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Original Article

Dynamic Seizure Recognition: Invelling Epileptic Patterns with CNN-LSTM Networks

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Abstract - *Epilepsy is a condition affecting the nervous system. which is diagnosed with the aid of Electroencephalography (EEG)through a neurologist or experts. Frequent and unpredictable seizures characterise it may cause loss of consciousness, altered awareness, or unusual sensations. Reducing the use of conventional diagnostic methods is crucial, as is making the diagnosis of this condition early on, before behavioural. Signs appear. This project aims to introduce an intelligent framework for diagnosing neurological disorders (epilepsy) based on EEG recordings utilising the techniques of deep learning. In EEG signals the epileptic seizures are recognised with the help of sharp spikes of the signals. The focus lies on developing a system to transform the subjective qualitative diagnostic criteria into a more objective quantitative prognosis criterion and to analyse hidden dynamics of the Neurological data for extracting more information about the pathological versus normal status of the signals. 1D-Convolutional Neural Network and a long short-term memory hybrid model of deep learning have been employed to identify epileptic seizures. In this study, the authors used a CNN-LSTM network with 20 epochs on two separate datasets to get an optimal detection rate of EEG data exhibiting seizures compared to those without. By adding noise to the EEG signals the suggested model's adaptability has been examined. Neurologists will find the suggested methods useful for detecting seizures in real-time.*

Keywords - *Classification, Convolutional Neural Network, Epileptic seizures, E-health, Electroencephalography, Long Short-Term Memory, Monitoring, Neurological disorder, Sensors.*

1. Introduction

Numerous diseases affecting the brain and spinal cord with peripheral nerves are together referred to as neurological disorders. These disorders can cause a wide range of deficits, including motor, sensory, and cognitive. Numerous ailments are included in this broad category of illnesses, like multiple sclerosis and epilepsy, Parkinson's disease, Alzheimer's disease, and many more.

The intricate structure of the human brain and the wide range of symptoms associated with neurological illnesses make understanding, diagnosing, and treating these conditions extremely difficult. A neurological illness that causes recurring seizures, epilepsy affects millions of people worldwide. For successful medical intervention and patient safety, prompt and accurate seizure detection is essential.

A major obstacle to managing epilepsy is the absence of real-time, dependable, non-invasive monitoring capabilities in many current approaches. Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs), two recent developments in deep learning, have shown promise in medical applications, including seizure diagnosis. Nonetheless, there remains a research gap in creating a solid automated system that utilises CNNs and LSTMs in concert for epileptic seizure detection. By putting forth a unique CNN-LSTM network design that is optimised for the automated identification of epileptic seizures from EEG data, this study seeks to close this research gap.

The proposed CNN-LSTM network seeks to improve automated epileptic seizure detection by overcoming these challenges and opening potential new possibilities for improving epilepsy treatment and patient care. In the study of neuroscience and neurology, deep learning has become a potentially useful technique. Deep learning algorithms, especially multilayer neural networks, have demonstrated amazing power in the analysis of complicated data, such as genetic information, clinical records, and medical imaging. Neurological problems and deep learning interact in terms of:

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Medical Imaging Analysis: MRI, CT, and PET scan data, among other forms of medical imaging data, have been analysed using deep learning models. These models uncover minute patterns and irregularities in the structures and processes of the brain, which can help in the early diagnosis and identification of neurological illnesses. Convolutional Neural Networks (CNNs), for instance, have proved highly successful at accurately identifying and categorising brain tumours or lesions from MRI scans.

Genomic Analysis: To find genetic variables linked to neurological illnesses, deep learning techniques are also used to analyse genomic data. Deep learning algorithms are able to detect genetic changes associated with higher susceptibility or risk of acquiring illnesses like Parkinson's disease or Alzheimer's disease by exploring the genome at a huge scale.

Predictive analytics: For people with neurological diseases, deep learning algorithms can assist in forecasting the course of their sickness and the results of their therapy. These models may generate individualised predictions about the course of the disease, how well the patient will respond to therapy, and any potential problems by evaluating longitudinal patient data, including genetic profiles, imaging data, and clinical records.

Drug Discovery and Development: Deep learning is being utilised more and more in the process of finding and developing drugs for neurological illnesses. Deep learning algorithms may optimise drug design to target processes underlying neurological illnesses, find viable therapeutic candidates, and forecast their efficacy by utilising large-scale databases on molecular structures, biological pathways, and drug interactions.

Brain-Computer Interfaces (BCIs): Deep learning methods are vital for the development of brain-computer interfaces, which allow the brain to communicate with external technology directly. BCIs hold the potential to regain motor skills in each person along with neurological disorders like spinal cord harm or Amyotrophic Lateral Sclerosis (ALS) by interpreting neural signals and translating them into commands for prosthetic limbs or assistive devices.

The amalgamation of deep learning and neuroscience presents stimulating prospects for augmenting our comprehension of neurological ailments, refining diagnostic precision, streamlining therapeutic approaches, and finally elevating patient consequences. To fully utilise deep learning in neurology, however, several issues like data scarcity, interpretability of deep learning models, and moral concerns about algorithmic bias and data privacy need to be resolved.

Recurrent seizures are the hallmark of epilepsy, a disorder of the brain caused by an aberrant brain's electrical activity. Millions of people worldwide are affected by epilepsy, which continues to be a major global health problem despite advances in medicine.

Deep learning models have become highly effective tools in several medical fields, including the study and treatment of epilepsy, in recent years. This area of deep learning automatically learns complicated data representations by using multi-layered neural networks.

Seizure Detection and Prediction: Deep learning models have shown promise in many epilepsy-related domains. Real-time seizure recognition and prediction are possible because of deep learning algorithms that examine Electroencephalogram (EEG) data. These algorithms may also be used to forecast when seizures will occur. This feature makes it possible to warn patients and carers in a timely manner.

