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PREDICTING STATES OF EPILEPSY PATIENTS USING DEEP LEARNING MODELS

Abstract

In this study, the authors present and scrutinize two deep learning models designed for predicting the states of epilepsy patients by utilizing extracted data from their brain's electrical activities recorded in electroencephalography (EEG) signals. The proposed models leverage deep learning networks, with the first being a recurrent neural network known as Long Short-Term Memory (LSTM), and the second a non-recurrent network in the form of a Deep Feedforward Network (DFN) architecture. To construct and execute the DFN and LSTM architectures, the authors rely on 22 characteristics extracted from diverse EEG signals, forming a comprehensive dataset from five patients. The primary goal is to forecast impending epilepsy seizures and categorize three distinct states of brain activity in epilepsy patients. The models put forward yield promising results, particularly in terms of classification rates, across various preceding seizure timeframes ranging from 5 to 50 minutes.

1. INFORMATION

The Epilepsy is a prevalent neurological disorder that impacts the central nervous system, leading to seizures. It is a widespread neurological condition globally. The disorder disrupts the typical neural activity, giving rise to unusual sensations, seizures, muscle spasms, and loss of consciousness. Predicting epilepsy seizures becomes imperative in aiding both patients and specialists in managing this condition effectively. A crucial preliminary step involves registering the electrical activity in various regions of the brain. The primary tool for this purpose is the electroencephalograph (EEG), which facilitates the collection of brain electrical activities. EEG is going more importance in the diagnosis of epilepsy. It provides valuable information about brain function, helping clinicians and researchers understand brain dynamics and identify abnormalities. EEG recording based on the placement of a set of electrodes using the 10-20 system ensures that data is comparable across different sessions and subjects, providing a reliable basis for clinical diagnosis. Electrode placement and selection depend on the specific clinical or research needs. There are mainly two methods: Scalp (Non-invasive) Approach: Electrodes are placed on the scalp to measure the brain's electrical activity from its surface. Invasive Approach: Electrodes are placed under the skin or directly on the brain. These provide high-resolution recordings and are essential for detailed insights into brain activity in specific medical and research applications.

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However, the visual analysis and examination of EEG takes time and may be ineffective for patients. Consequently, automatic analysis of the EEG signal can facilitate the diagnosis of epilepsy and helps the specialist to understand the contents of EEG signals. The analysis of EEG is crucial for understanding brain function. Consequently, various studies have been conducted on EEG processing, including the work presented in (Krukow et al., 2019), and the seizure review by (Yindeedej et al., 2024), and the correlation between scalp and invasive EEG detailed in (Ramantani et al., 2016). Additionally, (Ramgopal et al., 2014; Willems et al., 2019) provide comprehensive descriptions of EEG analysis, as well as its application in prediction and detection.

On the other hand, several works have been paid to automatic seizure prediction, using machine learning tools. The process of prediction consists of two stages: The first step is features extraction. It's an important step in the pattern recognition process, which aims to describe the behavior of EEG signals and transform them into numerical vectors of pertinent data or pieces of information. To get the best classifier, the feature extraction step should decrease the original signal to a smaller dimension than possible without losing pieces of information necessary for prediction. The second stage is mandatory based on the results of the first one, concerning this, a machine learning tool provides a set of methods able to perform classification or prediction tasks, of two or multi classes. The prediction of epilepsy seizures can be approached as a binary problem when the objective is to anticipate the onset of a seizure and as a multiclass problem when aiming to identify various states of an epilepsy patient. Numerous methods have been put forth to enhance the efficacy of automatic seizure prediction, including neural networks (NN), support vector machines (SVM), decision trees, among others.

The prediction of epilepsy seizures based on the EEG is considered a classification task, with two classes or plus. In this context, many works are proposed for automatic prediction from EEG signals such as the work cited in (Tzallas et al., 2009; Tzallas et al., 2007), in both works, authors use the time-frequency analysis to classify EEG Signals for epilepsy seizure detection. Moreover, authors in (Tzallas et al., 2007) are considering the features extracted as inputs in an artificial neural network architecture for seizure classification. In reference (Martinez-del-Rincon et al., 2017), the authors introduce an innovative method for automated epilepsy seizure detection, incorporating two key elements: the application of non-linear classifiers using the "kernel trick" and the introduction of a Bag-of-Words model for deriving a non-linear feature representation from the input data. On the other hand, the authors referenced in (Li et al., 2020) utilize a convolutional network featuring three convolution blocks to extract pertinent features from EEG signals. These extracted features serve as input for the Nested Long Short-Term Memory (NLSTM) model, aiming to uncover the inherent temporal dependencies within EEG signals.

