Performance Analysis of DL Architectures for Predicting and Classifying Neural Diseases Using EEG Datasets

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Abstract. Epilepsy is one of the most common neurological diseases in the world. The way it affects brain signals makes it suitable for automatic detection based on electroencephalogram (EEG) readings through machine learning architectures. This paper aims to provide an overview of the field of generative neural networks. It takes a look at different papers and their respective approaches in order to surmise both the results achieved and the open problems still existent. Using an open-source dataset and inspired by an article that tries to push the boundaries of the classification task that is usually used for EEG data collected from both epileptic patients and healthy controls, we implemented an algorithm meant to find the brain signals that are only 'masquerading' as being from a seizure. These type of signals -while fakes themselves- could be used as an early warning for on the onset of the seizure.

Keywords: epilepsy · seizure prediction · classification · electroencephalogram · EEG · GAN · CNN · RNN · LSTM · ictal · non-ictal

1 Introduction

The synergy between deep learning and neuroimaging has given rise to unprecedented opportunities for unraveling complex neural patterns and decoding the intricate workings of the brain. The motivation behind this state-of-the-art report lies in the transformative potential of leveraging deep learning and generative neural networks to decipher the underlying structure of brain activity. The fusion of deep learning techniques with fMRI and EEG data holds immense promise for developing innovative diagnostic tools and therapeutic interventions. The ability to generate realistic and meaningful representations of brain activity using generative neural networks opens new avenues for medicine, enabling targeted interventions based on individualized neural profiles.

This is an unique convergence point for biology, mathematics and computer science that fascinates us.

The purpose of this paper is to analyze the performance of various DL architectures (e.g. RNN, CNN) for prediction of epileptic seizures. These architectures reduce such predictions to a simple classification task.

It would be very helpful for doctors to detect epilepsy seizures both for the safety of the patient and for eventual treatment optimization. Also this could be used for further research into the underlying mechanisms of epilepsy that could lead to the development of more effective treatments and interventions for managing the condition.

In order to improve seizure prediction, we took a closer look at how brain signals are classified. Building on a pre-existing paper [16], we tried to find out the 'false seizure' signals that happen in between seizures. From a medical point of view, this would be an important development as it could help doctors root out false alarms.

2 Problem specification

The problem we tackle in our SOTA is the use and performance of different DL architectures for predicting epileptic seizures from EEG data.

This paper aims to provide an overview of the field of generative neural networks. It takes a look at different papers and their respective approaches in order to surmise both the results achieved and the open problems still existent.

Using an open-source dataset and inspired by an article that tries to push the boundaries of the classification task that is usually used for EEG data collected from both epileptic patients and healthy controls, we implemented an algorithm meant to find the brain signals that are only 'masquerading' as being from a seizure. These type of signals -while fakes themselves- could be used as an early warning for on the onset of the seizure.

3 Theoretical background

Epilepsy is defined as a chronic disorder of the brain characterized by an enduring disposition towards recurrent unprovoked seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition. The diagnosis of epilepsy requires at least two unprovoked seizures occurring greater than twenty-four hours apart. Seizures are defined as transient symptoms and signs due to abnormal excessive or simultaneous neuronal activity of a population of neuronal cells in the brain.

Seizure occurrence period (SOP) is defined as the period during which the epileptic seizure is to be expected, while seizure prediction horizon (SPH) is defined as the minimum window of time between the beginning of SOP and any alarm. Seizures should be delimited in time, but the borders of ictal (during a seizure), interictal (between seizures) and postictal (after a seizure) often are indistinct.

In the field of epileptic seizure applications, building a predictive model involves multiple steps, which are electroencephalogram (EEG) data acquisition, data preprocessing, development of a machine learning or deep learning model, and a final performance evaluation step. During the EEG data acquisition step, electrodes are placed on the human head to capture EEG signals through special equipment. This data is composed of different readings for each electrode, usually called a recording channel, and is stored for relevant use. The data preprocessing step involves data cleaning such as removing artifacts, removing noise from the signal, omitting missing records, and data normalization.

Artficial Neural Networks (ANNs) are used in the medical field to provide care at a reduced cost. Applications of ANN in health care include clinical diagnosis, prediction of cancer, speech recognition, prediction of length of stay, image analysis and interpretation and drug development. EEG may detect abnormalities within the brain that cannot be found with other imaging techniques.