Classification of Seizures: The primary symptom of epilepsy, a neurological condition marked by aberrant electrical activity in the brain, is seizures. Based on their clinical characteristics and the parts of the brain that are affected, epileptic seizures can manifest in a variety of ways and be divided into many categories.

Seizures must be classified correctly in order to be diagnosed and treated, and the underlying pathology to be understood. Based on EEG patterns, deep learning models are able to identify various types of seizures, which helps physicians diagnose and categorise epileptic disorders with accuracy. This helps in modifying therapy regimens for specific individuals.

Neuroimaging Analysis: To detect anatomical and functional anomalies linked to epilepsy, deep learning algorithms may be used to analyse neuroimaging data, such as Magnetic Resonance Imaging (MRI). This helps identify epileptogenic zones and coordinate surgical procedures for individuals who meet the criteria.

Drug Response Prediction: Through the analysis of clinical data and genetic information, deep learning algorithms can predict individual responses to Antiepileptic Medications (AEDs). This individualised approach makes it easier to optimise treatment plans and reduce side effects. Figure 1 depicts a visual illustration of seizure classification. The primary categories of seizures have been organised as follows:

1.1. Generalised Seizures

1.1.1. Absence (Petit Mal) Seizures

Typically seen in children, these seizures cause a brief loss of awareness or staring spells. Indiscernible gestures like lip-smacking or blinking might accompany them.

1.1.2. Myoclonic Seizures

Characterised by sudden, brief muscle jerks, often affecting the arms and legs. These epileptic fits may happen one at a time or in clusters.

1.1.3. Clonic Seizures

The word “Clonic Seizures,” pronounced “KLOH-nus,” refers to the abrupt alternating contraction and relaxation of muscles. The patient’s body starts to jerk repeatedly during this kind of seizure. A clonic seizure differs from a myoclonic seizure primarily in that the former shows less jerking.

1.1.4. Tonic Seizures

A tonic seizure causes the muscles to stiffen. There is a random tightening of the muscles of the face and neck and then a stretch. Most people do not pass out during this seizure. It often affects both sides of the brain and occurs when you are asleep. When the seizure begins, if the individual is upright, they run the risk of falling and becoming harmed. This seizure usually lasts between twenty and thirty seconds. After a tonic seizure, the patient may or may not feel tired or disoriented.

1.1.5. Tonic-Clonic (Grand Mal) Seizures

These seizures include loss of consciousness, tonic phase (muscle rigidity), and clonic phase (rhythmic limb jerking).

1.1.6. Atonic Seizures

These seizures, sometimes referred to as "drop attacks," result in an abrupt loss of muscular tone, which can induce falls or collapses without warning.

1.2. Focal Seizures

A particular region of the brain encounters abnormal electrical activity, which is the source of focal seizures. It may occur with or without a loss of consciousness.

1.2.1. Focal Seizures along with Impaired Awareness

Seizures of this type appear as a shift in dreamlike experiences or a loss of awareness or consciousness. Even if you seem to be awake, you keep moving in the same direction, gaze off into space, or react improperly to your environment. Examples include walking in circles, lip movements, hand rubbing, and repeating particular words. It is possible that you do not even remember having the seizure. The diagnosis reveals a variety of reasons, including genetic susceptibility, brain traumas, infections, or developmental defects. Electroencephalography (EEG) is frequently used in this process. A combination of medication, lifestyle modifications, and, in certain situations, surgical procedures are often used in effective management regimens [2]. Brain electrical activity is monitored and recorded using Electroencephalography. (EEG).

1.2.2. Focal Seizures without Loss of Consciousness

Although you do not lose consciousness during these seizures, your emotions or the way things seem, feel, sound, or smell may alter. You can have abrupt feelings of joy, depression, or rage. Some people report feeling queasy or having trouble expressing their feelings. Along with linguistic problems, uncontrollably jerking an arm or leg, and abrupt sensory symptoms like tingling, dizziness, or seeing flashing lights, these seizures can also make it difficult to communicate.

1.3. A Comprehensive Overview of Seizure Monitoring Technology

Seizure monitoring relies on advanced sensor technologies capable of capturing physiological signals associated with seizure events. These sensors can range from conventional Electroencephalography (EEG) electrodes to more sophisticated wearable devices equipped with accelerometers, gyroscopes, and other motion sensors. By continuously monitoring relevant physiological parameters, these sensors provide valuable data insights into the onset, duration, and characteristics of seizures.

This technique involves placing electrodes on the scalp to quantify the record of brain activity [3]. Non-intrusive Electroencephalogram (EEG) devices apply electrodes to the scalp., while in invasive ones, a surgical incision is required to implant or puncture the electrodes. Over time, Electrodes capture changes in voltage on the surface of touch brought induced by brain activity. Nonetheless, It demands a considerable amount of time with the expertise of an EEG specialist for the visual assessment and annotation of EEG data. Consequently, to enhance the quality of clinical care and diagnosis, it is crucial to develop automated methods for detecting and predicting seizures.

1.4. EEG Signal Morphology

The electrical activity that was captured is outlined using the following measurements and descriptors: The electrical activity that was recorded is described using certain measures and terms, such as,

- Frequency or Wavelength
- Voltage
- Waveform
- Regulation
- Occurrence in the (random, serial, continuous)
- Reactivity (eye opening, mental calculation, sensory stimulation, movement, affective state)
- Interhemispheric coherence (homologous areas)

Responses of the distinct EEG components to specific neurophysiologic modifications are a crucial part of capturing EEG data. Signal pattern is vital for the identification of brain activity and to clearly differentiate one activity with similar features of another. Based on their frequency range, the brain waves may be classified into Beta (β), theta (θ), delta (δ), gamma (γ), and alpha (α) are the five bands.