In (Vani et al., 2019), the authors put forth a pioneering deep-learning approach designed for the detection of seizures in pediatric patients. This method relies on classifying multichannel EEG signals, Leveraging the automatic feature learning abilities of a neural network-based classifier integrated with a two-dimensional deep convolution auto-encoder. Moving on to (Kim et al., 2020), the authors offer a comprehensive review of Epileptic Seizure Detection. Through this review, their aim is to provide a panoramic perspective on recent signal processing methods and classification algorithms used for detecting and categorizing seizures. In Behbahani et al. (2014), the authors introduce an algorithm geared towards detecting the presence of epilepsy seizures in heart rate variability. This algorithm encompasses feature extraction and classification, incorporating ten features derived from time and frequency domain analysis, along with nonlinear features extracted from EEG signals. The features that were extracted, as described in the previous context, were employed as the input for a multilayer perceptron neural network. Many other applications of neural networks, especially deep learning, are proposed in the literature, such as works in (Kumar et al., 2019; Hu et al., 2021; Yoki Donzia & Kon Kim, 2019). A state of the art of non-invasive method is presented in (Yuan et al., 2021).

This paper introduces two effective architectures rooted in deep learning neural networks. These architectures leverage features extracted from EEG signals to enhance the performance of seizure prediction systems for epilepsy patients. The objective is to develop two deep learning models to improve the quality of epileptic seizure prediction, considering the richness of EEG data and the proven theoretical and historical performance of neural networks in classification tasks.

The subsequent sections of the paper are structured as follows: Section two provides a concise overview of deep learning types. Section three introduces the concepts of epilepsy seizure prediction and feature extraction from EEG signals. Following that, Section four thoroughly discusses the proposed architectures, namely DFN and LSTM. Section five is dedicated to the implementation part. The paper then concludes with the presentation of experiment results, followed by a final section summarizing the findings and the conclusions reached.

2. DEEP LEARNING

Deep learning (DL) is a specialized field within the broader domain of machine learning, characterized by neural networks with multiple hidden layers. In practice, deep learning involves using neural networks with an increased number of these hidden layers. These networks aim to emulate the functioning of the human brain, where data inputs, weights, and biases collaboratively contribute to the accurate recognition, classification, and description of classes within the provided data. Notably, deep learning requires less pre-processing compared to some other classification algorithms. Rooted in the concept of artificial neural networks, deep learning models are inspired by the organizational structure of the human brain's connectivity, particularly drawing inspiration from the arrangement found in the visual cortex.

Both architectures feedforward and recurrent neural networks are generally proposed in deep learning. Deep learning architectures are structured with distinct layers, including an input layer, hidden layers (which can be recurrent or non-recurrent), and an output layer. Within each layer, nodes are interconnected with others in the subsequent layer, and each connection is associated with a weight. Additionally, each node incorporates an activation function that influences the output. The output of individual nodes is transmitted to the next layer of the network. There are popular architectures within deep learning, such as Convolutional Neural Networks (CNNs), designed for tasks like image recognition, and Long Short-Term Memory (LSTM) networks, suitable for handling sequential data and preserving contextual information over extended periods. These architectures have proven effective in various applications, showcasing the versatility of deep learning in handling complex tasks across different domains.

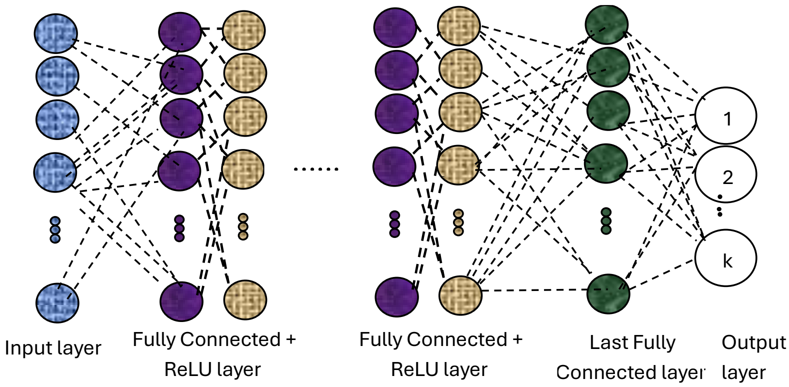

Fig. 1. Standard architecture of deep Feedforward Network

2.1. Deep Feedforward Network

The Deep Feedforward Network (DFN) outlined in this paper adheres to a feedforward architecture, structured with consecutive layers. The network initiation involves the input layer, followed by a series of blocks. Each block comprises a fully connected layer, a normalization layer, and an activation layer. Towards the conclusion of the architecture, an output block is incorporated, encompassing a fully connected layer coupled with a classification layer. This DFN is specifically crafted to autonomously and flexibly acquire spatial hierarchies of features by means of a backpropagation algorithm. The architecture iteratively consists of repeated layers, as illustrated in Figure 1, portraying the network's capability to learn and represent intricate patterns in the input data.