Interpreting correctly the data collected is very important for doctors and as such it is useful to have artificial neural networks that can be used to do this task, saving medical professionals time and effort.

When it comes to patients who suffer from epilepsy there is no universal treatment for them. They range from anti-epileptic drugs to surgery - during which the 'malfunctioning' part of the brain is removed - to even special diets that can help control seizures. This comes as a natural result of the fact that the underlying mechanisms of this disease are not completely understood.

A typical EEG analysis including four main stages:

1. **Signal acquisition**: The first step consists of a collection of raw EEG data from a human brain using EEG recording methodologies.
2. **Preprocessing**: Set of manipulation steps applied to raw EEG data allowing to prepare for further processing step. It is mainly including artifacts and noise control. This step purposes to reduce the original noise signals for further processing.
3. **Feature extraction**: The third step consists of analyzing the pre-processed signal and extracting any important and hidden features using a specific technique.
4. **Feature classification**: The fourth and last step consists of designing a well-structured and well-defined classifier model to detect/predict any disease or detect any pattern in the signal.

The process of teaching a computer to use data it has already seen to solve issues is known as machine learning (ML). When it comes to reading EEG data, ML is used for simple classification tasks where the objective is to sort the data into predefined categories, a task that would otherwise be time-consuming for humans.

One ML method that constantly shows up in this field is a support vector machine (SVM). This is a type of supervised learning machine mostly used for classification and regression.

Deep Learning (DL) is the subset of machine learning that uses neural networks for these tasks.

A convolutional neural network (CNN) [12] is a type of feed-forward neural network that learns features by itself by using kernel optimization. It had been applied for classifying a wide variety of data: from text to audio to images, in all fields.

Recurrent neural networks (RNNs) [15] are another class of neural networks, that process the data sequentially. This makes them well-suited for text, speech, and time series processing. Long short-term memory (LSTM) is a type of RNN that deal with vanishing gradient problem.

Generative adversarial networks (GAN) [13] are unique due to the fact that they encompass two two neural networks compete with each other where one agent's gain is another agent's loss. They have gained popularity due to their ability to create fake data that closely mirrors real world data, thus 'expanding' the given dataset.

4 Methodology of research

The papers chosen for this report have been selected based on their relevance and impact in the field, the year they have been published in -and as such how actual the knowledge provided by them is- and based on how clear and well-structured they are. In particular were considered papers that have presented their problem, methods, results and possible limitations in a rigorous way. As the field of generative neural networks is vast, the papers chosen cover a diverse number of areas and a couple other state-of-the-art reports have been included in order to achieve an optimal overview of the topic.

While the first human EEG was recorded back in 1924 [2]. the history of epileptic seizure prediction started in the 1970s when linear measures were used in order to try and predict pre-ictal signals. The next decade, non-linear methods started being used as well. As such, during the 20th century, scientist tried to classify brain signals gathered from patients. The study of epilepsy became far more popular in the 20th century, with the first international workshop on seizure prediction (IWSP1), large EEG datasets popped up -including the creation of the database EPILEPSIAE- and several challanges were launched (American epilepsy society prediction challange - 2014, Melbourne University NIH seizure prediction challange -2016). Around the 2010s, machine learning started being used for classifying EEG readings. At first, ML architectures such as SVM and kNN were heavily used, seizure prediction being seen as a classification task, distinguishing between ictal and non-ictal signals.

Around the year 2016, neural networks also began to be implemented. CNNs were used together with SVMs [7]. As CNNs had proven themselves very adept at feature extraction due to the fractal dimension of both EEG readings and medical imagining [4]. LSTMs appeared around the same time, both neural networks gaining a boom in popularity in 2018. As for GANs, [10] proposed an unsupervised method for seizure prediction in 2019, and from 2020 onwards, they had been one of the most used DLs methods in the field.

The bibliographical resources used were Google Scholar, Scopus, ScienceDirect, Web of Science and arxiv. We conducted a chronological review of the aforementioned academic resources to determine the progression and milestones in the application of machine learning, particularly deep learning, for epileptic seizure prediction using EEG data over the years.