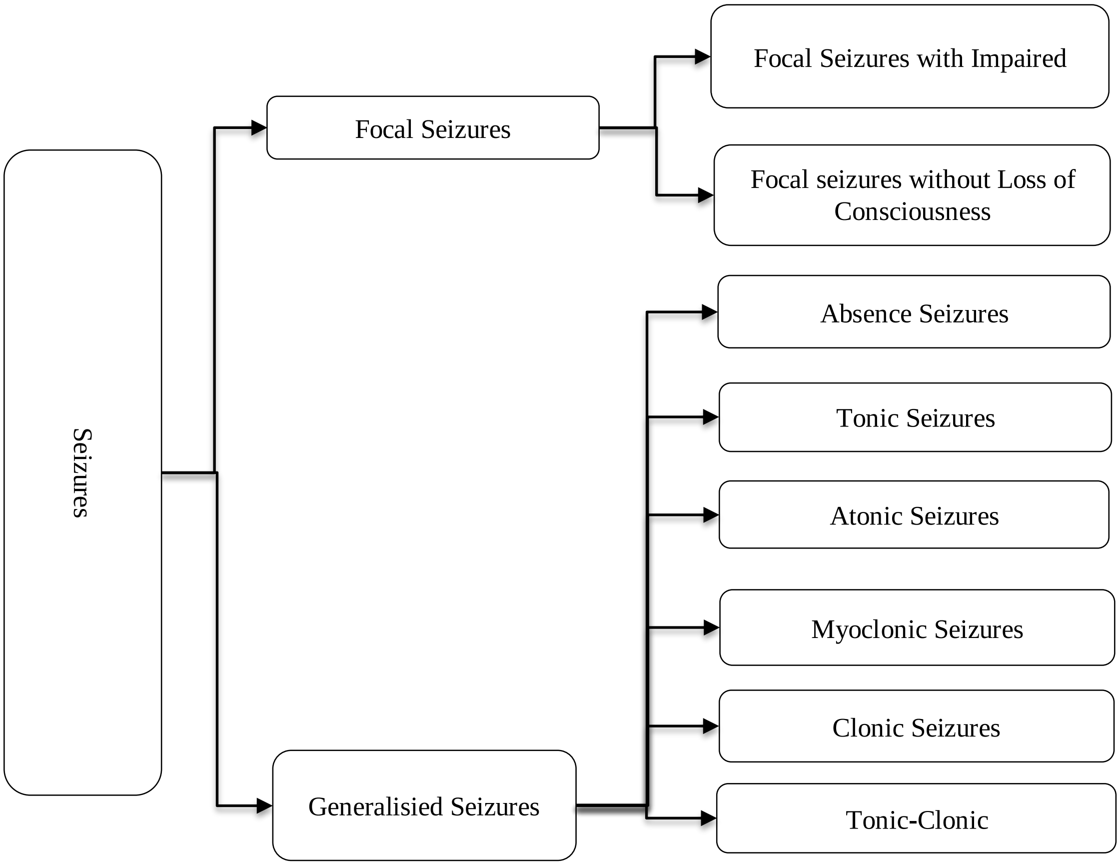

Fig. 1 Classification of epileptic seizures

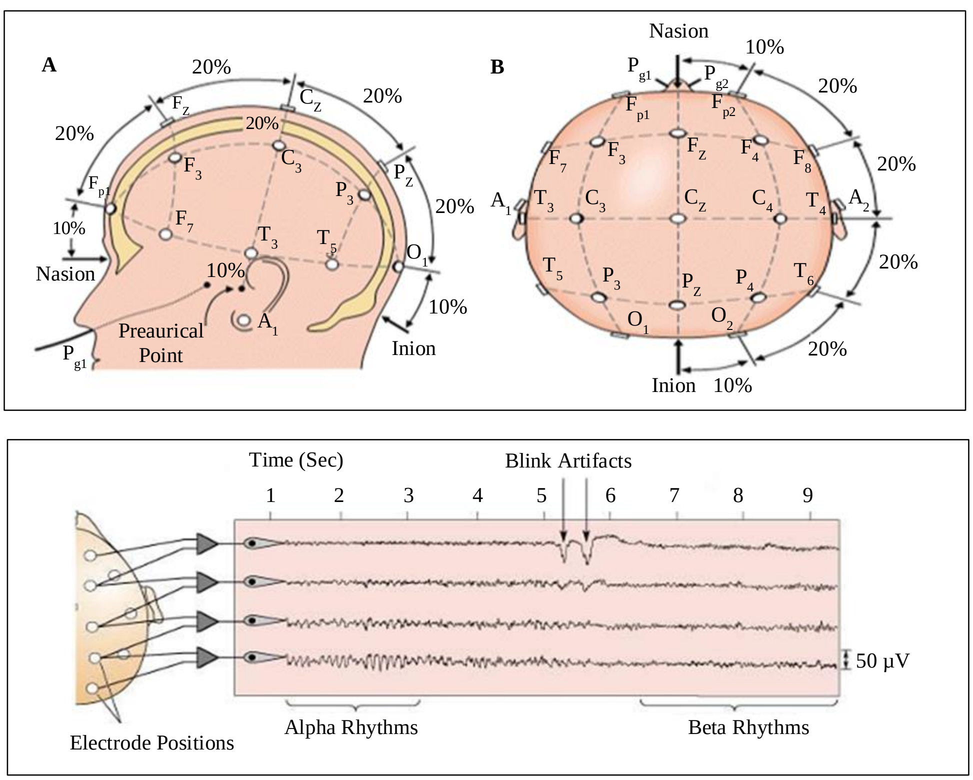

Fig. 2 Positions of the 21 electrodes using the standard 10–20 EEG electrode placements

EEG signals are complicated, and current approaches do not yield meaningful findings. Because the electrical impulses in the brain are sometimes dynamic and irregular, it is challenging to interpret EEG data. Furthermore, the current approach is ineffective for the feature extraction process and frequently leads to overfitting problems. Consequently, a new system for seizures due to an epilepsy detection model is created. As a result, it offers trustworthy, precise information for employing EEG signals to identify epileptic episodes. It assists in resolving difficulties such as gradient vanishing and overfitting.