2.2. Long Short-Term Memory

Long Short-Term Memory (LSTM) is an advanced type of neural network designed to address the challenge of capturing and preserving both short-term and long-term dependencies in sequential data. By splitting the signal input into these two parts, LSTMs can selectively focus on capturing short-term variations through the hidden state while simultaneously preserving and utilizing important long-term information through the cell state. This capability makes LSTMs well-suited for tasks involving sequential data, where maintaining context and understanding dependencies over time is crucial for accurate predictions or classifications.

The architecture of an LSTM involves three crucial components, allowing it to effectively manage information over extended periods:

- Input Stage: In first stage, the input signal is divided into two significant components. The first component focuses on capturing important short-term information, achieved through the hidden state. The second component concentrates on retaining crucial long-term information, accomplished through the cell state.
- Hidden State and Cell State: The hidden state in an LSTM captures short-term information and is updated dynamically as the network processes sequential data. However, the cell state, on the other hand, serves as a memory unit for preserving long-term information.

- Three-Gate Mechanism: LSTMs utilize a unique three-gate mechanism to control the flow of information.
  1. Forget Gate: Determines which information from the cell state should be discarded or retained.
  2. Input Gate: Decides what new information should be added to the cell state.
  3. Output Gate: Determines the next hidden state based on the current input and the updated cell state.

Typically, LSTM networks consist of an input layer, followed by hidden recurrent layers called LSTM Layer, and an output layer, for a more detailed description of CNN, see (Nielsen, 2015; Awad & Khanna, 2015; Webb & Copsey, 2002; Boualoulou et al., 2023).

3. EPILEPSY SEIZURE PREDICTION

Absolutely, the ability to predict epilepsy seizures in advance is crucial for enhancing the management and quality of life for individuals with epilepsy. Automatic seizure prediction machines aim to forecast seizures before they occur. Various machine learning algorithms are employed to analyze different biometric signals in order to achieve this predictive capability. These algorithms leverage features extracted from biometric signals, such as electroencephalography (EEG) data, to discern patterns and trends associated with impending seizure, typical two-step process in building automatic seizure prediction systems:

- In the first step, relevant features are extracted from biometric signals, particularly electroencephalograph (EEG) signals. These features serve as the input for subsequent classification. The goal is to capture key characteristics in the signal data that can be indicative of impending seizures.
- Following feature extraction step, a classifier model is developed to predict seizures. This model is typically derived from machine learning methods, which learn patterns and relationships within the extracted features. The model is trained on a labeled dataset known as the training data, which consists of instances where the presence or absence of seizures is known. Once trained, the model's performance is evaluated on a separate dataset called testing data to ensure its generalizability.

This paper focuses on computing features from EEG signals and constructing two classifier models: the first is based on LSTM network and the second is created by the proposed deep feedforward network (DFN), and the last is based on, in the context of a supervised learning problem.

In this study, the authors focus on the epilepsy seizures problem and define three distinct classes to represent various states of epilepsy patients:

- Pre-seizure: This class likely corresponds to the period leading up to an epileptic seizure.
- Seizure: This class represents the actual occurrence of an epileptic seizure.
- After-seizure: The after-seizure class may encompass the postictal phase, which is the period following the seizure.

3.1. Feature extraction from EEG signal

The acquisition of brain electrical activity through Electroencephalography (EEG) stands as one of the most valuable and information-rich sources in epilepsy research. Recognized for its real-time data provision and excellent temporal resolution, EEG plays a crucial role in the diagnosis and classification of epilepsy seizures. It remains one of the primary diagnostic tests for epilepsy, offering unparalleled insights into the dynamic electrical patterns of the brain.

While electroencephalography (EEG) provides valuable data for analyzing and interpreting brain activity, the practicality of prolonged wear of EEG electrodes can be challenging for patients. This challenge is especially significant in scenarios where continuous monitoring over an extended period is necessary.

It's important to mention that this study utilizes features extracted from EEG signals captured by electrodes placed on the scalp for the purpose of distinguishing between different classes of epilepsy. In this work, the uathors use 22 features defined in the EPILAB project of the Center for Informatics and Systems (Klatt et al., 2012; Teixeira et al., 2011), they suggest a standardized set of features that have been identified and defined for epilepsy research. These features likely encompass various aspects of the EEG signal that are relevant for differentiating between different states or phases of epilepsy, such as pre-seizure, seizure, and after-seizure. Three parameters are determined during the feature extraction step:

- Window size is fixed at 5 min.
- Different selected prediction seizure times (periods) is made: 50 min, 30 min, 10 min and 5 min.
- Selection of electrodes or channels, this operation is an important step for feature selection.

