figure 1. Comparison between preictal (left) and ictal (right) segments from a single EEG channel of a subject

B. Data Preprocessing

EEG signals, distinguished by nonstationarity, stochasticity, and nonlinearity, necessitate meticulous preprocessing to mitigate distortions. The CHB-MIT dataset undergoes preprocessing by detecting epileptic intervals from .edf files utilizing patient-specific summary files. Ictal and preictal periods are extracted and stored in distinct .csv files for enhanced labeling efficiency. Data from 24 patients is consolidated, retaining 23 critical EEG channels following the verification of electrode errors. Preictal and ictal data are designated as 0 and 1, respectively, yielding a balanced dataset comprising 68 minutes of seizure and non-seizure data. Normalization is executed via Standard Scaler, modifying the data to achieve a zero mean and unit variance to improve model efficacy. A bandpass Butterworth filter (0.5–70 Hz) eliminates low-frequency drift and high-frequency artifacts, thereby preserving cerebral activity. A 60 Hz notch filter removes power line interference, thereby enhancing signal clarity and improving the precision of EEG analysis and machine learning models.

IV. Methodology

A deep learning architecture for seizure detection using EEG inputs from the CHB-MIT dataset. The technique started with the acquisition of EEG data from the CHB-MIT dataset, succeeded by a preliminary preprocessing phase in which ictal and preictal segments were isolated, balanced, and transformed into a comma separated values (CSV) format for efficient analysis. In addition preprocessing measures such as normalization, noise elimination, and artifact suppression, were implemented to guarantee data integrity. The preprocessed signals were divided into short overlapping segments to be used as input for a custom-designed LD-CNN model. The model was subjected to training and hyperparameter optimization to improve its performance.

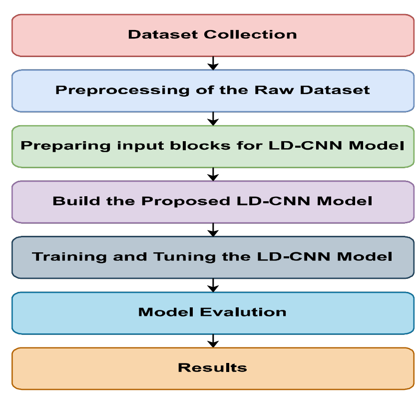

Figure 2. Block diagram of the proposed model

A. Proposed deep convolutional neural network (CNN)

The proposed architecture for seizure detection is a deep convolutional neural network (CNN) intended to analyze low dimensional EEG inputs for binary classification. Convolutional layers collect high-level characteristics and downsample the data, whereas a flatten layer connects the convolutional and fully connected layers maintaining essential information for classification. Two fully connected layers containing 64 and 32 neurons with rectified linear unit (ReLU) activations, identify higher-level patterns while the output layer employs a sigmoid activation function to deliver seizure predictions. Batch normalization and max pooling improve feature extraction and reduce dimensionality. The model effectively identifies seizures by integrating local and global information, providing a reliable instrument for real-world detection and prediction.

TABLE I
SUMMARY OF THE PROPOSED LD-CNN MODEL

Layer Type	Output Shape	Number of Parameters
InputLayer	(None,512,23)	0
Conv1D	(None, 510, 32)	2,240
BatchNormalization	(None, 510, 32)	128
MaxPooling1D	(None, 255, 32)	0
Conv1D	(None, 253, 64)	6,208
BatchNormalization	(None, 253, 64)	256
MaxPooling1D	(None, 126, 64)	0
Conv1D	(None, 124, 128)	24,704
BatchNormalization	(None, 124, 128)	512
MaxPooling1D	(None, 62, 128)	0
Flatten	(None, 7936)	0
Dense	(None, 64)	507,968
Dropout	(None, 64)	0
Dense	(None, 32)	2,080
OutputLayer	(None, 1)	33

1) Convolution: Convolution is a fundamental step in convolutional neural networks (CNNs), crucial for feature extraction from data such as images. The process entails the application of a filter (kernel) to an input tensor resulting in a feature map that emphasises patterns such as edges or textures. This strategy markedly decreases the parameter count relative to fully connected layers, enhancing the model's efficiency.

$$(Y * W)(i, j) = \sum_m \sum_n X(i + m, j + n) \cdot W(m, n) \quad (1)$$

Where X is the input, W is the filter, and Y is the output feature map.

2) Batch Normalization: Batch normalization enhances and speeds up training by standardizing the inputs of each layer to possess a mean of zero and a variance of one. This procedure reduces internal covariate shift, enhances gradient propagation, and functions as a regularizer, hence facilitating deeper networks and reducing overfitting.

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_B)^2 \qquad \text{where} \quad \hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}, \quad (2)$$

$$\mu_B = \frac{1}{m} \sum_{i=1}^{m} x_i, \qquad \text{and} \quad y_i = \gamma \hat{x}_i + \beta. \quad (3)$$

Where ϵ is a small constant for numerical stability, and γ and β are learnable parameters.

3) MaxPooling: Max pooling is a downsampling method that reduces the spatial dimensions of the input by extracting the maximum value within a specified window from the input matrix X. This renders the model robust to minor translations and distortions while reducing overfitting by constraining the number of parameters.

$$Y(i, j) = \max_{m,n} \{X(i \cdot s + m, j \cdot s + n)\}, \quad \text{for } 0 \leq m, n < k \quad (4)$$

Where s is the stride of the filter.