We chose to focus on a few papers for the three DL methods that are most relevant to us -CNN, LTSM-RNN and GAN- as well as a few recent literature reviews that helped us better understand the current state of affairs.

5 Description of papers

5.1 About CNNs

CNNs are one of the three DL architectures that have been -and still are- heavily used for interpreting EEG readings and medical diagnosis. We focused on two papers that deal with predicting epileptic seizures using CNNs that are widely spaced apart, one having been published in 2008, and the other a decade later, in 2018, when using DL methods -and especially CNNs- for medical diagnosis was a hot topic.

Going back to the begining

This article from 2008 [5] summarizes the state of the art of seizure prediction: despite over three decades of research in seizure prediction, no method has achieved both high sensitivity and zero false alarms, limiting clinical applicability. Two major limitations of current algorithms are identified: (1) the unnecessary reduction of EEG features, and (2) overly simplistic binary classification approaches. These methods typically average EEG-derived features across time and channels, then apply binary classification with threshold tuning, which has shown weak performance. ML algorithms can address these shortcomings by using non-linear classification in a high-dimensional feature space, with better validation through in-sample learning and out-of-sample testing. However, ML has mostly been applied for feature selection rather than classification, so far. The authors propose two contributions: (1) aggregating bivariate features into spatially- and temporally-varying patterns, and (2) applying regularized ML methods (logistic regression, convolutional networks, and support vector machines) to classify brain activity into interictal (non-seizure) and preictal (seizure-impending) states.

The study used the intracranial EEG Freiburg dataset of 21 patients.

Because, as the authors point out, the ultimate goal is more the epileptic patient's quality of life rather than the classification task itself, seizure prediction performance is measured in terms of false positives (alarms) per hour and of sensitivity (number of seizures where at least one preictal sample is correctly classified). During CNN training, a stronger penalty was applied for false positives than for false negatives, which helped optimize seizure prediction results.

They report 100% sensitivity and no false alarms using the Freiburg EEG dataset, significantly outperforming previous studies, which reported only 42% sensitivity with 3 false predictions per day. This is a big jump especially for a paper so old, knowing that such sensitivity is not usual even in more recent studies, thus suggesting that overfitting had occured. Still CNNs being particularly effective in predicting seizures on average 60 minutes before onset, with the performance confirmed across the entire dataset, suggests high reliability in the CNN approach for seizure prediction, something that countless other studies would reaffirm in the future.

In the middle of the CNN craze

A more recent article [6] focuses on using CNN for seizure prediction as a result of the remarkable results obtained by this type of neural network in computer vision.

The authors focus on developing a Convolutional Neural Network (CNN) for detecting epileptic seizures by leveraging CNN's ability to preserve spatial relationships, motivated by how visual inspection helps experts identify seizures. The approach aims to consider both spatial and temporal correlations between EEG channels, crucial for seizure detection. The network first uses 1D convolution for each EEG channel to capture temporal evolution, followed by 2D convolution to process the spatial-temporal correlation. The network includes 8 convolutional layers followed by 2 fully connected layers. The last layer uses a sigmoid activation function, while other layers use a rectified linear activation function (ReLU). A low-pass filter is applied to the EEG data to remove artifacts (non-cerebral activity) before feeding the data into the network.

The network is tested on two EEG datasets, achieving 90.5% prediction accuracy on the SNUH-HYU dataset and 85.6% on the CHB-MIT dataset. The accuracy improves with longer EEG segments but also introduces more error in seizure event timing. These results feel more realistic than what we have seen in the previous paper and the use of two datasets reduces the risk of overfitting.

While promising results were achieved, the model needs to be trained and tested on more datasets for clinical use in epilepsy diagnosis and treatment. Additionally, the authors plan to extend their work to localize the brain regions where seizures originate.

5.2 About RNNs

RNNs, particularly advanced architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are effective for predicting epileptic seizures due to their ability to handle sequential data such as EEG signals. These models can identify temporal patterns in preictal (before seizure) and interictal (between seizures) phases, making them useful for seizure prediction [3].

We have taken a look at one of the papers [11] that had come out during 2018, when LTSMs and RNNs were having a boom in this field.