3.2. Electrodes selection

The selection of electrodes or channels is indeed a crucial step in the preprocessing phase of analyzing EEG signals. This operation plays a significant role in feature selection and can impact the quality of the features extracted for subsequent analysis. In this study, electrodes were selected according to three hypotheses:

- Electrodes of highest frequency: In this case, we are specifically focusing on electrodes that provide signals of high frequency for each patient, as indicated in Table (1). This approach suggests a targeted analysis of high-frequency components in the EEG signals captured by these electrodes. Electrodes capturing high-frequency signals are likely to be sensitive to rapid changes and oscillations in neural activity. This focus can be relevant for capturing specific patterns associated with certain types of seizures or neurological events.
- Electrodes of the left part: Choosing electrodes based on their lateral position (left part of the head) suggests an interest in analyzing neural activity specific to the left hemisphere. This can be relevant for studying lateralized effects or understanding how epileptic activity manifests in particular brain regions. Focusing on specific lateral regions may help in localizing seizure activity and understanding the asymmetry or lateralization of epilepsy-related neural patterns. By concentrating on

even-numbered electrodes on the left side of the head can contribute to a focused investigation into left-hemispheric neural activity and its role in epilepsy.
- Electrodes of the right part: In this case, we are choosing electrodes positioned on the right part of the head for each patient, this selection criterion is based on odd-numbered electrodes. This can be important for understanding lateralized effects and patterns associated with epilepsy in right brain region.

4. PROPOSED MODELS

In this section, the authors present two deep learning models to predict epilepsy seizures. The models in their study are developed to predict epilepsy seizures, treating the task as two distinct problems:

- Binary Classification for Ongoing Seizure Prediction: The first problem involves binary classification, specifically predicting the ongoing seizure. In this case, it's framed as distinguishing between the pre-seizure class and the rest of the classes of the patient. The pre-seizure class represents the period leading up to a seizure, and the objective is to accurately identify instances when a seizure is imminent.
- Multiclass Classification for Other Seizure States: The prediction of three brain states of the patient as a multiclass problem, specifically classifying instances into three distinct brain states of the patient: pre-seizure, seizure, and after-seizure. The two proposed models for this task are the Deep Feedforward Network (DFN) and the Long Short-Term Memory (LSTM) Network.

4.1. Deep Feedforward Network

This section presents a deep feedforward network (DFN) architecture, in effect, based on the classic feedforward network with a fully connected layer, a normalization layer, an activation layer, and a backpropagation algorithm. The implemented architecture used is shown in figure 2. In practice, DFN architecture is composed of an input layer represented as a vector comprising 22 features multiplied by the selected number of channels for each patient, followed by two blocks, each one consisting of fully connected layers, a normalization layer, and an activation layer with a ReLU function. ReLU is given by the formula:

$$Re\,L\,U(z) = \begin{cases} z & z > 0 \\ 0 & z \leq 0 \end{cases} \tag{1}$$

Ultimately, the output layer comprises k neurons, where k equals the number of classes (k=2) in the binary case., and k=3 in the multiclass case with three classes). Followed by a softmax layer, with the function given in next formula:

$$Softmax(z) = \frac{e^z}{\sum_j e^{zj}} \tag{2}$$

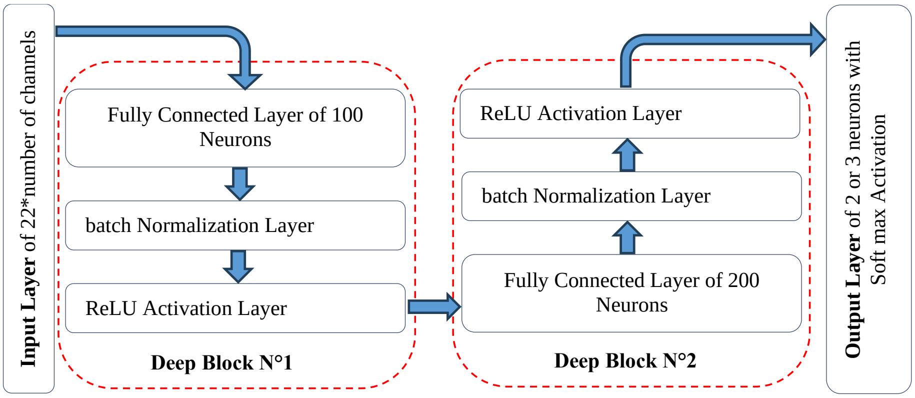

Fig. 2. Deep Feedforward Network (DFN) proposed

4.2. LSTM Network

The LSTM architecture proposed in this work is composed of an input layer composed of (22 features*the number of channels selected), followed by two LSTM layers of 100 cells, and finally an output layer of k classes. The architecture implemented is shown in figure 3.

