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AUTOMATED CLASSIFICATION OF THE EPILEPTIC SEIZURES – A SURVEY ON CONVENTIONAL METHODOLOGIES

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Abstract

Recurrent seizures define epilepsy, an electrical condition of the brain. By recognizing the signals coming from specific brain areas that are damaged, this condition may be identified. By placing a number of electrodes on the brain, an electroencephalogram (EEG) sensor can record these impulses. The signals that are picked up by the brain's damaged areas are focused, whereas the signals that are picked up by its healthy regions are non-focused. Consequently, automated classifications of EEG data are necessary. The limitations of the many standard techniques discussed in this study for the detection and categorization of EEG signals are stated. Using "deep learning (DL)" approaches, a thorough review of studies on automated epileptic seizure identification is provided in this article. A number of techniques are presented for autonomously detecting epileptic seizure utilizing EEG and MRI modalities. The significant difficulties in precise automated epileptic seizure identification utilizing DL with EEG and MRI modalities are explored. We show the benefits and drawbacks of using DL-based approaches to diagnose epileptic seizures. The most promising DL models suggested and potential future research on automated epileptic seizure detection are finally outlined.

Keywords: Epileptic seizure, electroencephalogram (EEG), deep learning (DL)

1. INTRODUCTION

One of the most prevalent neurological illnesses in humans, epilepsy is a non-communicable condition that is often characterised by rapid attacks (Ghassemi et al. [30]). A seizure is a sudden and brief disruption of the brain's normally occurring electrical activity that may affect any area of the body (Shoeibi et al. [7]). More than 60 million individuals worldwide suffer from epilepsy globally (Kulaseharan et al. [31]). Mind-altering symptoms are sometimes triggered by these assaults, which may have devastating harm to the patient's physical condition. In addition, "epileptic seizure (ES)" patients can experience mental anguish as a result of humiliation and an unsuitable social standing. As a result, patients may benefit and have a higher quality of life if ES are detected early (Zazzaro et al. [32]).

There are two key types of functional and structural neuro imaging modalities used in screening strategies for ES diagnosis. Functional neuro imaging offers doctors and neurologists with crucial information on brain function during ES occurrence (Mooij et al. [33], Pianou et al. [34]). The structural neuroimaging techniques give important information to clinicians about the brain anatomy of ES patients. The most significant functional (fMRI) approaches are “EEG (Pirrone et al. [1]), magneto encephalography (MEG) (Feys et al. [2]), positron emission tomography (PET) (Parel et al. [3]), single-photon emission computed tomography (SPECT) (Verger et al. [8]), fMRI, electrocorticography (ECoG), and functional near-infrared spectroscopy (fNIRS)” (Arif et al. [9]). In contrast, “structural MRI (sMRI) and diffusion tensor imaging (DTI)” are key structural neuroimaging methods (Agostinho et al. [10]). The detection of ES often involves the use of functional neuroimaging techniques rather than structural modalities. “Electro encephalogram (EEG)” signals are favoured because they are cheap, easily transportable, and display obvious rhythms in the frequency domain. Bioelectric activity in the brain is measured by the EEG and is represented by voltage fluctuations caused by the ionic current of neurons (Brookes et al. [4]). In order to identify ES, extensive recordings are required. Furthermore, these signals are captured in many channels, complicating the investigation. This will make it difficult for doctors to detect ES using noisy EEG signals (Qureshi et al. [11]). To solve these challenges, investigators are employing EEG, MRI, and DL to identify and predict ES. Systems employ DL for ES diagnosis (Perez-Sanchez et al. [26]). Many machine learning techniques have been developed to identify ES. In traditional machine learning, features and classifiers are selected through trial-and-error. Accurate modeling requires understanding of signal processing and data mining. These models work with minimal data. Increasing data availability may hinder machine learning approaches (Shoeibi et al. [30]). As a result, cutting-edge DL approaches have been used. Unlike traditional machine learning methods, DL models need a lot of data throughout the training process. This is due to the fact that these models include several feature spaces and encounter the issue of over fitting in the absence of data (Craik et al. [35]).

