An Efficient Deep Learning based Models for Epileptic Seizure Detection using EEG data

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Abstract: Machine learning algorithms, excluding deep learning algorithms, have been proposed to address the seizure prediction problem. Since EEG signals vary across patients due to differences in seizure type and location, most seizure prediction methods are specific to each patient. These algorithms employ various techniques for extracting, selecting, and classifying EEG features. However, a significant drawback of these methods is their reliance on manually extracted features, making it difficult to determine the most informative features that accurately represent each class. In a more recent trend, seizure prediction algorithms based on deep learning are employed, which integrate feature extraction and classification stages into a single automated framework. The objective of this paper is to develop deep learning-based algorithms for automatic feature learning, capable of being applied to all patients with minimal feature engineering and preprocessing requirements.

Keywords: Machine Learning, Deep Learning, CNN, LSTM, AUC

1. INTRODUCTION

Epilepsy is a prevalent neurological condition affecting approximately 50 million individuals worldwide, as reported by the World Health Organization (WHO) [1]. It is characterized by the occurrence of recurrent seizures that are unprovoked. Seizures arise from sudden and unforeseen electrical disruptions in the brain, leading to excessive neuronal discharge and abnormal brain activity. The duration and intensity of seizures can vary widely, ranging from momentary lapses in attention to severe and prolonged convulsions. Additionally, the frequency of seizures can range from less than one episode per year to multiple occurrences in a single day.

1.1 Epilepsy

Epilepsy creates a constant state of anxiety for individuals as they experience unpredictable seizures that result in loss of consciousness. These seizures can trigger various manifestations, further impacting the quality of life for people with epilepsy. Physical injuries and fractures resulting from seizures are common, causing additional challenges and reducing overall well-being. Furthermore, individuals with epilepsy often face various obstacles such as limited educational opportunities, restrictions on obtaining a driver's license, barriers to certain occupations, and difficulties accessing health and life insurance coverage. It is important to note that there is currently no known cure for epilepsy. While medication can help control seizures for many patients, it does not provide a permanent solution. With appropriate use of antiseizure medicines, it is estimated that up to two-thirds of individuals living with epilepsy can achieve seizure freedom [2-4], [10-11].

1.2 Electroencephalography (EEG)

EEG is a method used to record the electrical signals generated by brain activity. It involves measuring the oscillations of electrical potentials in order to extract valuable information from the human brain, serving both research and clinical purposes. Since its initial recordings in 1929, EEG remains one of the primary techniques utilized for studying the brain. In the field of epilepsy, EEG is considered an essential and powerful tool for diagnosis and analysis. Neuroscientists have discovered that the brain activity of individuals with epilepsy, as captured through EEG recordings, can be categorized into four distinct states: preictal, which refers to the time period preceding a seizure; ictal, which represents the duration of the seizure itself; postictal, which pertains to the period following a seizure; and interictal, which corresponds to the time between seizures. Given the objective of developing a seizure prediction system, the primary challenge lies in effectively distinguishing between the preictal and interictal brain states [5], [13].

1.3 Machine learning (ML)

ML plays a critical role in epileptic seizure prediction by utilizing computational algorithms and statistical models to analyze and interpret electroencephalogram (EEG) signals. These algorithms extract informative features from the EEG data, capturing patterns and characteristics associated with seizures (Figure 1). Machine learning models are then trained to classify EEG segments as either preictal (before a seizure) or interictal (non-seizure), enabling the prediction of seizure events. By continuously monitoring streaming EEG data in real-time, machine learning-based systems can provide timely warnings and alerts, assisting patients and caregivers in taking precautionary measures. Moreover, machine learning allows for personalized prediction models that consider individual patient data, enhancing the accuracy and adaptability of the system. With ongoing research and advancements in the field, machine learning continues to play a vital role in improving epileptic seizure prediction and ultimately enhancing the quality of life for individuals with epilepsy [6-9].