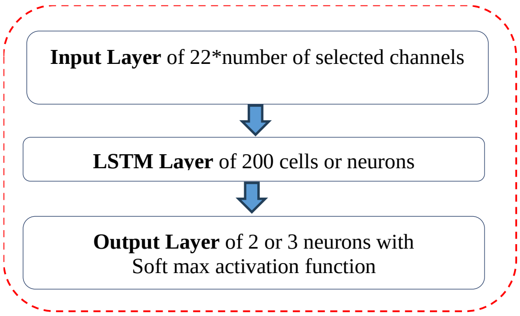

Fig. 3. LSTM architecture proposed

5. IMPLEMENTATION

In this section, the authors present the architectures (models) implemented according to two cases: in the first, each patient is considered alone (individual models), in the second case, all patients are processed together (global models).

5.1. Individual Models

In this section, the authors present deep learning models to predict epilepsy seizures for each patient i.e. each patient has an individual models. These models are treating the task as binary and multiclass problems: a binary classification problem (pre-seizure class versus the rest of the classes of the patient). The prediction of three brain states of the patient as a multiclass problem (classification with three classes: pre-seizure, seizure, after-seizure).

5.2. Global Models

In this section, we present two deep learning models to predict epilepsy seizures for all patients. Global models are developed to predict the ongoing seizure for all patients (as a binary classification problem: pre-seizure class versus the rest of the classes of the patient), and to predict three brain states of all patients (as a multiclass problem with three classes: pre-seizure, seizure, after-seizure). Due to the large number of channels of all patients, we decided to select only highest frequency channels. The table (1) presents highest frequency channels for all patients.

Tab. 1. Selection of electrodes capturing the highest frequency signals

Patient	Highest frequency electrodes
Patient 1	AF7, F7, T7, P7, F9, T9, FT7, FT9, TP7
Patient 2	AF7, F7, T7, P7, F9, T9, FT7
Patient 3	FP2, F8, T8, P8, AF8, F10, T10, FT8
Patient 4	AF7, F7, T7, F9, T9, FT7, FT9
Patient 5	F7, F3, T7, C3, P7, P3, F9, T9, FT7

5.3. Evaluation

In the evaluation step, statistical measures for evaluating the classification models are implemented such as accuracy and F1-score. Firstly, accuracy is indeed a commonly used metric to assess the overall performance of a classification model. It's given by the formula:

$$Accuracy = \frac{True\ positives + True\ negatives}{Total\ number} \tag{3}$$

While the accuracy is calculated by summing up the number of correct predictions across all classes and dividing it by the total number of predictions, so it provides an overall measure of the model's correctness.

The F1-score is a measure used to evaluate the performance of a classification model. It considers both precision and recall to provide a single metric that balances the two. It is the harmonic mean of precision and recall. It is given by the formula:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Where:

$$Precision = \frac{True\ positives}{True\ positives + False\ positives} \tag{5}$$

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \tag{6}$$

To perform our architectures LSTM and DFN, we are used a dataset consists of 5 patients from the EEG dataset of Coimbra university. The 22 features extracted are used to construct the 8 architectures as follow (see table 2).

Tab. 2. Models implemented

Patient	Binary classification	Multiclass classification
Individual	Binary-DFN	Multiclass-DFN
	Binary-LSTM	Multiclass-LSTM
Global	G-Binary-DFN	G-Multiclass-DFN
	G-Binary-LSTM	G-Multiclass-LSTM

All the experiments were run on standard Intel i3 CPU 3.40 with 4 Go memory running the Windows 7 operating system, and with MATLAB 2020b version. In experiments reported below, we used 60% of data for training and 30% for testing the proposed models. The dataset used in this paper is belong from EPILAB project of Center for Informatics and Systems for Informatics and Systems, Department of Informatics Engineering, University of Coimbra, Portugal (Juliane Klatt and all. 2012).

6. RESULTS AND DISCUSSION

The following tables (3 and 4) summarize the best-obtained results by the Binary-DFN, Multiclass-DFN, Binary-LSTM, and Multiclass-LSTM architectures respectively, for each patient with the highest frequency channels. In both tables, the "Binary case" column presents the accuracy of ongoing seizure prediction considering 4 pre-seizure periods. However, in the " Multiclass case " column, we give the best prediction accuracy of the three classes considered in this work (pre-seizure, seizure, and after-seizure).