2. A SURVEY ON DEEP LEARNING TECHNIQUES

“Deep neural networks”, in contrast to shallow networks, include more than 2 unknown layer. This growth in network size leads in a large rise in network parameters, necessitating adequate techniques for learning and precautions to minimise over fitting. “Convolutional networks (CN)” convolve input patterns using filters instead of multiplying a weight matrix, reducing trainable parameters (Tanveer et al. [13]). Pooling layers minimise the following convolutional layers (CL's) input size.

2.1 Convolutional Neural Networks

The majority of machine learning research has been focused on one type of the most well-known DL networks, CNNs. They were primarily developed for process the image, but more recently, they have been used to 1D, 2D structures for the detection and forecasting of illnesses utilising biological data. ES detection utilising EEG signals is a common application for this type of DL networks. By using visualisation techniques like spectrograms, higher-order bispectrum, and wavelet transforms, 1D EEG waves are translated into 2D plots for 2D-CNN and used as input.CN receive EEG data as input in a 1D form in 1D design. These networks modify the 2D-basic CNN's design in order to enable it to analyse 1D-EEG data (Pham et al. [27]). Since 1D-CNNs and 2D-CNNs are both used in the identification of ES, each is examined independently.

2.1.1 2D CNN

"Deep 2D networks" are utilised to diagnose COVID-19 in computed tomography scan, X-ray and autistic spectrum disorders in Magnetic resonance imaging**.** Yang et al. [14] Introduced this net to address image categorization issues and immediately employed related network for other tasks, Such as clinical image categorization, to avoid earlier networks' issues and solve more complicated tasks. Figure 1 displays a detection of ES using 2D-CNN.

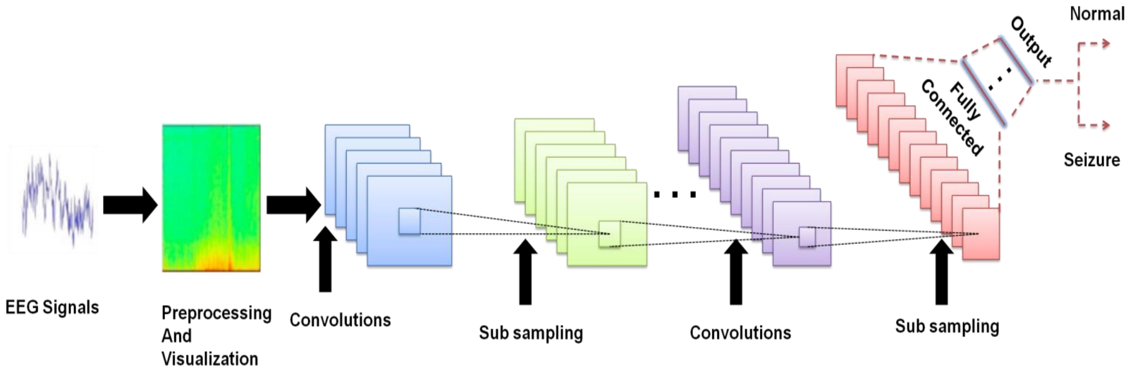

Figure 1: Detection of ES using 2D-CNN

Avcu et al. [36] introduces the SeizNet 16-layer CN, which has extra "dropout layers and batch normalisation (BN)" below every CL. This network has a structure like the "VGG-Net". This study develops an "end-to-end seizure onset detection" solution. They design SeizNet, a CNN for seizure detection. To compare seizNet with classical machine learning, a baseline classifier combining spectrum band power characteristics and SVMs is constructed (BPsvm). EEG data was collected from 29 paediatric patients hospitalised to KK Woman's and Children's Hospital with typical absence seizures. "End-to-end seizure detection" techniques remove feature extraction, which can slow real-time signal processing. Takayanagi et al. [15] were able to diagnose "higher-frequency oscillations (HFO) epilepsy". CL with intense connections is used in a DL framework called SeizureNet, which is introduced in (Naze et al. [16]). Covert et al. [25] proposed a brand-new DL model known as the "temporal graph convolutional network (TGCN)", which consists of five designs with 14, 18, 22, 23, and 26 layers.