The study introduces LSTM networks into EEG-based seizure prediction, where they previously have been underutilized. It demonstrates that LSTM networks outperform traditional classifiers and CNNs for this task by effectively capturing temporal changes in EEG signals that precede seizures. This contributes significantly to improving seizure prediction sensitivity and reducing false alarms.

The authors employ a LSTM deep learning network for seizure prediction, which leverages its ability to capture temporal dependencies in EEG data. A two-layer LSTM model is developed and tested with a range of preictal window lengths (15 minutes to 2 hours) to determine its effectiveness across different temporal contexts. Features from both the time and frequency domains, as well as graph-theoretic measures, are extracted and used as inputs to the LSTM model, which is evaluated on the CHB-MIT scalp EEG database.

Overall, the LSTM model demonstrated high accuracy, low false prediction rates, and strong robustness in predicting seizures, outperforming previous traditional machine learning approaches in this domain. The methodology performed consistently across different patients, providing personalized seizure prediction by adapting to patient-specific characteristics without requiring separate feature selection for each case. In 11–17 out of the 24 cases, the LSTM achieved zero false alarms, particularly when longer preictal windows (30-120 minutes) were used.

5.3 About GANs

GANs have shown promising applications in epileptic seizure prediction, particularly in addressing challenges like imbalanced datasets and enhancing the performance of predictive models. Their capacity to create synthetic data that closely mirrors real data is an invaluable asset in medicine, where large datasets are hard to come by.

How to detect Ictal-like Non-Ictal Signal; or 'who's the fake?'

The study [16] tries to detect epileptic seizures from EEGs, taking into consideration the multimodality [14] of EEGs, by discerning the signals that are non-ictal and different from most non-ictal signals at the same time, and then enhance the effect of these signals in the learning of the binary classifier. In layman's terms, the authors want to 'catch' the signals that predict false seizures. These fake ictal signals are called *boundary signals.*

The methods used are the k Nearest Neighbour (kNN) algorithm - used for clustering for boundary signals- and a GAN - introduced to discern more boundary signals by use of some deep features. Then a GAN network is used for creating and categorizing the non-ictal and ictal class.

It was noticed that the sensitivity (the rate of the true positives) was high, around 98%, in almost all cases. Along with the increasing of boundary signal amount used for training, the sensitivity does not vary obviously, but almost remains unchanged. It indicates that the identification of boundary-type samples can reduce false positive ratio, therefore increase the performance of seizure detection. It was also found that in EEGs of healthy subjects some signals are similar to those of epileptic patients. During classification, some signals that belong to a healthy subject are prone to be misclassified as signals of epilepsy. As such, the research concludes that multi-class categorizing is possible to be more effective for seizure detection than the binary classification used here.

5.4 Reviews and surveys through the years

The begining of the DL in epilepsy boom - year 2019

The goal of this study [9] is to review recent methods for detecting and predicting epileptic seizures, focusing on feature extraction and classification techniques across traditional and deep learning approaches, and comparing them based on sensitivity, prediction time, and false alarm rate.

Most papers treat the prediction of epileptic seizures as a binary classification problem to discriminate between non-pre-ictal state and pre-ictal states. SVM, K-Nearest Neighbor (KNN) and Naïve Bayes are some of the most used architectures, since DL methods work better on larger datasets, and most medical datasets that deal with neural conditions like epilepsy are made up of a rather small sample of people.

The study highlights that high-dimensional EEG data require effective feature extraction techniques to improve classification accuracy in applications like seizure prediction. It highlights that feature extraction can be performed on univariate, bivariate, or multivariate data using different approaches, categorized mainly into time-domain, frequency-domain, and wavelet-based methods. Time-domain techniques, like the zero-crossing algorithm, handle noise well, while frequency-domain techniques (e.g., Fast Fourier Transform) and wavelet transforms address challenges posed by non-stationary and non-linear signals. Additionally, advanced deep learning techniques, such as autoencoders, LSTM, and CNNs, are increasingly utilized to automatically extract relevant features for EEG-based medical applications.