Tab. 3. Results of prediction obtained by individual DFN model, for binary and multiclass cases

Patient	Pre-seizure	Binary classification		Multiclass classification
		Accuracy (%)	F1-score (%)	Accuracy (%)
Patient1	50	89.58	94.09	84.68
	30	93.67	96.60	88.30
	10	97.59	98.77	93.93
	5	98.68	99.33	96.16
Patient 2	50	96.54	98.22	95.33
	30	98.15	99.06	97.10
	10	99.38	99.69	98.89
	5	99.75	99.88	99.15
Patient 3	50	94.73	97.27	90.11
	30	96.77	98.35	93.46
	10	98.97	99.48	97.25
	5	99.51	99.76	98.03
Patient 4	50	96.47	98.20	94.11
	30	97.71	98.84	96.36
	10	99.09	99.54	98.64
	5	99.53	99.77	99.09
Patient 5	50	96.52	98.21	93.12
	30	97.85	98.90	95.42
	10	99.20	99.60	98.20
	5	99.57	99.78	98.90

Tab. 4. Results of prediction obtained by individual LSTM model, for binary and multiclass cases

Patient	Pre-seizure	Binary classification		Multiclass classification Accuracy (%)
		Accuracy (%)	F1-score (%)	
Patient1	50	77.63	87.41	85.83
	30	85.28	92.06	87.68
	10	94.63	97.24	92.90
	5	97.27	98.61	95.49
Patient 2	50	95.22	97.55	95.04
	30	97.13	98.55	96.95
	10	99.04	99.52	98.86
	5	99.52	99.76	99.34
Patient 3	50	90.61	95.07	90.18
	30	94.12	96.97	93.65
	10	98.04	99.01	97.57
	5	99.02	99.51	98.55
Patient 4	50	94.26	97.04	94.07
	30	96.55	98.25	96.33
	10	98.85	99.42	98.63
	5	99.43	99.71	99.21
Patient 5	50	92.62	96.17	92.28
	30	95.42	97.66	95.08
	10	98.35	99.17	98.01
	5	99.12	99.56	98.78

On the other hand, the best results obtained by different architectures, specifically G-Binary-DFN, G-Multiclass-DFN, G-Binary-LSTM, and G-Multiclass-LSTM, as presented in tables 5 and 6. These tables likely provide a comprehensive overview of the performance of these architectures across all patients with the use of the highest frequency channels

Tab. 5. Results of prediction obtained by global G-DFN model, for binary and multiclass cases

Patient	Pre-seizure	Binary classification		Multiclass classification Accuracy (%)
		Accuracy (%)	F1-score (%)	
All Patients	50	94.83	97.34	89.47
	30	96.98	98.47	90.13
	10	98.99	99.49	92.38
	5	99.49	99.74	95.26

Tab. 6. Results of prediction obtained by global LSTM architecture, for binary and multiclass cases

Patient	Pre-seizure	Binary classification		Multiclass classification Accuracy (%)
		Accuracy (%)	F1-score (%)	
All Patients	50	82.66	90.48	82.48
	30	88.88	94.11	85.93
	10	97.26	98.61	90.19
	5	98.62	99.30	93.27

As illustrated in tables 3, 4, 5 and 6 above the accuracy is increases while we are close to the seizure instance. As a global vision, the results obtained are good and competitive. We note that all results presented in this paper are obtained with the highest frequency channels. An accuracy ranging from 81% to 89% for the global models is indeed a promising and encouraging result, especially considering the heterogeneity of data across various patients.

On the other hand, Figures 4 and 5 below show the variation of accuracy with different previous seizure periods, for each patient. These figures present the prediction of the ongoing seizure by our proposal architecture DFN and LSTM network, in the binary classification case. Figures 6 and 9 show a comparison between DFN and LSTM for patient 1. Figures 7 and 8 present the variation of accuracy with different previous seizure periods, obtained by DFN and LSTM respectively.

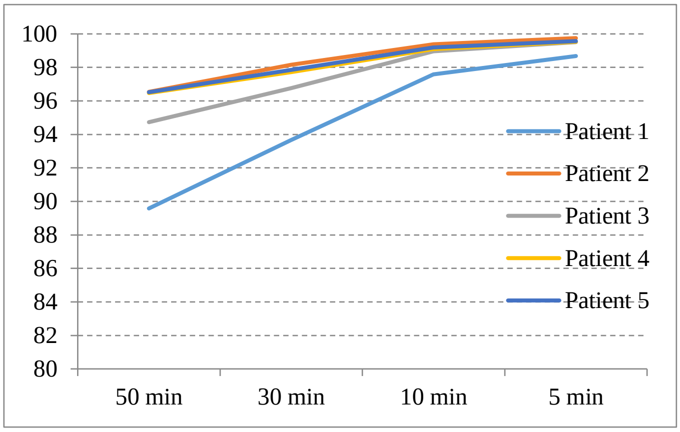

Fig. 4. Variation of accuracy for 5 patients, to predict the ongoing seizure by DFN architecture, with 50 min, 30 min, 10 min, and 5 min as previous time duration