2.1.2 One dimensional - Convolutional Neural Network

1D- CNN is well-suited for analysing biosignal like EEG for ES detection. Due to fewer parameters, these systems are simpler and quicker than 2D CNN. The main benefit of one- dimensional; over two-dimensional structure is the ability to use larger pooling and CLs. Furthermore, as signals are 1D in nature, information loss might result from preprocessing techniques used to convert them to 2D. Figure 2 displays a 1D-CNN for seizure detection.

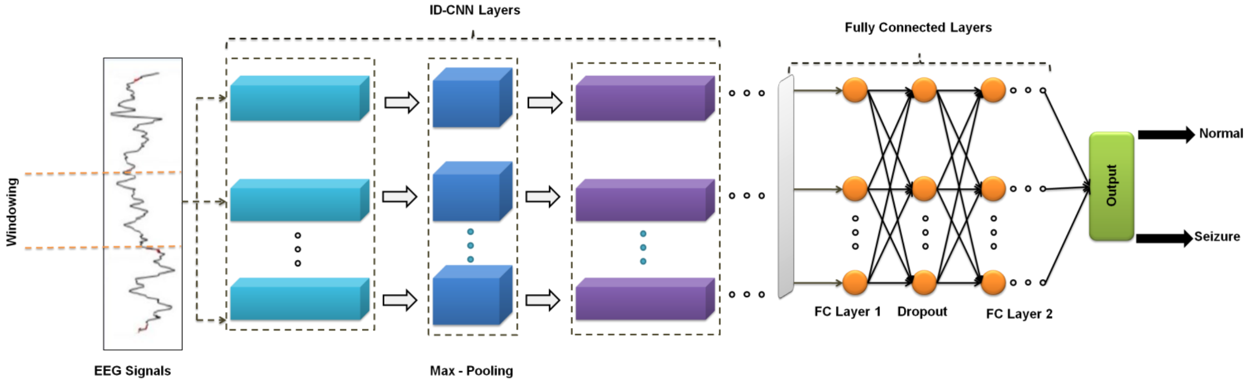

Figure 2: 1D-CNN for seizure detection

1D-CNN was used in (Yildiz et al. [17]) as a method for extracting features. For other tasks, the researchers in (Craley et al. [38]) employed 1D-CNN. The biosignal from each channel were divided into four second intervals using the CHB-MIT dataset overlapping segments were also allowed to boost the information and reliability. They used CNN and the "empirical mode decomposition (EMD)" technique to feature extract in order to complete the multi - classification tasks with good performance. Dataset: Epileptic seizures are diverse. Generalized seizures affect the whole brain, whereas focal seizures start in one location and spread. They test our technique on two heterogeneous datasets. The first involves 90 seizures from 15 adults with “focal epilepsy at Johns Hopkins Hospital (JHH)”. The second is a CHB dataset of undefined epilepsy kinds. 185 paediatric patient recordings were used. They won't analyse DL architectures with wider receptive fields or multichannel CNN training for scalp integration. Combining CNNs with traditional feature extraction methods was investigated in (Yan et al. [18]). Manocha et al. [19] suggest a sequential 1D CNN, together with cutting-edge architectures like the 1D inception module and 1D ResNet module, to categorise time series EEG data as having epilepsy or not. Jaoude et al. [28] presented a paradigm for the identification of ES that combines DL advancements with the capacity to analyse “probabilistic graphical models (PGMs)”. A CNN-BP with a 1D-CNN architecture was proposed. In this study, they made use of patient data tracked using combination “foramen ovale (FO)” and EEG surface electrodes.

2.2 Recurrent Neural Networks

Text, signals, and videos are examples of sequential data that exhibit features like varied and vast duration, making them unsuitable for straightforward DL techniques. The necessity for DL-based techniques to handle various forms of data is compelled by the fact that these data makes up a significant portion of all available information. RNNs, which are often utilised for physiological signals, are the proposed remedy to solve the difficulties.