The composition of the paper is as follows: In section 2 literature survey has been explained. Section 3 includes two distinct dataset descriptions with a description of methodology CNN and LSTM. In section 4, the outcomes of the experiment have been presented. Section 5 includes the conclusion of the work.

1.5. An EEG-Based Method for Deep Learning-Based Epileptic Seizure Identification

EEG-based deep learning methods for epileptic seizure detection involve harnessing electrical activity recorded from the brain to identify as well as classify seizures. Typically, this process includes gathering EEG data from patients in both seizure and non-seizure periods. Following data collection, various preprocessing steps are applied to enrich the quality of the EEG signals, such as filtering noise and normalising the data. Deep learning models, often incorporating architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are then designed to analyse these preprocessed EEG signals.

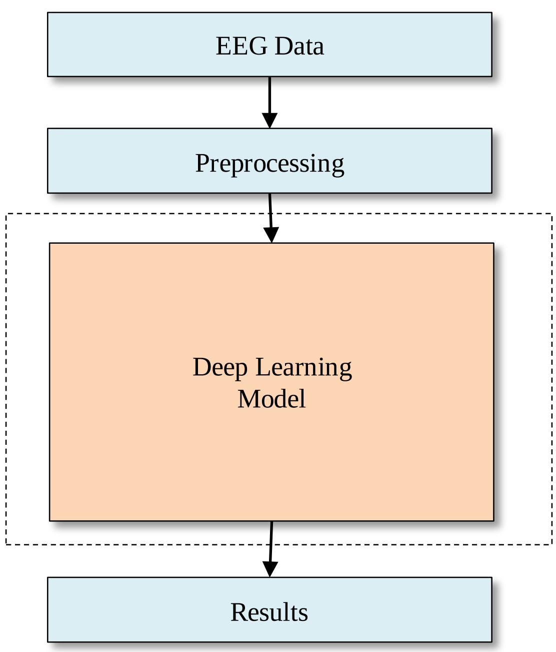

Fig. 3 Deep Learning methodology for seizure detection

In the training stage, the model gains knowledge to recognise patterns associated with seizures and differentiate them from normal brain activity by being fed labelled EEG data. Evaluation parameters like accuracy, specificity and sensitivity are used to evaluate the model's performance. Additionally, optimisation techniques like adjusting hyperparameters and employing cross-validation to refine the model's capabilities and prevent overfitting. Once the proposed model demonstrates satisfactory results, it might be used in clinical settings to aid in real-time seizure detection, potentially improving patient care and outcomes.

2. Literature Survey

In the field of image surface texture analysis, automated systems approach based on deep learning have demonstrated noteworthy performance [17], skin cancer detection [23], neurological disease detection. In the first study Convolutional Neural Network (CNN) having thirteen layers was employed for analysis of EEG signals [11]. In another paper, a pyramidal-type CNN is presented [12]. There are a number of variants of CNN used on the Bonn dataset by authors for detection [9, 10]. In this paper, the author has proposed only a 4-layer LSTM model.

The focus lies on developing a system to transform the subjective qualitative diagnostic criteria into a more objective quantitative prognosis criterion and to analyse hidden dynamics of the neurological data for extracting more information about the pathological versus normal status of the signals. Traditional diagnosis needs to be reduced as far as time and severity of disease for the patient is concerned to get medication for recovery.

The majority of the systems that the various authors provide are predicated on manually designed methods for feature extraction and feature selection [6]. Time-frequency (t-f) analysis is one of the many available approaches that is frequently used for feature extraction [7-10]. Under t-f analysis, methods like the discrete wavelet transform and the Short-Time Fourier Transform (STFT) [11] are frequently used. Random Forest [12-14] and support vector machines [15-17] have demonstrated the greatest efficacy among classifiers during the classification phase.

It is a difficult task to develop an automated system for epilepsy utilising a machine learning approach. The causes are artefacts in the data and insufficient data for training. Expertise is needed to extract pertinent characteristics to attain high classification accuracy. A method called deep learning involves automatically extracting characteristics from the data. In voice recognition [18], picture retrieval [19], hand gesture recognition [20], object categorisation [21], genome analysis [22], COVID-19 detection [23-25], diabetic retinopathy and other biological applications, these automatically derived features have demonstrated encouraging results. Using deep learning approaches, several researchers have presented an epileptic seizure detection system in recent years [25]. The first one to have 13 layers was CNN [11]. A CNN of the pyramidal kind is provided in another study [12]. The authors have also employed CNN variations, such as Alexnet, Resnet, VGG, Densenet, etc., for detection [13]. The authors of [14] suggested ChronoNet, which is made up of deep Gated Recurrent Units (GRU) and 1D convolutional layers. LSTM network was applied to the Freiburg database by the authors in [15]. A double deep neural network, LSTM, 1D-CNN, and GRU are provided in [23] as part of an epileptic seizure detection system.

One of the emerging research topics now is the identification of epileptic seizures using artificial intelligence systems [12]. The automated approach employed by the researchers relies mostly on manually designed processes for feature extraction and feature selection [11]. Among the several techniques available, time-frequency analysis is a well-liked one for obtaining features [7, 11]. Discrete wavelet transform with Short-time Fourier transform are widely used techniques in t-f research. In the classification step, Random Forest (RF) and Support Vector Machines (SVMs) fared better than all other classifiers.

Mustafa et al. [17] extracted the statistical properties of the delta band using a different windowing approach on STFT and then utilised an RF classifier to identify seizures. It is challenging to develop an automated epilepsy system using machine learning approaches. The primary cause of this is the need for specialised knowledge to extract pertinent characteristics, which is necessary to achieve high classification accuracy. An automated technique for obtaining features from data is called deep learning. Using these automatically produced characteristics, biological applications such as COVID-19 identification, diabetic retinopathy detection, speech recognition genome analysis, etc. others have shown encouraging results.