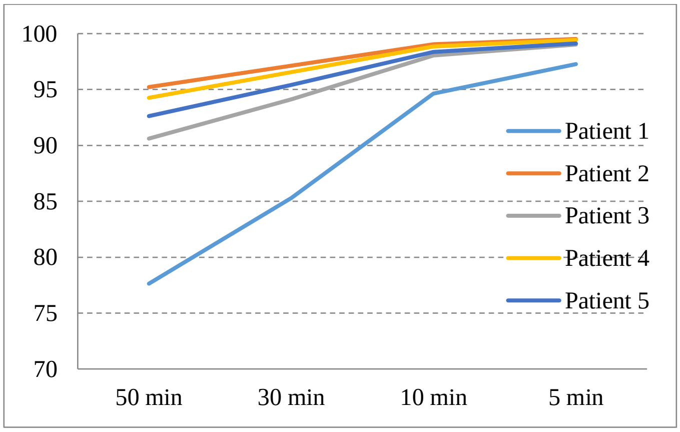

Fig. 5. Variation of accuracy for 5 patients, to predict the ongoing seizure LSTM network, with 50 min, 30 min, 10 min, and 5 min as previous time duration

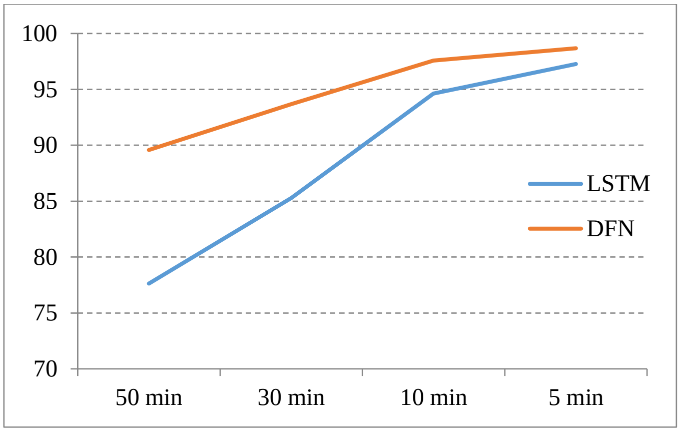

Fig. 6. Comparison of accuracy obtained by the two architectures DFN and LSTM, to predict the ongoing seizure, for patient 1, with different previous time duration

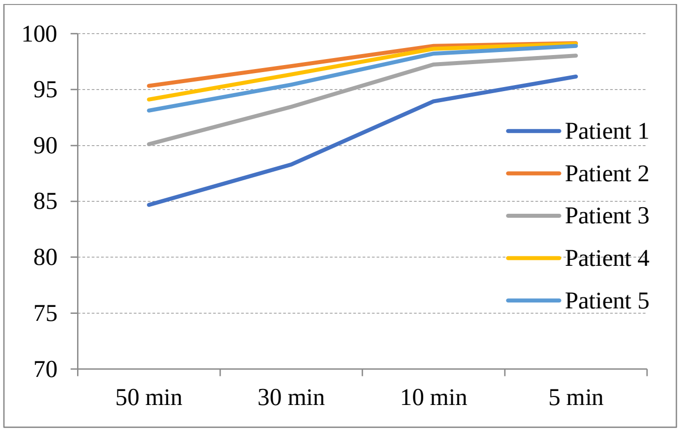

Fig. 7. Variation of accuracy for 5 patients, to predict three states about seizure, by DFN architecture, with 50 min, 30 min, 10 min, and 5 min as previous time duration

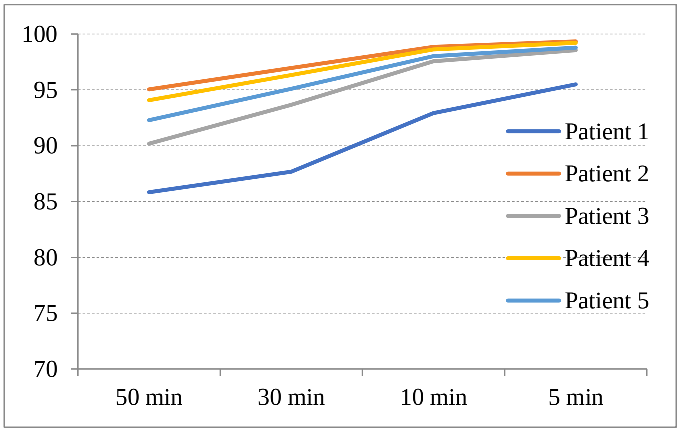

Fig. 8. Variation of accuracy for 5 patients, to predict three states about seizure, by LSTM architecture, with 50 min, 30 min, 10 min, and 5 min as previous time duration