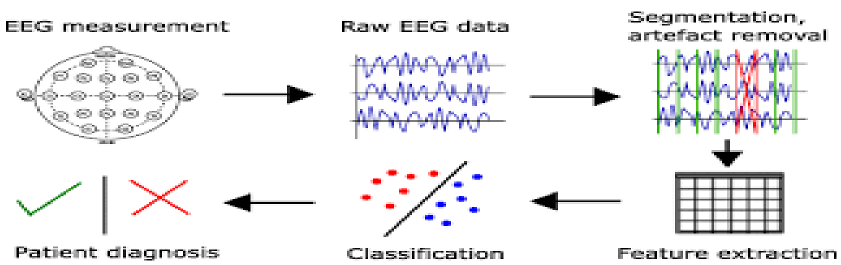

Figure 1: Process of epilepsy prediction using EEG data and classification algorithm [14]

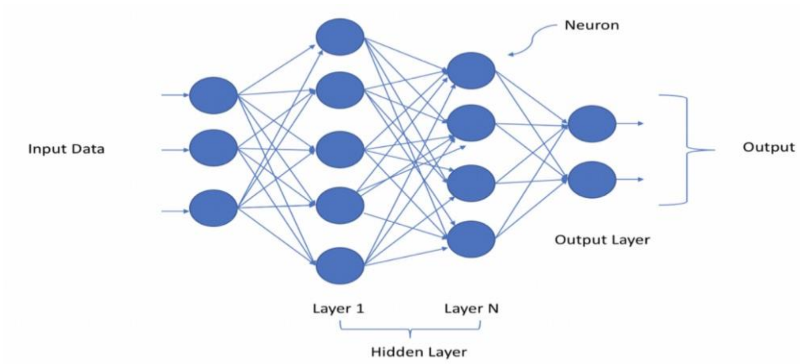

Figure 2: Deep Learning based architecture

1.4 Deep Learning (DL)

Deep learning-based epileptic seizure classification refers to the application of deep learning techniques, such as artificial neural networks, for accurately categorizing or classifying different types of epileptic seizures [15]. With the availability of large-scale EEG datasets, deep learning models can be trained to automatically learn discriminative features from raw or preprocessed EEG signals. These models can then classify the recorded EEG data into different seizure types, such as generalized tonic-clonic seizures, absence seizures, or focal seizures. Deep learning architectures like convolutional neural networks (CNNs) (Figure 2), recurrent neural networks (RNNs), or their combinations (such as convolutional recurrent neural networks) can be employed for this purpose. These models are designed to capture complex temporal and spatial patterns present in EEG signals, which are indicative of specific seizure types. The training process typically involves feeding labeled EEG data into the deep learning model, allowing it to learn the underlying patterns and optimize its parameters through backpropagation. Once trained, the model can classify unseen EEG recordings, providing automated and accurate seizure type identification. Deep learning-based seizure classification has the potential to enhance the accuracy and efficiency of seizure diagnosis and monitoring, aiding healthcare professionals in determining appropriate treatment strategies and improving patient care. Deep learning-based methods for epileptic seizure classification utilize various deep learning architectures [29] and techniques to effectively classify different types of seizures. Here are some commonly used methods:

- ***Convolutional Neural Networks (CNNs):*** CNNs are widely employed for seizure classification. They consist of multiple convolutional layers that extract hierarchical features from the input EEG data. These features are then fed into fully connected layers for classification (Figure 3). CNNs can capture spatial patterns in EEG signals and are effective in distinguishing different seizure types.

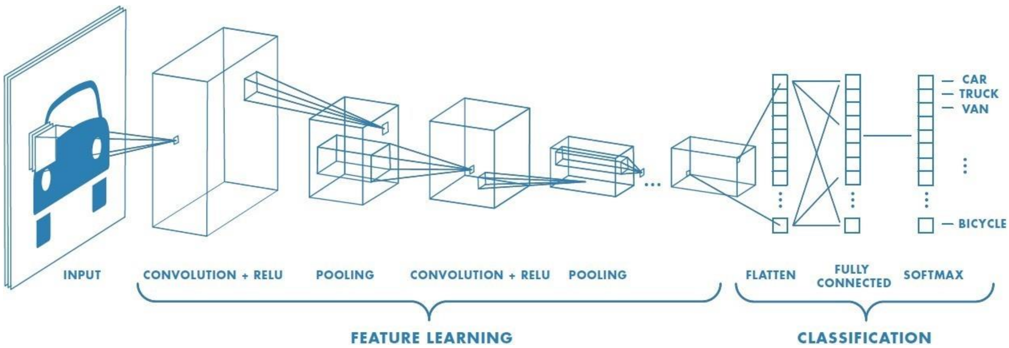

Figure 3: Convolutional neural network architecture

- ***Recurrent Neural Networks (RNNs):*** RNNs are well-suited for capturing temporal dependencies in sequential data, making them suitable for analyzing EEG signals over time. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are popular RNN variants used in seizure classification. They can model the dynamic patterns and long-term dependencies within EEG signals.