2.2.1 Long Short-Term Memory

RNN may leave out essential information in long-sequence data because it has trouble in transferring information. Back-propagating gradients create the difficulty. LSTM gates address short-term memory issues (Ghassemi et al. [30]). Information flow may be gated. Gates may retain a lengthy succession of needed data and discard unwanted ones. LSTM relies on cell states and gates. Figure 3 depicts the RNN for epilepsy seizure detection.

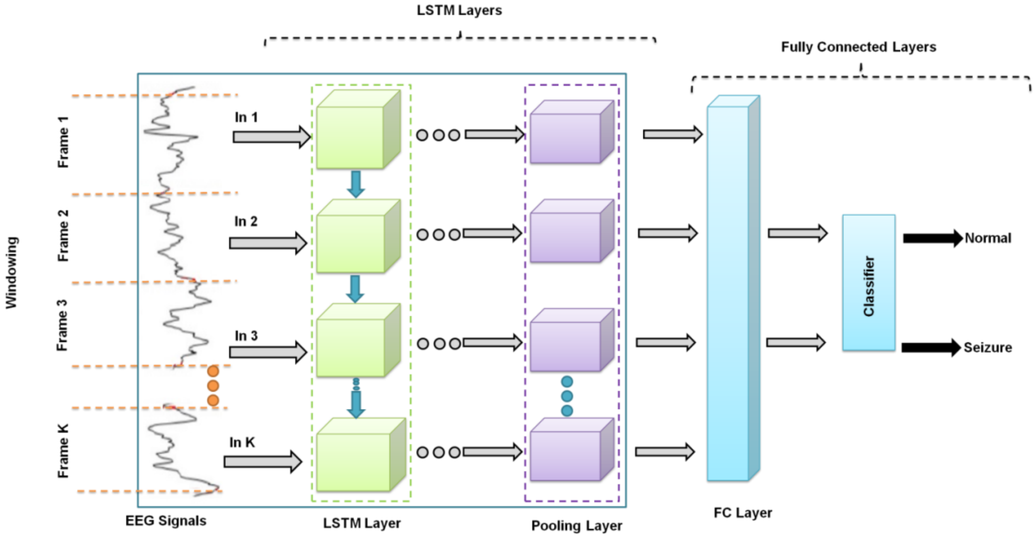

Figure 3: RNN for epilepsy seizure detection.

In this part, Golmohammadi et al. [43] investigated three and four-layer LSTM architectures with the Softmax classifier and found successful performance. This study reports initial TUSZ findings. The training and evaluation corpus was TUSZ. TUSZ was obtained using many generations of Natus EEG equipment under diverse recording conditions. Table 1 indicates overview of TUSZ corpus.

Table 1: Overview of TUSZ corpus

Description	**TUHS**	
	Eval	**Train**
Files	985	1,028
Seizure (S)	17,686	45,649
Non – Seizure (S)	556,033	596,696
Patients	50	64
Session	229	281
Total (S)	601,682	614,382

Deep learning architectures for automated EEG categorization, including a hybrid CNN-LSTM architecture, perform better than other deep structures but don't satisfy clinicians' demands. Ge et al. [21] uses 3-layer LSTMs to extract and classify features. "Last fully connected (FC) layer classification" uses sigmoid active function. Fukumori et al. [40], they used "Long Short-Term Memory and Gated Recurrent Unit". This model contains layers has reshape, four LSTM/GRU, and "one FC layer with sigmoid activator".

2.2.2 Gated Recurrent Unit (GRU)

Input/forgets gates are combined into one revise gate in the GRU variant of the LSTM (Sharifrazi et al. [29]). It combines the input/forgets gates in addition to making modifications. The amount of gating signals is decreased to two. The updating gate is one, and the reset gate is another. Which information needs to be sent to the output is determined by these two gates. Roy et al. [41] used a 5-layer "GRU network with Softmax classifier". They offer ChronoNet, a modular and extensible network architecture for analysing EEG time-series data. The "TUH Abnormal EEG Corpus" comprises clinically "abnormal (AN) and normal (N)" EEG recordings. The "TUH EEG Corpus" is the world's biggest openly accessible database of clinical EEG data. "TUH's EEG Corpus has 23257 sessions from 13551 patients". 75% of the EEG results are AN. The "TUH EEG Abnormal Corpus" was created by manually reviewing 1488 AN and 1529 N EEG sessions. These sets were divided into a training set (1361 AN/1379 N) and a test set (127 AN/150 N). This new RNN architecture exceeds the greatest accuracy on the dataset. The network's characteristics are not sufficient and the more complex model over fits the data.