4) ReLU (Rectified Linear Unit): ReLU is an activation function used to include non-linearity into a neural network. It is computationally efficient and reduces the vanishing gradient issue commonly associated with sigmoid or tanh functions.

$$f(x) = \max(0, x) \quad (5)$$

Where x is the input. By allowing only positive inputs to pass through, it enables the model to learn complex patterns while avoiding the computational bottlenecks of more complicated functions.

V. EXPERIMENTS AND RESULT ANALYSIS

Figure-3 illustrates the training and validation accuracy curves for the proposed LD-CNN model throughout 200 epochs. Both curves demonstrate a swift enhancement in accuracy during the early epochs, stabilizing close to 100% as training advances. The proximity of the training and validation accuracy curves indicates the model's robust generalization capabilities and minimal overfitting. The findings demonstrate that the model effectively learns from the data, attaining high accuracy on both the training and validation datasets. This underscores the dependability and robustness of the LD-CNN in the specified task.

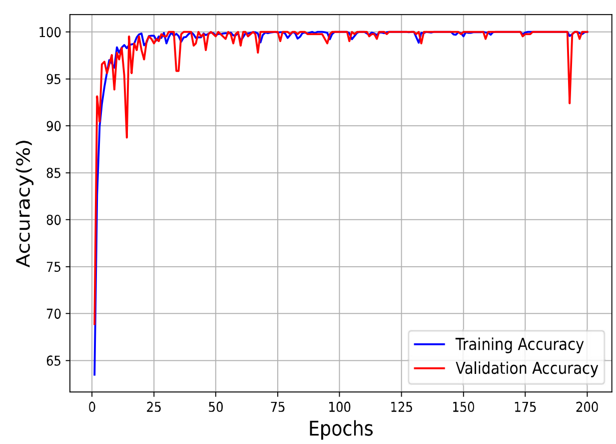

Figure 3. LD-CNN model training and validation accuracy curve

Figure-4 illustrates the confusion matrix for the proposed LD-CNN Model. The confusion matrix indicates a classification model with an overall accuracy of 99.91%. It demonstrates exceptional performance, accurately recognizing 567 pre-ictal and 524 ictal events, with merely 1 false positive and no false negatives. The model exhibits remarkable precision of 99.81% and perfect recall of 100% and F1 score of 99.90% for the Ictal class, rendering it extremely dependable for seizure detection.

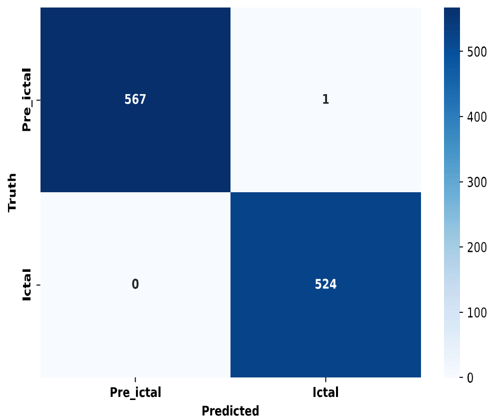

Figure 4. Confusion matrix

The proposed LD-CNN model attains exceptional performance with an accuracy of 99.91%, exceeding other advanced methodologies such as convolutional neural network-gated recurrent unit-attention mechanism (CNN-GRU-AM) 99.35%, Bi-directional long short-term memory (LSTM) with min-max scaler 99.37%, and support vector machines 99.08%. Its capacity to effectively extract temporal EEG patterns without extensive preprocessing distinguishes it from conventional models, which frequently necessitate considerable computer resources. The architectural simplicity of the LD-CNN model improves its scalability, rendering it appropriate for real-time clinical applications. This method meets essential clinical requirements by merging high sensitivity with specificity, guaranteeing dependable seizure identification and smooth incorporation into practical diagnostic processes.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	Accuracy
CNN-GRU-AM [10]	99.35%
Bi-directional LSTM + Min-Max Scaler [11]	99.37%
Bi-directional LSTM [12]	99.18%
Support Vector Machines [13]	99.08%
Proposed LD-CNN	**99.91%**

VI. CONCLUSIONS

In this paper, we provide a deep learning method based on LD-CNNs for automated seizure detection from EEG signals with an impressive 99.91% accuracy rate using the CHB-MIT dataset. The study illustrates the suggested model's clinical applicability and scalability, opening the door for precise, real-time neurological diagnostics. Deep learning's revolutionary potential in medical applications is highlighted by this work, which could lead to better patient outcomes and care. The proposed LD-CNN model exhibited high accuracy in distinguishing between seizure (ictal) and non-seizure (preictal) periods. However, it is restricted to binary classification. This method fails to elucidate the precise brain regions where seizures originate, a critical factor for effective therapy and surgical procedures. Furthermore, its generalizability to a variety of populations is limited by its dependence on the CHB-MIT dataset. Another obstacle to a thorough knowledge of seizure is the lack of multi-modal data, such as genetic or imaging data. Future research may mitigate these limitations by integrating datasets containing comprehensive annotations for seizure localization. This would allow models to not only detect seizures but also identify their origins, so improving their clinical value. Furthermore, the incorporation of hybrid models (LD-CNN + recurrent neural network) may improve accuracy by effectively capturing both spatial and temporal EEG characteristics. Enhancing research with varied datasets and integrating multi-modal data such as genetic and imaging information, may augment the model's generalizability and predictive capability. Ultimately, the creation of real-time seizure detection algorithms for wearable EEG equipment would provide prompt clinical treatments, thereby enhancing seizure management and patient care.

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