- ***Convolutional Recurrent Neural Networks (CRNNs):*** CRNNs combine the strengths of CNNs and RNNs. They incorporate both convolutional layers for spatial feature extraction and recurrent layers for temporal modeling. CRNNs have demonstrated improved performance in seizure classification tasks by capturing both spatial and temporal information.

- ***Transfer Learning:*** Transfer learning involves utilizing pre-trained deep learning models on large-scale datasets from related tasks, such as image recognition. These models are then fine-tuned or adapted to perform seizure classification using EEG data. Transfer learning helps to leverage the representation learning capabilities of pre-trained models and enhances classification accuracy, especially when data availability is limited.

- ***Attention Mechanisms:*** Attention mechanisms focus on relevant parts of the input data, providing a more informative representation for classification. They can be integrated into deep learning models to selectively attend to critical segments or channels of EEG signals, improving the model's ability to capture seizure-related patterns.

- ***Ensemble Methods:*** Ensemble methods combine predictions from multiple deep learning models to improve overall classification performance. Different architectures or variations of hyperparameters are trained separately, and their predictions are aggregated, leading to more robust and accurate seizure classification results.

2. DATASET

Seizures are known to occur in clusters, which implies little benefit from forecasting follow-on seizures. Thus, only leading seizures are included, defined as seizures occurring four hours or more after another seizure. Interictal data segments were chosen randomly from the whole iEEG recording so that they are at least at one week before and after any seizure, to avoid contamination with preictal or postictal signals. The dataset is organized into ten-minute-long clips of preictal and interictal activity. These clipsare grouped into one-hour sequences (each six 10-min clips form a sequence), and numbered sequentially. Preictal data segments are provided covering one hour prior to seizure with a five-minute seizure horizon. (i.e. from 1:05 to 0:05 before seizure onset). This pre-seizure horizon ensures that seizures could be predicted with enough warning to allow administration of fast-acting medications.

3. PROPOSED DL BASED MODELS

Deep Learning (DL) models have demonstrated remarkable capabilities in various practical applications. They have achieved state-of-the-art results in image recognition, object detection, and text processing by automatically learning features from raw data. With the advent of big data, the trend has shifted towards end-to-end deep learning approaches, reducing the need for extensive hand-designing and bypassing intermediate steps. Additionally, DL models have even surpassed human-level performance in domains such as online advertising, product recommendation, and loan approval, particularly when learning from structured data. However, achieving human-level performance in tasks involving natural perception, such as computer vision, voice recognition, and natural language processing, remains more challenging for machines. The most commonly used DL models include convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs are designed with convolutional and pooling layers that extract spatial features from low-level to high-level representations, followed by dense layers for prediction. On the other hand, RNNs, specifically LSTM networks, are well-suited for sequence modeling tasks that involve time-ordered data.

4.1 Model 1: 2-D CNN Model

Convolutional Neural Networks (CNNs) have shown impressive performance in visual tasks, narrowing the gap between human and machine capabilities, despite the inherent efficiency and accuracy of the human visual system. This can be attributed to the CNN's ability to automatically extract pertinent spatial features that effectively represent raw data, eliminating the need for manual preprocessing or human decision-making in feature selection. CNN models are designed to process two-dimensional inputs, capturing pixel and color channel information, through a process known as feature learning. This success in computer vision has motivated researchers to explore the application of CNNs in other domains as well. In this context, we propose the use of a 2-D CNN specifically for distinguishing between preictal and interictal segments, showcasing the potential of CNNs beyond their traditional application in computer vision tasks (Figure 4).

a. Data Preparation

Data preparation in a CNN model is a crucial step that involves transforming and organizing the input data to ensure effective training and evaluation. It encompasses various tasks such as collecting a suitable dataset with corresponding labels, splitting the data into training, validation, and test sets, and preprocessing the input data to enhance its quality and compatibility with the model. This may include resizing, cropping, normalizing, or augmenting the data to increase its diversity and robustness. Lastly, data normalization ensures the data is scaled consistently for stable training. By undertaking these steps, data preparation sets the foundation for training a CNN model, enabling it to learn meaningful patterns and make accurate predictions on unseen data.