2.3 Autoencoders (AEs)

AE is a paradigm for unsupervised machine learning when the input and output are same. From the compressed latent-space representation, output is produced. AE combines compression and decompression using a neural network. "Encoder, code, and decoder" comprise AE. AE networks are used to extract or reduce brain signal features. Figure 4 displays an AE used for detect ES.

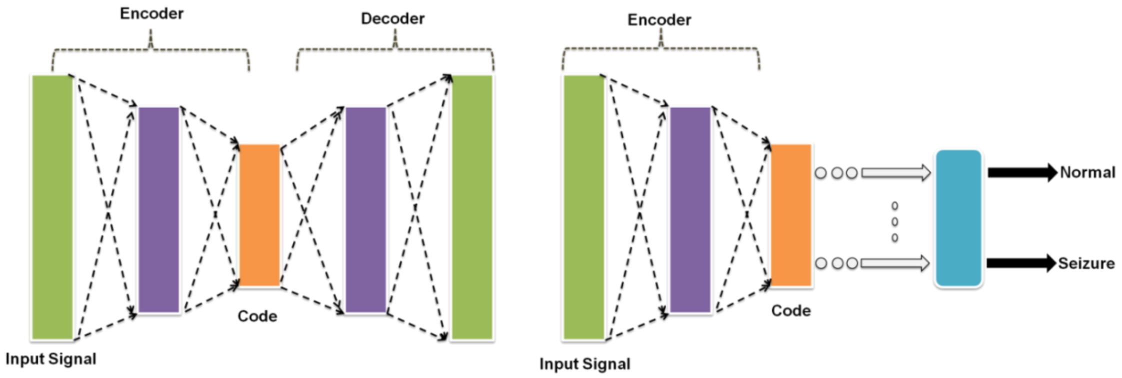

Figure 4: AE for epilepsy seizure detection

Independently examined the "expectation maximisation with principal component analysis (EM-PCA) and multilayer AE (MAE)" approaches to reduce the representation dimensional, and then categorizing data using GA (Ibrahim et al. [6]). Twenty epileptic patients from the "Department of Neurology at Sri Ramakrishna Hospital in Coimbatore, India," were used for the EEG data analysis carried out in this study. Dimensionality reduction approaches worked effectively with GAs. For more accurate epilepsy categorization from EEG data, improvements to genetic algorithms and dimensionality reduction approaches are required. Xu et al. [22] Suggested developing an automated method based on AEs to diagnose epilepsy using EEG data. "Box-counting (BC), multiresolution BC (MRBC), and Katz fractal dimension (KFD)" were used to extract fractal characteristics from each of the frequency sub-bands after the signal had first been decomposed using "harmonic wavelet packet transform (HWPT)".

2.4 Deep Belief Networks (DBNs)

"Deep Boltzmann machines (DBM)" an unguided graphic model are both subtypes of "restricted Boltzmann machines (RBM)". The hidden units could also be connected via the RBM. RBMs are the building blocks of a DBN, which is created by stacking them. DBNs are generative DL models that are probabilistic and unsupervised and include numerous layers of latent and random parameters. "Convolutional DBN (CDBN)" scales high-dimensional models successfully and uses spatial features from surrounding pixels. DBNs are stochastic, dynamic, unsupervised DL models with numerous layers of hidden units that are accessible to the user.