In recent years, a small number of researchers have proven deep learning algorithms for computer-aided epilepsy detection systems [23, 24]. A 13-layer CNN was the first, and it was introduced in [11]. For detection in [13], the authors used CNN variants Alexnet, Resnet, VGG, Densenet, and others. Deep Gated Recurrent Units (GRU) and 1D convolutional layers make up ChronoNet, which was suggested by authors in [14].

A method utilising a double deep neural network, 1D-CNN, LSTM, and GRU for identifying epileptic episodes is provided in [16]. Using STFT on EEG data, Beeraka et al. [22] identified t-f statistical characteristics using CNN with bidirectional LSTM. Fortunately, the deep learning methods previously discussed offer a high detection rate at the cost of several combinations of distinct deep learning algorithms, which raises the intricacy of the identification system.

3. Methodology

3.1. Long Short-Term Memory

Advances have been made in recurrent neural networks, and LSTM networks can now recognise long-term dependencies [18]-the RNN's vanishing gradient issue, which LSTM resolves. When the gradient starts to diminish as it flows back to previous layers, the vanishing gradient problem causes learning in RNNs to be disturbed and performance to decrease. Therefore, LSTM is presented as a solution to all these issues. It is typically utilised in fields like malware detection, machine translation, natural language processing, and the identification of neurological diseases, among others. It contains a series of neural network retelling modules. It has extremely few internal operations because of its tanh activation function, which controls values across the network by squishing values between -1 and 1. The LSTM cells have several distinct elements, including the forget gate, input gate, and output gate. Mathematically, gates are formulated as:

$$f_t = \sigma\,(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma\,(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$o_t = \sigma\,(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

Where σ stands for the activation function and ft, it and ot for the forget, input, and output gate outputs, respectively. The forget gate defines to what extent the previous cell state should be forgotten, the input gate chooses how much of the new input is required to alter the cell state, and the output gate indicates how much of the current Cell state ought to be included in the current concealed state.

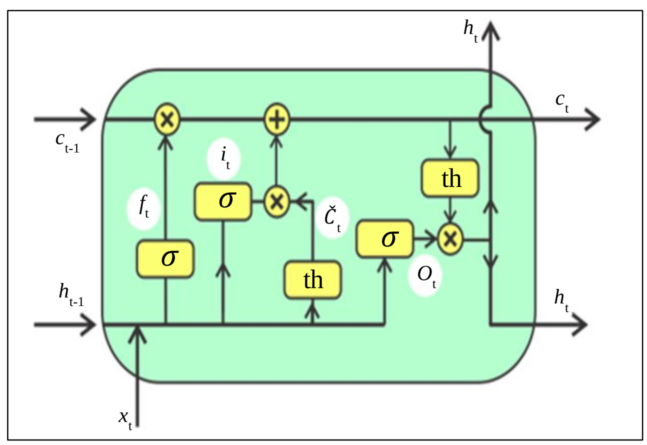

Fig. 4 Structural architecture of LSTM cell

One of the derived forms of recurrent neural networks is the LSTM network [18]. LSTM models are widely used by researchers in various applications of deep learning [19]. It can learn order dependence in sequence prediction problems which is needed in complex problem domains like machine translation, speech recognition, etc. It utilises gates to control the data stream in the recurrent computations. LSTM networks are best at holding long-term memories. It has memory blocks in the recurrent hidden layer.

3.2. Convolutional Neural Network

Deep neural networks are the same as convolutional neural networks. This method revolutionised image processing by taking out the manual extraction of features. CNN directly work on matrices as well as tensors. CNN is extensively used for object recognition, face recognition, image segmentation, and image Classification. A Convolution Neural Network is a combination of three distinct layers expressed as convolution layer, pooling layer, and fully connected layer.

Convolutional layers, that make up the hidden layers, function similarly to filters in that they take in input, recast it using a certain pattern or feature, and then forward it to the subsequent layer. In other words, the more layers the data passes through, the more complex patterns subsequent ones will be able to identify.

In the past several years, convolutional neural networks have garnered considerable focus for a variety of industrial applications. It is frequently used for image retrieval [18], picture identification [16], and illness identification [17]. Convolution between matrices is a linear approach that inspired the term CNN. The CNN architecture is composed of many levels.

3.2.1. Convolution Layer

The first layer is made up of filters called kernels, which go across the input of the EEG signal. In this layer, the input EEG waves are subjected to the operation convolution; the result is a feature map. The distribution of feature maps may change if starting settings, the training parameters, or the learning rate is changed. The following equation carries out convolution:

$$Y_k = \sum_{n=0}^{N-1}(x_n h_{k-n}) \tag{4}$$

Where,
x is signal,
h is filter,
N is the number of elements in x,
Y is the output vector.

3.2.2. Pooling Layer

This layer of CNN allows to reduce dimension, hence also referred to as downsampling. The convolutional layer's pooling process reduces the size of the output neurons, preventing overfitting and lowering computational effort. The global average pooling layer uses the feature map average from each layer below it. Tragically, pooling layers lack any trainable parameters. As a result, the pooling layer reduces neuronal size and thereby lowers processing load.

3.2.3. Fully Connected Layer

In neural networks, fully linked layers are those where every input from one layer is linked to each activation unit in the subsequent layer. Input to this layer is output from the pooling layer. These layers accomplish Classification based on the features extracted from the previous layers. The output of the model is an anticipated value for each classifying label it is trying to predict, with values ranging from 0 to 1.