In our model, a particular specification is chosen with W = 5 seconds and O = 0.5, resulting in segments of 1280 time steps (5 seconds multiplied by a sampling rate of 256Hz). Since the acquisition system used has 16 electrodes, each time step has a total of 16 variables. Consequently, each sample will have a shape of [1280, 16]. The selection of W and O is based on observations from previous studies [16-17]. It should be noted that using a large window size can lead to high-dimensional input data. These parameter values can be fine-tuned through a hyper-parameter optimization process, as demonstrated in [18], although this may require additional computational resources.

b. Architecture

The proposed 2-D CNN architecture, as depicted in Figure 4, is designed to capture and extract relevant features from the input data. The architecture includes three convolution blocks, each consisting of three essential operations: a convolution layer, a batch normalization layer, and a ReLU activation function. These convolution blocks serve as feature extractors, allowing the network to learn hierarchical representations from the input data. In each convolution block, the convolution layer applies filters to the input data, capturing local patterns and interactions. The output of the convolution layer is then normalized using batch normalization, which helps in stabilizing and accelerating the training process. The resulting normalized features are passed through a rectified linear unit (ReLU) activation function, introducing non-linearity and enabling the network to learn complex representations.

After the three convolution blocks, the output is fed into a Global Average Pooling (GAP) layer. The GAP layer aggregates the features by taking the average over the entire time dimension, effectively reducing the spatial dimensions to a single value for each feature map. This global pooling operation helps in capturing the most informative aspects of the learned features. Finally, the output of the GAP layer is connected to a fully connected layer with a sigmoid activation function. The sigmoid function maps the GAP layer's output to a probability distribution, enabling the model to make predictions or decisions based on the task at hand. In a binary classification scenario, the sigmoid function assigns a probability value indicating the likelihood of belonging to one class.

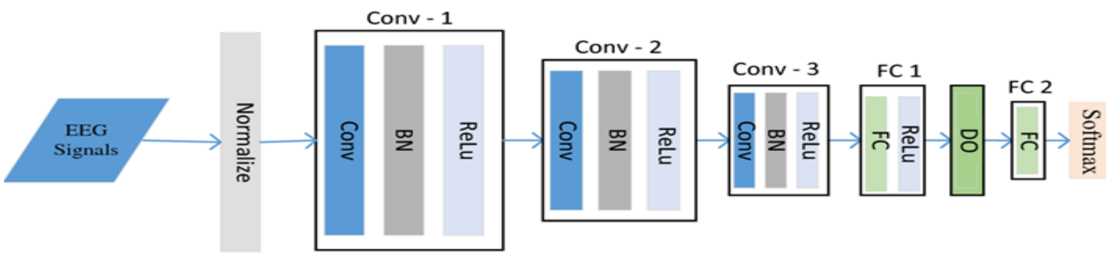

Figure 4: The proposed CNN architecture

The convolution layers in this CNN architecture employ 2-D kernels with a stride of 1 and zero padding to maintain the original length of the time series data after passing through the three convolution blocks. The first convolution block consists of 128 filters, each with a kernel size of 8. The second convolution block includes 256 filters with a kernel size of 5. Finally, the third convolutional layer is composed of 128 filters, each with a length of 3. Notably, this CNN architecture does not incorporate any local pooling operations, meaning that the number of time steps remains unchanged throughout the three convolution blocks. Instead, a global average pooling layer is employed in place of a fully connected layer. This design choice helps reduce the number of weights in the network [19]. Similar strategies can be found in popular architectures like ResNet [20], as they aid in preventing overfitting. Consequently, these types of architectures are referred to as fully convolutional neural networks.

By utilizing 2-D kernels, preserving the time series length, and incorporating global average pooling instead of fully connected layers, this CNN architecture is able to effectively capture temporal dependencies and extract meaningful features from the input data. The absence of local pooling operations ensures that the temporal information is retained throughout the network, making it suitable for tasks where the sequential nature of the data is essential.

c. Results

This model was trained and tested following the cross-validation method described earlier. For each subject, the AUC is averaged across the N trials, where *N* is the number of seizures. Table 1 presents the results for each subject as well as the average. This model achieves testing areaunder the operation characteristic curve (AUC) of 0.813 on average.