2.5 Convolutional Recurrent Neural Networks (CNN-RNNs)

The CNN-RNN architecture is a powerful DL network combo that is used to forecast and identify ES from EEG information. Because RNN characteristics are better suited for time-series data, adding CLs to RNN aids in successfully locating geographically close patterns. Ambati et al. [5], they utilised several preprocessing approaches and then suggested 13-layer CNN-LSTM architecture with a sigmoid final layer. The recommended method performed better. Different CNN-RNN hybrid designs were employed by Sadeghi et al. [12] to enhance the experimental outcomes. The second network is a “3D CNN-GRU network”. Whereas the previous network has a seven-layer, one-dimensional CNN-GRU convolutions design (Fang et al. [40]) employed the “Inception-V3 network”. A preliminary training was applied on this network. To fine-tune this structural design, an “RNN-based network dubbed spatial temporal GRU (ST-GRU)” was implemented. Dataset: Over 300 hospital, residential, and public video records are collected. Some of these films include many patients in various circumstances. 768 X 512 pixels, 30fps sampling rate. These videos are labelled with epileptic seizure start and finish times. These videos' action lasts 6s to 40s. This dataset is 10:1 for training and assessment. ST-GRU Early epileptic seizure detection and precise seizure initiation time localization are both possible with ConvNets. Data sample, which is inadequate to include more semiology components, is a drawback. Choi et al. [42] suggested a 3D-CNN with RNN to identify ES. The RNN module uses the CNN module's output. The RNN module has a “unilateral GRU layer” that extracts ES temporal features, which are categorised by an FC layer.

2.6 Convolutional Autoencoders (CNN-AEs)

CLs may decrease the amount of parameters in structures like AEs in addition to discovering neighbouring patterns. Due to these two factors, its combination is appropriate for a variety of tasks, including “unsupervised feature extraction” for ES detection. Jana et al. [23] proposed a CNN-AE-based technique. The “supervised and unsupervised features” were extracted using AE and 2D-CNN. Un - supervised characteristics were created from input signals and supervised from the spectrogram. For categorization, Softmax was used. Wei et al. [24] presented a “deep fusional attention network (DFAN)” to extract “channel-aware EEG” representations. They created a fusional attention layer that employed a fusional gate to combine multi-view data to dynamically estimate biological channels contributions. The integrated DL model was trained using a “multi-view convolution encoding layer and CNN”. Dataset: CHB-MIT. Using the open “CHB-MIT dataset” made available by “Children's Hospital Boston”, they carried out the job of multi-channel EEG seizure identification. The 23-channel, 256 Hz EEG waveforms in this dataset. Medical professionals meticulously label each seizure. They produced 252, 862 input vectors from all 23 patients using the segmentation experience, setting the window size and step length to 1 second. It was demonstrated through experiments, “FusionAtt” was effective in fusing channel-aware data from multi-channel biosignals. It interpreted clinical observations by assessing biological channel contributions. It can be used in various task-oriented applications where channel awareness is an issue. The following table indicates the listing of current works.