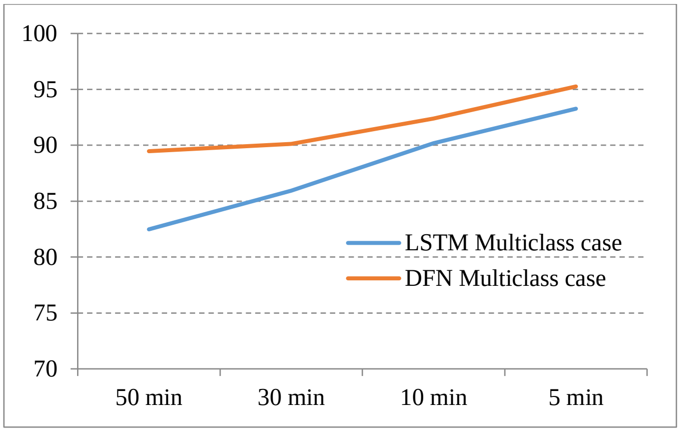

Fig. 9. Comparison of accuracy obtained by the two architectures DFN and LSTM, to predict the ongoing seizure, for patient 1, with different previous time duration

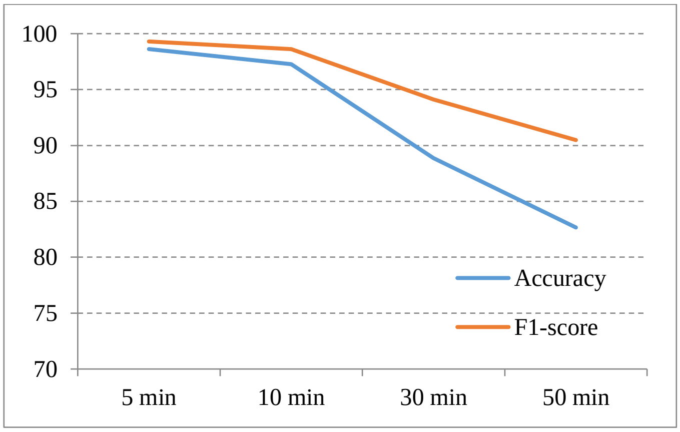

Fig. 10. Comparison of accuracy and F1-score obtained by global LSTM architecture, to predict the ongoing seizure before 50 min, for 5 patients

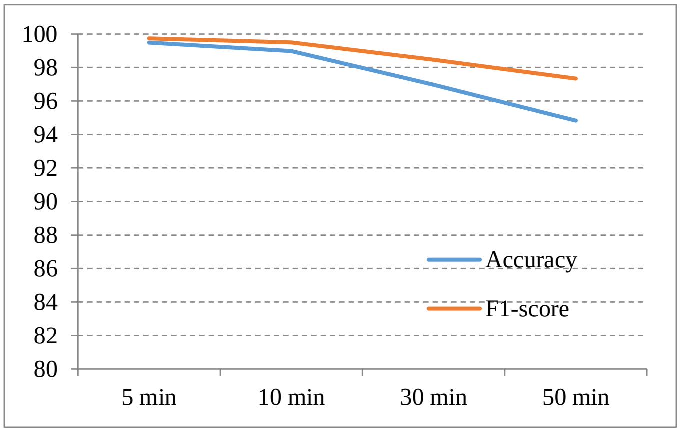

Fig. 11. Comparison of accuracy and F1-score obtained by global DFN architecture, to predict the ongoing seizure before 50 min, for 5 patients

7. CONCLUSION

In this work, the authors proposed and implemented two deep neural network architectures named: Deep Feedforward Network (DFN) and long short-term memory (LSTM) architecture, in the subject to predict the ongoing seizures. Before the training of the proposal architectures, the selection of channels (electrodes) is necessary in order to extract the best features. After training and testing our models, we can conclude that:

– Achieving accuracy levels in the range of 81% to 89% by global models, and 85% to 99% by individual models, is generally considered good in many machine learning applications. It indicates that presented models are performing well in distinguishing between different states of epilepsy for diverse patients.
– There is no distinction in results between the left and right positions of the electrodes, as they yield similar outcomes.
– Choosing electrodes based on their sufficient highest frequency.
– In terms of training parameters, we conclude that two or three blocks of layers are sufficient, moreover the number of neurons in each layer can be defined according to the number of the inputs. Also, there are no difference between solvers used for training neural network: SGDM, RMSProp and ADAM.
– The DFN model has proven to be effective in predicting epilepsy seizures, it may indeed have potential applications in other domains, such as face recognition and speech classification.

Finally, this comparative analysis of the different architectures (DFN versus LSTM, Binary versus Multiclass, Individual versus global) provides insights into their relative strengths and weaknesses. This information can guide future research and development in seizure prediction systems.

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Conflicts of Interest

The author declare that he has no conflicts of interest

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