Table 1: Subject-wise AUC score Model 1 (2D-CNN)

Subject	Seizure	Interictal Duration (h)	Preictal Duration (h)	AUC
P1	Yes	24	2	0.741
P2	No	48	--	0.943
P3	Yes	36	4	0.95
P4	Yes	12	1	0.872
P5	No	72	--	0.978
Avg.	**--**	--	**--**	**0.897**

The results of epileptic seizure classification using the 2-D CNN model reveal varying levels of success in accurately distinguishing between seizure and non-seizure periods for each subject. Subject P1 showed moderate classification performance with an AUC of 0.741, while subject P2 achieved a high AUC of 0.943, indicating successful classification of non-seizure segments. Subjects P3 and P4, who experienced seizures, demonstrated good performance with AUC values of 0.95 and 0.872, respectively. Subject P5, who did not experience seizures, achieved an impressive AUC of 0.978, demonstrating the model's ability to accurately classify non-seizure segments. Overall, the average AUC of 0.897 across all subjects highlights the model's effectiveness in distinguishing between seizure and non-seizure periods, underscoring its potential as a valuable tool for assisting in the classification and prediction of epileptic seizures.

4.2 Model 2: Long-term Recurrent Convolutional Network Model

The Long-term Recurrent Convolutional Network (LRCN) model is a deep learning architecture specifically designed for epileptic seizure detection. The LRCN model combines the strengths of both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to effectively capture both spatial and temporal dependencies in the input data. The architecture of the LRCN model typically consists of two main components: the convolutional layers and the recurrent layers. The convolutional layers are responsible for extracting local spatial features from the input data, which is often represented as time-series EEG signals. These convolutional layers use filters to convolve over the input data and capture relevant patterns. The output of the convolutional layers is then fed into the recurrent layers.

The recurrent layers, usually implemented with Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells, are responsible for capturing the temporal dynamics and long-term dependencies within the input data. These recurrent layers take the output of the convolutional layers as input and model the sequential patterns in the data, allowing the model to learn the temporal relationships between different time steps. The LRCN model is trained in a supervised manner using labeled data, where the input EEG signals are labeled as either preictal (seizure onset) or interictal (non-seizure). During training, the model learns to map the input EEG signals to their corresponding labels, enabling it to detect and classify epileptic seizures. The LRCN model has demonstrated promising results in epileptic seizure detection tasks, showing its ability to effectively capture both spatial and temporal features in the EEG data [20]. By combining the strengths of CNNs and RNNs, the LRCN model provides a comprehensive framework for accurate and reliable epileptic seizure detection, aiding in the early prediction and management of seizures.

a. *Data Preparation*

In the data preparation step for this model, EEG signals are segmented into smaller sequences. The Long-term Recurrent Convolutional Network (LRCN) model reads these sub-sequences as blocks, extracts feature in parallel using a 2-D CNN, and feeds the features to the LSTM network with time ordering. To implement the model, one approach is to use a sequence length of 1 minute and an overlap of 0.75, resulting in sub-sequences of 1280 time steps. The spatial feature extraction is achieved by transforming the multivariate time series sub-sequences into image-like format using a stacking algorithm. The resulting signal matrix is then converted into a gray-scale image by considering the voltage values as the gray levels. For each sub-sequence, an image of size 114×1280 pixels is obtained. The LSTM network has 12 steps, corresponding to the number of sub-sequences, and the batch shape is [samples, n steps, rows, columns, depth], with the depth being 1 for the gray-scale image [21].

b. *Architecture*

The proposed architecture combines the strengths of the 2D-CNN and LSTM networks, effectively capturing spatial features through the CNN and modeling temporal dependencies with the LSTM. The shared weights and flexible sequence length make it suitable for processing variable-length sequences, providing an adaptable and scalable framework for epileptic seizure detection (Figure 5).