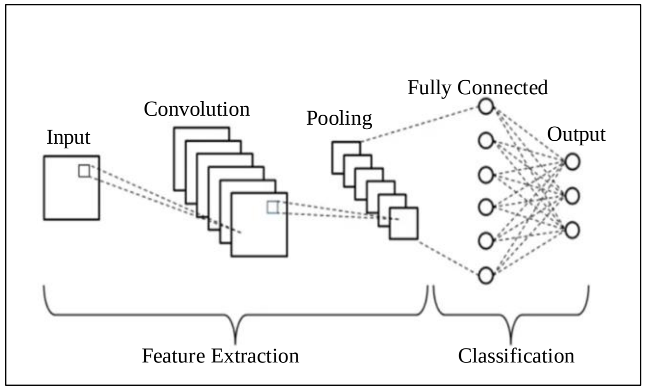

Fig. 5 Illustration of CNN

A fully connected layer is utilised to establish connections between every neuron. Finally, it utilises an activation function to determine the proper category. Because Batch Normalisation (BN) allows for fast convergence and does away with the requirement for specific parameter configuration, it may be used to enhance learning. Trial and error have been considered while adjusting parameters (such as kernel size). This CNN-constructed structure has two layers of convolution: one batch normalisation layer one global average pooling layer, with one fully connected layer. The preset value step (stride) is the first. Two groups are ultimately classified using the two output neurons of the last layer-the proposed architecture of the 1D-CNN model illustrated in Table 1.

CNNs are a form of artificial neural network that has its roots in the neuroscience notion of receptive fields. They have made significant progress in both image classification and computer vision. A feed-forward neural network does the convolution process in a different way than a CNN. A feature extraction method is employed in the convolution process by the kernel-specific matrix. A matrix is fed into a convolution, which produces a new matrix that has the input matrix's form. The output matrix's components are created by adding up each Hadamard product component, which is obtained by convolving the kernel over the input by the corresponding input region element one by one. In Figure 3, the convolution process is displayed.

The kernel moves one column to the right (called a stride) to compute the Hadamard product sum at each step. The kernel travels along a row and restarts on the left when it encounters the right edge. Convolution ends as soon as the kernel reaches the bottom edge. In the convolutional procedure, just the input's weighted moving sum is utilised.

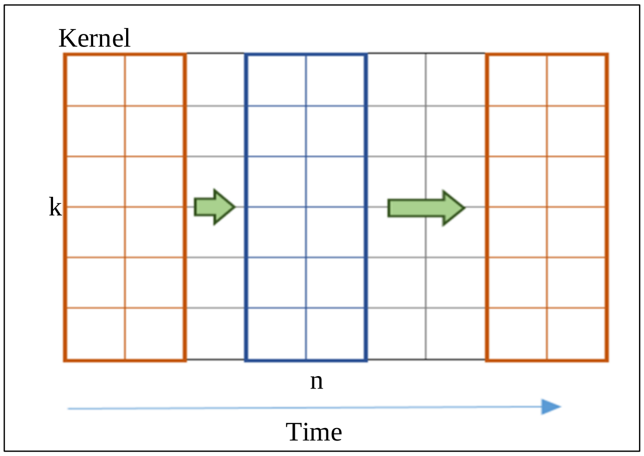

Fig. 6 Operation of 1D convolution

In Figure 6, x of length n serves as the convolutional layer's input, but the kernel has length k. In a CNN, a max-pooling process usually occurs later to convolutional operation. Like convolutions, max pooling creates matrices by extracting data from certain spatial areas of the input. Max pooling, on either side, is not dependent on any kernel. It reports everything that has been pulled via a 1D input into a given window. Convolutional neural networks extract visual characteristics for picture categorisation.

Essentially, convolving a kernel over an image involves looking for certain features, such as corners and edges, in that area of the picture. When convolutional layers are layered, higher convolutional layers learn more about other anatomical characteristics and complex features like eyes and noses first.

Consequently, CNN has achieved great success and is currently at the forefront of perfection in the field of image categorisation. Traditionally, convolutional layers are applied to tasks requiring visual images. However, because of their much-reduced computational cost, they are now being employed more and more in language models, where they are starting to beat recurrent networks.

4. Experimental Results

4.1. Dataset 1

EEG segments from Germany's Bonn University were employed in this stated system. (produced by Andrzejak et al., 2001). This dataset is available for free [20]. There are a total of five healthy scenarios, four of which are typical and include people who are not having epileptic seizures.

Healthy individuals with closed eyes, subjects with their eyes open (A & B), and patients having brain tumours (C & E) are all depicted in these subject recordings. The fifth condition (marked as E) documents the patient's epileptic seizure state. Five different people provided a total of 100 EEG signals for every dataset in this collection.

With a resolution of 12 bits, a sampling frequency of 173.6, and 4097 data points gathered over a 23.6-second duration, every signal is a documented sample of brain activity. There are 4097 points have been documented for every sample. The Section of the classes A, B, C, D, and E is displayed in Figure 7.

4.2. Dataset 2

The Neurology and Sleep Centre in New Delhi, India, generated a database at a 200Hz sample rate utilising Grass Telefactor Comet AS40 amplification equipment belonging to 10 epileptic patients. The EEG signals were collected in a setup of 10–20 electrodes, and then they were filtered using a bandpass filter (0.5 Hz to 70 Hz). Pre-ictal, inter-ictal, and ictal phases are the different categories into which the entire information is arranged. Each set consists of fifty EEG segments structured in MAT. There are ten thousand twenty-four data points in every 5.12-second interval.

The CNN-LSTM deep learning model's performance was assessed using the Python Tensorflow and Keras tools. The cross-entropy function is utilised as the loss function during model training. The loss function is very useful for classification problems since it allows parameter updates even when the output of a neuron is saturated. The cross-entropy function that was averaged across the training set was found using the Adam mini-batch optimisation approach.