CNN is used to classify high dimensional patterns and multi-variate time series. It is a nonlinear multi-layer back propagation neural network followed by a sigmoid function. CNN was applied by several researchers to detect the pre-ictal state. LSTM is used recently in seizure prediction. It is an extension of the Recurrent Neural Networks (RNN) that was used in this field formerly. LSTM deep network model can outperform other deep learning techniques with large datasets. It has an advantage over CNN which is having the capability of isolating the brain's temporal characteristics throughout different states. In 2019, CNN and LTSM were the two most prominent DL methods used for this task, while SVM was the most used linear classifier.

LSTM is used recently in seizure prediction [29]. It [34] is an extension of the Recurrent Neural Networks (RNN) that was used in this field formerly [35]. LSTM deep network model can outperform other deep learning techniques with large datasets. It has an advantage over CNN which is having the capability of isolating the brain's temporal characteristics throughout different states.

The review compares papers by sensitivity, as they are interested to find out the number of true positives, in other words, how many times the model predicted a seizure correctly.

The deep neural network can be used in both feature extraction and classification phases. CNN proved its efficiency in the extraction of high-level features and also in discrimination between inter-ictal and pre-ictal states.

The paper suggests future studies in the field should focus on efficient analysis of EEG signals to accurately detect the pre-ictal state well before the onset of a seizure.

The year everyone was interested in seizure prediction - 2020

This study [7] is a literature review done in 2020 about the use of machine learning in the detection of epileptic seizures. They provide a general introduction to various ML techniques (e.g.supervised learning, unsupervised learning, and reinforcement learning) that have been used in the field of neuroscience, but also highlight the pitfalls of these methods. The objective of this paper is to review and elaborate upon the primary advances in the employment of ML methods for epilepsy prediction.

The review creates a comprehensive timelines of the use of both traditional ML and Dl methods when it comes to epileptic predictions. It also took a look at a number of significant papers whose contribution to the field are summarized in Table 1.

Table 1. Summary of DL methods used for ES prediction

Year	**Author**	**Method**	**Sensitivity (Accuracy)**
2017	Haider et al.	Wavelet Transform (CNN)	87.8%
2018	Truong et al.	STFT (CNN)	81.4%, 81.2%, 82%
2018	Tsiouris et al.	Various time and frequency features (LSTM)	99.28%
2019	Ramy Hussain et al.	STFT (CNN)	87.8%
2019	Truong et al.	STFT (GAN)	N/M [1]
2019	Hisham et al.	Raw data (DCAE + Bi-LSTM)	99.72%
2020	Usman et al.	Feature extracted from CNN	92.7%
2020	Ranjan et al.	Feature extracted from CNN	68%

As we can see, by 2020, CNNs were the most popular architectures due to their good performance, followed by LSTMs.

It also analyzed the most used datasets and summarized them, as we can see in Table 2.

Table 2. Overview of EEG Databases

Database	**No. of Subjects**	**No. of Channels**	**Recording Type**	**No. of ES**	**Recording Duration (hrs)**	**Sampling Frequency (Hz)**
CHB-MIT	24	23	Scalp EEG	198	1 (some up to 4)	256
MSSM	28	22	Scalp	61	48-192	256
Freiburg	21	128	iEEG	88	≥ 24	256
Bonn	25 (5 sets of 5 subjects)	1 (100 single-channel files/set)	Scalp/iEEG	Set E is ictal stage	23.6	173
EPILEPSIAE	30	122	Scalp/iEEG	1800+	96	250-2500
TUH	10,874	24-36	iEEG	$\approx 14{,}777$	-	250

The paper concludes that the future of epilepsy seizure (ES) prediction using machine learning (ML) and deep learning (DL) will focus on overcoming challenges like data dimensionality, data annotation, real-time monitoring, and data privacy. Interpretability and security of ML/DL models are also key, as it's essential to make models understandable and protect patient data from adversarial attacks and privacy breaches. Future research should aim to develop robust and generalizable solutions to these issues.

How does the field look like today?
This review [8] focuses on both epilepsy diagnosis and prediction of seizures, from both EEG and MRI readings.

This paper is very useful for those uninitiated in the field, as it talks in great detail about both the medical side present in such a review (with special care afforded to the methods used for data extraction), as well as the more technical part that deals with the use of DL methods.