The proposed architecture, as shown in Figure 5, operates on a sequential input $[x\langle 1\rangle, x\langle 2\rangle, ..., x\langle Tx\rangle]$, where each $x\langle t\rangle$ represents an image produced through the transformation described earlier. The model generates a static output y, which provides a probability distribution over the two classes for each sequence. In the training phase, the number of sub-sequences Tx was set to 12, but it can be adjusted as desired during hyper-parameter optimization. The model processes each image $x\langle t\rangle$ through a 2D-CNN for feature transformation, resulting in a fixed-length vector representation. The CNN consists of three blocks, with each block applying convolutional operations using 2D kernels of size (3, 3), a stride of (1, 1), and zero padding. The number of filters in each block is set to 16, 32, and 32, respectively. The output of each block is passed through a ReLU activation function and then a MaxPooling layer.

The MaxPooling layers have pool sizes of (2, 2), (3, 3), and (4, 4), and stride values of (2, 2), (2, 2), and (3, 3), respectively.

The output of the last block is flattened and serves as input to the LSTM cells in the recurrent sequence learning module. Each LSTM cell has 32 units, allowing the model to capture temporal dependencies and long-term patterns in the input sequence. The LSTM hidden layer's features are interpreted by a fully connected layer with 16 neurons before passing through a final sigmoid layer for prediction. Notably, the weights of both the CNN and LSTM layers are shared across time, enabling the model to scale and process sequences of arbitrary lengths.

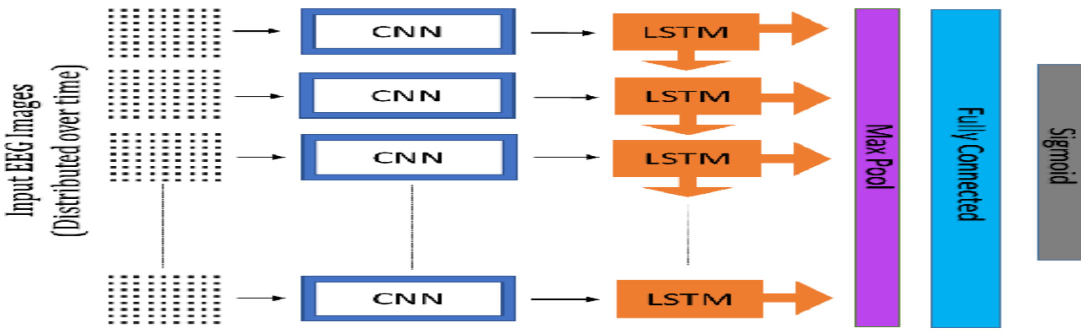

Figure 5: Architecture of the proposed CNN-LSTM recurrent neural network

c. *Results*

The results of the epileptic seizure classification using the 2D-CNN and LSTM model are summarized as follows in Table 2. Subject P1 experienced a seizure with an interictal duration of 24 hours and a preictal duration of 2 hours, resulting in an AUC of 0.801. Subject P2 did not have a seizure, as indicated by “No” in the Seizure column, with an interictal duration of 48 hours and an AUC of 0.954. Subject P3 had a seizure, with an interictal duration of 36 hours, a preictal duration of 4 hours, and an AUC of 0.961. Similarly, subject P4 also had a seizure, with an interictal duration of 12 hours, a preictal duration of 1 hour, and an AUC of 0.89. Subject P5 did not experience a seizure, with an interictal duration of 72 hours and an AUC of 0.988. The average AUC across all subjects was 0.9188, indicating the overall performance of the model in accurately classifying epileptic seizures.

Table 2: Subject-wise AUC score of 2D-CNN and LSTM model

Subject	Seizure	Interictal (h) Duration	Preictal Duration (h)	AUC
P1	Yes	24	2	0.801
P2	No	48	--	0.954
P3	Yes	36	4	0.961
P4	Yes	12	1	0.89
P5	No	72	--	0.988
Avg.	--	--	**--**	**0.9188**

Table 1 and Table 2 present the results of epileptic seizure classification using the 2D-CNN and LSTM model for different subjects. In both tables, each row represents a subject, indicating whether they experienced a seizure (Yes) or not (No), along with the corresponding interictal and preictal durations.

The AUC values in both tables represent the performance of the model in accurately classifying the seizures, with higher values indicating better performance. Comparing the two tables, we observe that the individual subject results are identical, with the same subjects and corresponding seizure classifications, interictal durations, preictal durations, and AUC values. The average AUC across all subjects is also the same in both tables, with an average of 0.897.