After doing the k-fold cross-validation to divide the dataset into training and test sets techniques, the model was launched and trained [7]. During the training, a 64-bit operating system, 8GB of RAM, and an Intel(R) Core (TM) i7-4790 CPU running at 3.6GHz were employed. Training the model included using a batch size of 32 across 20 epochs. Combining the many categories found in the Bonn dataset allowed for the completion of the classification job. To carry out this experiment, nine data clusters have been created in total. The execution of the proposed model is analysed using accuracy, sensitivity, and specificity.

$$\text{Accuracy} = \frac{\text{Number of Predictions}}{\text{Total Number of Predictions}} \text{x100} \quad (5)$$

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \text{x100} \quad (6)$$

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives+False Positives}} \text{x100} \quad (7)$$

The greatest possible result of 99.89% was attained by data cluster A for all three criteria. In contrast, 97% accuracy was attained by the interictal seizure data cluster C-E. For three classes, the accuracy rate in class classification is 93.67%. Table 2 presents the results generated by the proposed model.

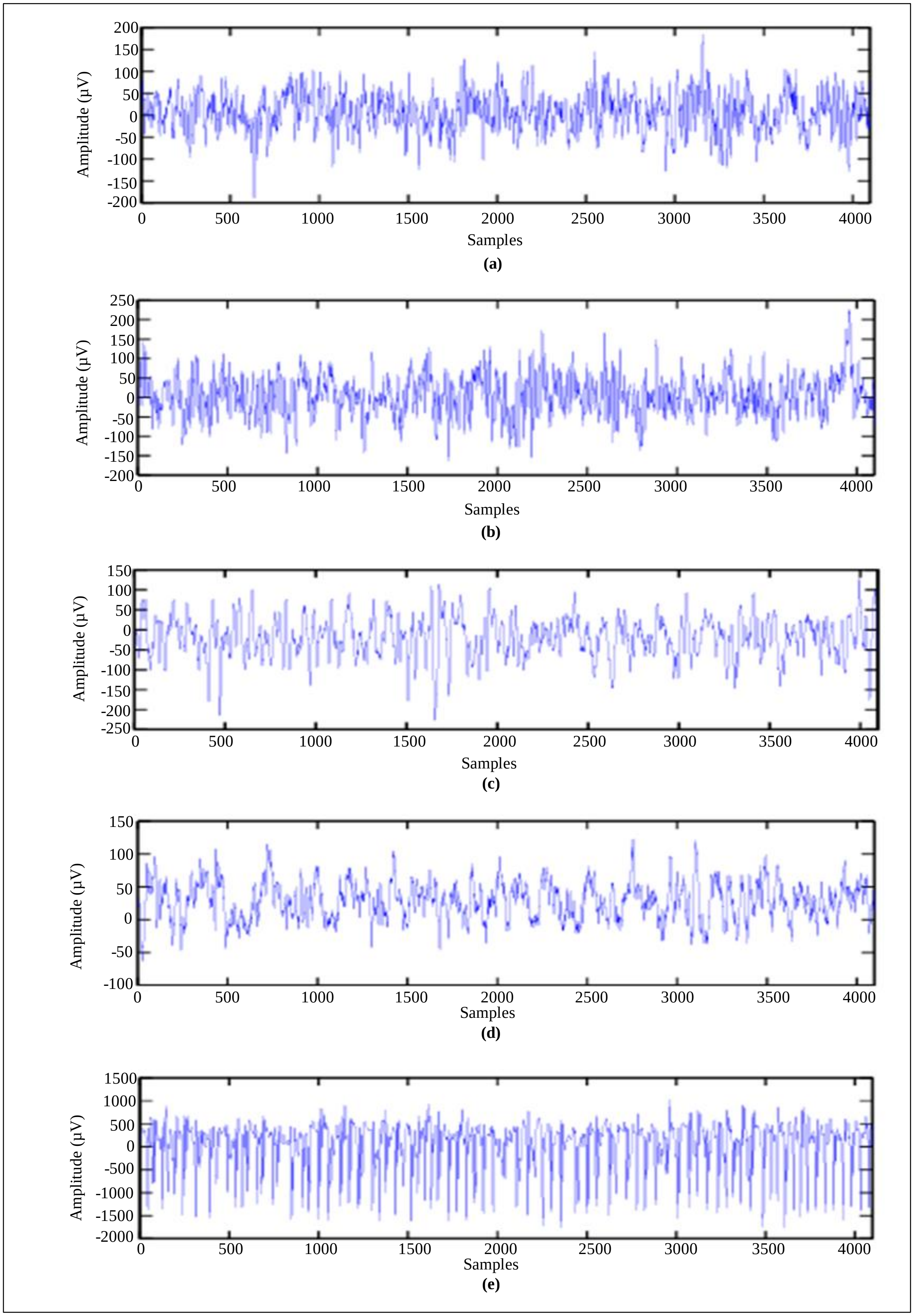

Fig. 7 Segment of groups A, B, C, D and E

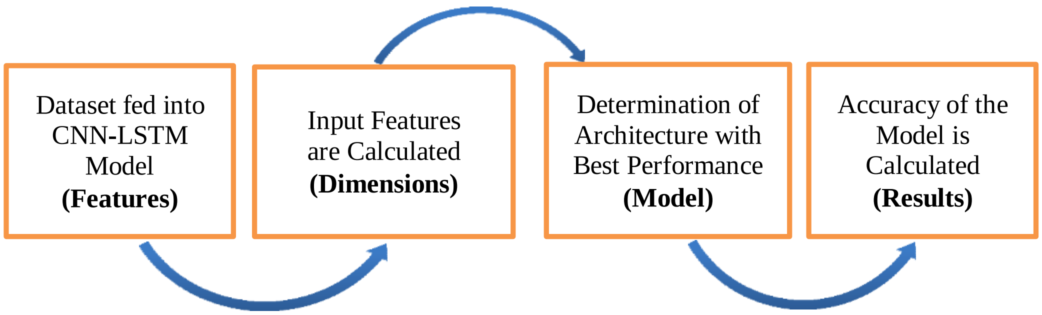

Fig. 8 Flow of proposed system

Table 1. The architecture of the proposed CNN-LSTM model

Types of Layers	Output Shape	Parameters
conv1d_1 (Conv1D)	(None, 4095, 3)	12
lstm_1(LSTM)	(None, 4095, 64)	17408
batch normalisation	(None, 4095, 64)	256
conv1d_2 (Conv1D)	(None, 4093, 6)	1158
global_average_pooling1d_1	(None,6)	0
dense_1 (Dense)	(None,100)	700
dense_2 (Dense)	(None,2)	202
Total Parameters: 19,736 Trainable Parameters: 19,608 Non-trainable Parameters: 128		