3. COMPARISON OF EXISTING ALGORITHM

San-Segundo et al. [37] introduced a “new 2D-CNN model” can extract spectrum and chronological EEG data to comprehend seizure structure. By combining 16-layer 2D-CNN with EEG recordings. Dataset: “Bern-Barcelona EEG and Epileptic Seizure Recognition (ESR)” were utilised. Both datasets were utilised to compare “EEG signals from epileptic and non-epileptic brain regions”, however only the ESR dataset was used to detect epileptic seizures. The Fourier transform was excellent for seizure identification because seizure signals had a distinct energy distribution pattern than other signals. Combining all transforms produced somewhat better results, but not statistically better than separate transforms. Covert et al. [25] presented a novel DL model that they referred to as the “temporal graph convolutional network (TGCN)”. This model is comprised of five different architectures that each include 14, 18, 22, 23, and 26 layers. Craley et al. [39] develop a “probabilistic graphical model-convolutional neural network (PGM-CNN)” for EEG seizure tracking. Our model uses deep learning to analyse raw EEG time series while maintaining therapeutically useful information with a latent PGM prior. Our hybrid model is validated using EEG data from two hospitals with different patient groups. Dataset: The first is a collection of ninety seizures from fifteen adult patients with focal epilepsy that was obtained from the “Johns Hopkins Hospital (JHH)”. Our PGM-CNN outperformed all baseline approaches in terms of AUC and true positive detection. The need for modelling enhancement, such as limitations on permitted onsets and enforcement of contemporaneous offsets across channels, is an ongoing area of research. Lin et al. [48] introduced a new framework for the automatic detection of epileptic EEG by combining SSAE with a softmax classifier. This allowed us to detect epileptic EEG more accurately. The experimental information was obtained from the University of Bonn's epileptology department [13]. The entire database is made up of five subsets, each of which has hundred single-channel EEG segments with duration of 23.6 seconds. A 128-channel amplifier was used to capture each segment, and the data was then digitally converted at a sampling rate of 173.61 Hz. The experiment results show that the framework performed well, achieving 96% accuracy. There aren't enough experiments applying the suggested framework with different EEG datasets. Different CNN-RNN hybrid designs were employed by Roy et al. [45] to enhance the experimental outcomes. The second network is a “3D CNN-GRU network”, while the first network has a seven-layer, one-dimensional CNN-GRU convolution design. Four distinct DL structures were proposed by Roy et al. [44], who focused on normal and pathological brain activity. Utilizing earlier models, the proposed ChronoNet model was created. Its test and training accuracy was 90.60% and 86.57%, respectively. Golmohammadi [43] describe a multi-component high-performance automated EEG analysis system based on big data and ML concepts. Three routes are then used for precise detection once the signal features have initially been extracted using LPCC coefficients (linear predictive cepstral coefficients). Hidden Markov models (HMMs) are used for sequential decoding in first pass, DL is used for “temporal and spatial context analysis” in the second pass, and a “probabilistic grammar” is used in the third pass. To reduce the representation dimensions and subsequently use the GA for classification, Rajaguru et al. [46] separately surveyed the “multilayer AE (MAE)” and “expectation-maximization with principal component analysis (EM-PCA)” approaches. To reduce the representation dimensions and subsequently use the GA for classification, they separately surveyed the” multilayer AE (MAE)” and EM-PCA. Golmohammadi [20] provides an ML-and-big-data-based EEG analysis approach. Three approaches are utilised to identify signals using LPCC coefficients. First, sequential decoding with HMMs, then context analysis with DL, and ultimately probabilistic grammar. Yuan et al. [47] presented a novel strategy based on CNN-AE. Two deep techniques, “AE and 2D-CNN”, were utilised to extract the “supervised and unsupervised features (SF & UF)”, respectively, at the feature extraction step. The SF were acquired using the spectrogram of the signals, while the UF were directly acquired from the input signals. Finally, classification was done using the Softmax classifier.

Table 1: Listing of current works

S. NO	Network used	No. of. layers	Classifier	Accuracy
1	2D-CNN [37]	9	Softmax	98.05
2	TGCN [25]	22	Sigmoid	NA
3	PGM-CNN [39]	10	Softmax	NA
4	GRU [41]	5	Softmax	NA
5	SSAE [48]	3	Softmax	100
6	TCNN-RNN [45]	10	Softmax	95.22
7	MAE [46]	NA	GA	93.92
8	ChronoNet [44]	14	Softmax	90.60
9	EYEM-SDA [20]	3 hidden layer	LR	NA
10	CNN-AE [47]	10	Softmax	94.37

The table shows existing works of ES detection based on DL techniques like CNN includes “2 dimensional CNN, 1dimensional CNN. Recurrent Neural Networks (RNNs) includes Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU). Autoencoder, Deep Belief Networks (DBNs), and Convolutional Recurrent Neural Networks (CNN-RNNs), Convolutional Autoencoders (CNN-AEs)”.

4. CONCLUSION

DL techniques have been extensively studied in the area of ES detection in recent years. This study presents a thorough assessment of research on ES detection utilising several DL approaches, such as CNNs, RNNs, and AEs. Using MRI and EEG modalities, several screening techniques have been created. Future study will focus heavily on hardware, which will help with accurate illness identification. Functional hardware boosts detection algorithms. Hospitals may store models on the cloud. Such models may be used in portable applications, smartphone or smart devices, and cloud servers conduct the computations. By using forecast models, these gadgets help prevent patients in a timely way. By using portable gadgets or wearable to detect ES, the patient may receive timely treatment. A cap containing EEG electrodes may send EEG readings to a cloud-based model for timely detection. If we can identify seizure early utilising interictal EEG data, the patient may take medicine to avoid it.

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