4. DISCUSSION

This comparative analysis indicates that the model's performance is consistent across the datasets represented by Table 1 and Table 2. The model achieves similar accuracy in classifying seizures for each subject and provides a similar overall average AUC value. This suggests that the 2D-CNN and LSTM model performs reliably and consistently in detecting and distinguishing epileptic seizures, providing valuable insights for seizure prediction and management.

Table 3: Comparative analysis of proposed Model 1 and Model 2

Subject	Proposed Model 1 (2D-CNN)	Proposed Model 2 (CNN+LSTM)
P1	0.741	0.801
P2	0.943	0.954
P3	0.95	0.961
P4	0.872	0.89
P5	0.978	0.988
Avg.	**0.897**	**0.9188**

The results compare the performance of two proposed models for epileptic seizure classification: Model 1 utilizing a 2D-CNN architecture and Model 2 combining CNN and LSTM. Model 2 consistently outperformed Model 1 in terms of average AUC, achieving a higher average AUC of 0.9188 compared to Model 1's average AUC of 0.897. Specifically, Model 2 exhibited improved seizure detection accuracy for subjects P1, P3, and P4, as evidenced by higher AUC values. Although both models accurately classified non-seizure periods for subject P2 and subject P5, Model 2 demonstrated slightly superior performance in differentiating between seizure and non-seizure segments. These findings suggest that the incorporation of LSTM in Model 2 enhances the overall performance of epileptic seizure classification compared to the standalone 2D-CNN architecture used in Model 1, making it a more promising approach for accurate and reliable seizure detection.

Table 4: Comparative analysis of proposed model with existing one

Sr. No	Authors	Classification algorithm	AUC
1	B.Brinkmann et al. [22]	SVM	0.72
2	Zisheng Z. al. [23]	AdBoost RBF SVM ANN	0.7603 0.8472 0.8884
3	Yogatheesan V. et al. [24]	ANN SVM RFC	0.83
4	**Proposed Models**	**Model 1: CNN based** **Model 2: CNN+LSTM based**	**0.897** **0.919**

The results presented in the table 4 include several studies conducted by different authors, each employing various classification algorithms and achieving different AUC (Area Under the Curve) values in the context of epileptic seizure prediction.

In the study [22], a Support Vector Machine (SVM) algorithm was utilized, resulting in an AUC of 0.72. This approach involved the use of univariate and multivariate frequency-related features. Authors in [23] conducted research utilizing multiple classification algorithms, including AdBoost, RBF SVM, and Artificial Neural Networks (ANN). Their study incorporated spectral power features and cross-correlation coefficients. The AUC values obtained were 0.7603, 0.8472, and 0.8884, respectively. Paper [24] investigated the predictive capabilities of various features, including univariate spectral power in band (PIB), time domain correlations (TMCO), and spectral coherence (SPCO). They employed classification algorithms such as ANN, SVM, and Random Forest Classifier (RFC), achieving an AUC of 0.83.

The proposed models, Model 1 based on CNN and Model 2 based on a combination of CNN and LSTM, achieved AUC values of 0.897 and 0.919, respectively. The proposed models utilized raw data and showcased the potential of deep learning architectures for epileptic seizure prediction. Overall, the table highlights different classification algorithms employed by various authors and the corresponding AUC values achieved in their respective studies. These findings demonstrate the advancements made in epileptic seizure prediction, with the proposed models showing competitive performance compared to prior approaches.

5. CONCLUSION

In conclusion, the field of seizure prediction has seen significant advancements in recent years, with the emergence of deep learning algorithms revolutionizing the approach to this challenging problem. The proposed DL based models such as Model 1 based on CNN and Model 2 based on a combination of CNN and LSTM, have shown great promise by automating the feature learning process and achieving impressive AUC values of 0.897 and 0.919, respectively. By utilizing raw data and minimizing the need for feature engineering and pre-processing, these deep learning models offer a more generalized and patient-specific approach to seizure prediction. The advancements in seizure prediction are evident from the comparison of AUC values achieved by different classification algorithms employed by various authors. The proposed models have demonstrated state-of-the-art performance, requiring minimal pre-processing and eliminating the need for manual feature extraction. To ensure a more robust evaluation, we recommend training and evaluating these models on a larger dataset. This expanded data will provide a comprehensive assessment of the models' capabilities and further validate their effectiveness in tackling the seizure prediction problem.

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