The authors consider that it's noteworthy that the most frequently cited publications in this domain predominantly appear in journals and databases from Springer, Elsevier, IEEE, and various other medical journals, including some less reputable like MDPI or Frontiers.

Since in-depth, reliable and accurate epileptic analysis relies heavily on datasets, the paper takes a close look at the most used datasets that are open source, as such serving also as a recommendation for future researchers, as an easy guide that explains in broad details what is most important to know about each database. Open source MRI datasets are sadly far more difficult to find.

Effective ML requires extracting manually constructed, handmade characteristics from the data, which calls for subject matter experts in the relevant fields. With the use of multi-layer structures and a more sophisticated methodology, DL enables automatic data extraction. Hence, DL classifiers [7] must be employed to save the extra work of extracting fea tures using the handmade method; nevertheless, for them to train with good performance, a large amount of data must be collected.

Various ML algo rithms were tested for binary classification tasks, including K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM), Stochastic Gradient Descent (SGDC), Gradient Boosting Classifier (GB), and Decision Tree (DT), with Naïve Bayes concluded as producing the best accuracy. For the same binary classification problem, the researchers also investigated DL techniques, including different artificial neural networks, and extreme learning machines (ELM). Overall DL methods have much better accuracy when it comes to such a simple binary classification task, with ELM having the highest accuracy, followed by LSTM. It's also noted that every algorithm and strategy has advantages and disadvantages. For example, kNN clustering may not yield as great an accuracy as other algorithms, but can handle extremely large-dimensional data sets. The paper also concludes that overall epilepsy diagnosis is easier than seizure prediction.

6 Experimental results

We chose to implement an algorithm from the 2022 paper we discussed above [16]. The basic idea was to discern the signals that are non-ictal and different from most other non-ictal signals at the same time. In order to accomplish their goal, they used a kNN and a GAN. The kNN was used to classify the such signals - called 'boundary'- while the GAN is used to create new data that follows the same pattern.

We used the same dataset [1] used in the original paper, the Bonn epilepsy EEG dataset. The data are multi-channel intracranial/- EEGs from continuously recorded from 5 healthy subjects and 5 epileptic patients. The data was clipped into records after the removal of some artifacts due to eye movements. Each record in this dataset is a single channel epoch with duration of 23.6 s. Specifically, Set O contains scalp EEGs acquired from 5 healthy subjects during eye-closed period; Set F and S are intracranial EEGs acquired from the patients, with the difference that Set F is from inter-ictal period when the patient is not undergoing a seizure while Set S from ictal of the same patients.

In order to be able to find out the non-ictal samples that masquarade as ictal, we need to classify the F samples -that are non-ictal- in three categories: safe (the normal non-ictal like signals), boundary (the fake ictal-like signals) and noise (everything else).

The kNN method is adapted to cluster the non-ictal EEGs into three types. The three-type criterion is: we assume that for a non-ictal sample, in its k nearest neighbors there are l samples that are non-ictal, too. If $k \geq l > k/2$ safe one; if $k/2 \geq l > 0$, the sample in question is clustered as a boundary one; if l is close to 0, it should be a noise sample.

We trained the kNN on O and S data, classifying O as safe - since it comes from healthy patients- and S as boundary since it comes from an epileptic patient that was experiencing a seizure. While in truth, S signals are ictal, since our goal is to find the ictal-like non-ictal signals, these samples can be used to train the kNN to classify the non-ictal data from F.

Then we implemented a a Conditional GAN (cGAN), specifically designed to generate EEG data based on specified class labels (safe, boundary, or noise). The generator creates synthetic EEG data samples based on a specified class label. The discriminator distinguishes between real EEG data and synthetic EEG data generated by the generator, while also considering the class label.

Then we applied the kNN again, in order to see how it classifies the synthetically generated data.

Unfortunately, the kNN has a low accuracy, mostly due the imbalanced dataset it was trained on. As a result, the GAN too, is unable to create realistic data as it can't differentiate easily between the three classes.

The implementation can be found in github: `https://github.com/dianajianuuvt/kNN_GAN_boundary_detection/tree/main`

7 Future work

In the future, we plan to tune both the kNN classifier and the GAN network, while also choosing a different architecture to evaluate the GAN's performance. A different dataset would also be useful, in order to compensate for the unbalanced data.

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