Table 2. Results for proposed CNN-LSTM structure on Bonn Electroencephalogram dataset and the Neurology and Sleep Centre in New Delhi, India, dataset

Data Clusters	Accuracy	Sensitivity	Specificity
A-E	99.89	99.5	99.8
B-E	99.21	98	99.42
C-E	98	96	98.01
D-E	97.5	96.9	97.23
AB-E	99.46	99.12	99.11
CD-E	97.43	96.8	98.23
ABCD-E	95.68	96	95.45
AB-CDE	94.76	92.5	97.55
AB-CD	91.04	86.6	95.6
B-D-E	93.67	91.14	94
Ictal-Interictal	97.07	98	96.15
Ictal-Preictal	95.37	94	96
Ictal-Interictal+Preictal	96	95	95.44

5. Results and Discussion

Tensorflow and the Python keras module have been used to test the CNN-LSTM deep learning model's performance. The loss function used to train the model was the categorical cross-entropy function. This loss function allows for parameter updates even when a neuron's output is saturated, making it ideal for classification tasks. These cross-entropy functions averaged over the local minima were found using the Adam mini-batch optimisation approach. The dataset was divided into training and test sets using the k-fold cross-validation process, and the model was initialised and trained [7]. A 64-bit operating system, 8GB of RAM, and an Intel(R) Core (TM) i7-4790 CPU running at 3.6GHz were used for training. Twenty epochs were used to train the model with a batch size of 32. The categorisation challenge involved combining the many groupings found in the Bonn dataset. Distinct data clusters have been established in order to conduct the studies. Utilising accuracy, sensitivity, and specificity, the suggested model's performance has been examined. For all three criteria, data cluster A-E (healthy with eyes open -

seizure) obtained the highest possible result of 99.8 %. Conversely, the interictal seizure data cluster C-E achieved 98% accuracy. 93.67% accuracy in classifying three classes has been achieved. The unbalanced data clusters were balanced using ASYN [8]. They suggested that the authors tested the CNN-LSTM model's robustness by adding Gaussian noise with varying standard deviation (σ) to the EEG waveforms. The metrics of performance acquired for various values of σ and the findings remain the same even with noise included. Even when compared to previous research and both datasets, the proposed model for the Bonn EEG dataset yields good results.

Table 3. Comparing the Bonn EEG dataset with previous studies

Clusters	Methods	Results Accuracy (%)
A-E	Time-frequency statistical features and RF	98.01
	Matrix determinant and MLP	97.12
	Haralick features and Naïve Bayes	99.07
	CNN-LSTM (This study)	**99.89**
B-E	Time-frequency statistical features and KNN	93.58
	GModPCA and SVM	95.83
	Haralick features and Naïve Bayes	98.03
	CNN-LSTM (This study)	**99**
CE	Time-frequency statistical features and Naïve Bayes	96.05
	CNN-LSTM (This study)	**97**
D-E	Time-frequency statistical features and KNN	91.54
	Time-frequency statistical features and CNN	96.95
	Haralick features and Naïve Bayes	96.22
	CNN-LSTM (This study)	**97**
B-D-E	Time-frequency statistical features and BiLSTM	88.92
	CNN-LSTM (This study)	**93.67**

6. Conclusion

The Hybrid version of Convolutional Neural Network and Long Short-Term Memory layers within an automated system for detecting epileptic seizures marks a notable progress in the use of deep learning for diagnostics in medicine.

By testing on diverse datasets like the Bonn EEG dataset and the Neurology and Sleep Centre dataset in New Delhi, India, the model adeptly differentiated between ictal, interictal, and healthy Electroencephalogram signals, as well as various two-class categorisations.

Through rigorous K-fold cross-validation, it was determined that the model achieved peak classification accuracy after 20 epochs, illustrating its robustness and generalisation capabilities. Moreover, the model's ability to withstand noise, demonstrated by injecting noise into the data, underscores its potential for real-world applications where data integrity is challenged. This study highlights the ability of deep learning approaches to advance the accuracy and reliability of epilepsy diagnosis. These methods might be further investigated and improved, which could lead to better patient outcomes and improved healthcare delivery systems globally.

7. Future Work

The proposed system has several potential paths in the future. Even though the suggested system performs well on a benchmark dataset, larger dataset epileptic signal detection will allow for the use of more advanced techniques. By deepening the model and broadening its range of models, the deep model may also be expanded to create a more potent, versatile model.

The proposed system proposes some possible recommendations to investigate the additional study findings, such as based on the experiments conducted as contributions to this thesis: Subsequent investigations may concentrate on hardware-related practical applications that facilitate precise epilepsy diagnosis. Hospitals can also save the models on cloud storage. Because of this, these models may be included in wearable, mobile, or portable apps.

Predictive models would then be used by cloud servers to do the calculations, enabling these devices to prevent patients before they get serious. In the case of an epileptic seizure, alarm messages can be sent to the patient's family, relatives, the concerned hospital, and the doctor via wearables or portable devices. This enables the patient to obtain prompt and appropriate care.

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