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

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Abstract. The human brain is one of the greatest mysteries of our time. In an attempt to understand it and its pathological conditions, several techniques like electroencephalogram (EEG) have been developed and machine learning (ML) architectures have been implemented in order to interpret the results. This state of the art report provides a comprehensive analysis of various deep learning (DL) architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs), to assess their effectiveness in epileptic seizure detection. We implement and evaluate a kNN-GAN approach to identify ictal-like non-ictal signals, revealing challenges in data imbalance and model performance. We also explore the impact of preprocessing techniques in enhancing classification accuracy and compare complex architectures with simpler models, such as a single-layer neural network and an MLPClassifier. While GANs offer potential in synthetic data generation for imbalanced datasets, further research is required to optimize their contribution to EEG-based seizure prediction. The findings underscore the need for robust, interpretable, and computationally efficient deep learning solutions for epilepsy diagnosis and prediction, but also the black box nature of neural networks and how far we still are from understanding and using them correctly in fields such as medicine.

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

1 Introduction

The intersection of deep learning and neuroimaging has revolutionized the analysis of brain activity, providing new insights into complex neural patterns and disorders. Epilepsy, one of the most well-known and thus well-researched diseases of the brain, presents many challenges for automated detection and prediction due to the variability and complexity of electroencephalogram (EEG) signals. Recent and not so recent advancements in deep learning, particularly in convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs), have significantly improved the reliability of seizure prediction models. This paper explores the performance of various deep learning architectures in classifying and predicting epileptic seizures using EEG data

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 Functional Magnetic Resonance Imaging (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 deep learning (DL) architectures (e.g. RNN, CNN) for prediction of epileptic seizures. These architectures are mostly used in order to 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 [20], 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.

We also took a look at an older paper and how it preprocessed the data before using a neural network to predict seizures from the newly-encoded data.

In the end, we also chose to look at much simpler architectures and their performance for seizure predictions, by simplifying the task into a binary classification one.

2 Problem specification

The problem we tackle in our state of the art (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 published across the years, 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.

Afterwards, we used the same dataset for the same task, but with a different architecture and following a series of detailed preprocessing steps.

In order to have a better undersating of how well these complex models actually perform seizure prediction, we took as comparison the performance of two very simple models (a neural network with one hidden layer and an MLPClassifier with two hidden layers) using the same EEG data.

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 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.

EEG is a test that records brain activity using small sensors placed on the scalp. It is a safe and painless way to measure electrical signals in the brain. EEG is commonly used in medicine and research because it can track brain activity in real time. While newer imaging technologies like MRI and CT scans are better for detecting brain tumors or strokes, EEG is still very important for diagnosing

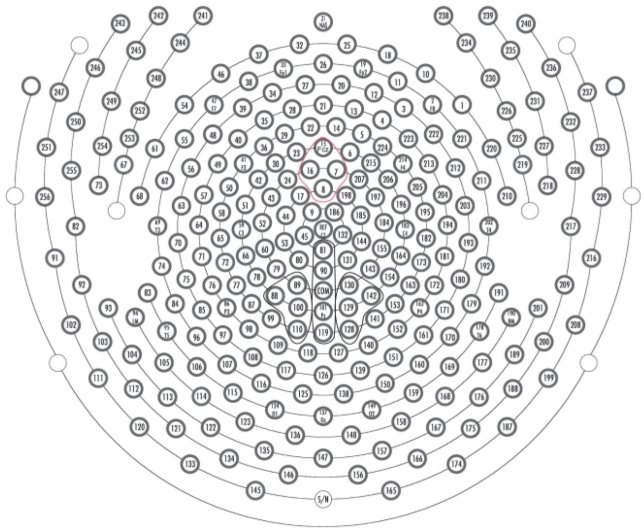


Fig. 1. An example of a 'net' of electrodes used for capturing the signals

conditions like epilepsy. It helps doctors find unusual electrical activity in the brain, monitor seizures, and study sleep disorders or other brain conditions.

EEG is the most important test for diagnosing epilepsy because it can detect unusual brain activity linked to seizures. These patterns, called *spikes* or *sharp waves* can help doctors understand where and how seizures start. However, a standard EEG does not always catch these patterns, and in some cases, a person with epilepsy might have a normal EEG result.

To improve accuracy, doctors may use longer EEG recordings, portable EEG monitors, or tests in a special hospital unit. Certain techniques, like flashing lights, deep breathing, or sleep deprivation, can also help trigger abnormal brain activity during the test. Although EEG isn't perfect and can sometimes give false results, it remains a key tool for diagnosing epilepsy because it shows real-time brain activity—something that other scans cannot do.

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. DL is the subset of machine learning that uses neural networks for these tasks.

A convolutional neural network (CNN) [16] 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. CNNs are one of the three DL architectures that have been -and still are- heavily used for interpreting EEG readings and medical diagnosis.

Recurrent neural networks (RNNs) [19] 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) [17] are unique due to the fact that they encompass 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. GANs have shown promising applications in epileptic seizure prediction, particularly in addressing challenges like imbalanced datasets and enhancing the performance of predictive models. This is due to their capacity to create synthetic data that closely mirrors real data, an invaluable asset in medicine, where large datasets are hard to come by.

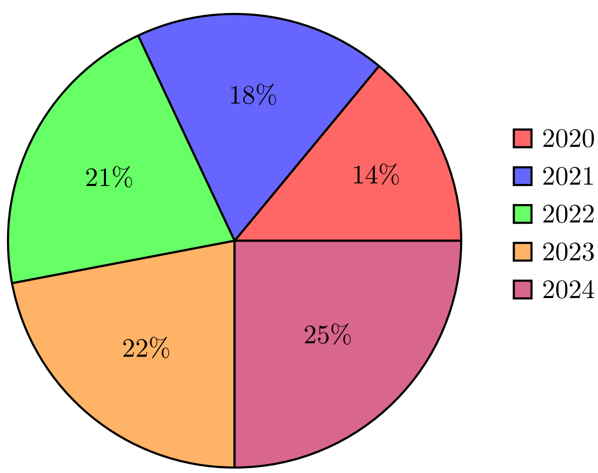
We are particularly interested in Conditional Generative Adversarial Networks (cGAN). With a conditional GAN, it's possible to send more precise information, called class labels, to both the generator and the discriminator to guide their data generation. These pieces of information help specify the data produced by the generator and the discriminator, allowing them to arrive at the desired results more quickly. The labels guide the generator's production to generate more specific information [4].

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.

To have even a shallow understanding of how vast this field is, we have created the following piechart to show the number of research papers that show up on Google Scholar when using the keywords *EEG*, *epilepsy* and *machine learning* that have been published in the last five years.

Papers using ML for detecting epilepsy from EEG data in the last 5 years



1. Year 2020 - 5010 results
2. Year 2021 - 6500 results
3. Year 2022 - 7490 results
4. Year 2023 - 7780 results
5. Year 2024 - 9100 results

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 k-Nearest Neighbour (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 [10], as CNNs had proven themselves very adept at feature extraction due to the fractal dimension of both EEG readings and medical imagining [6]. LSTMs appeared around the same time, both neural networks gaining an increase in popularity in 2018. As for GANs, [14] 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 for this paper 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 A closer look at our chosen field

5.1 Automatic spike detection

The paper [8] discusses a neural-network-based system for the automated detection of epilepsy from EEG recordings, addressing the challenges posed by long-term EEG monitoring. Manual analysis of such data is time-consuming and prone to human error, which has driven research toward automated diagnostic aids. Among these, ANNs have shown promise, particularly the LAMSTAR (Large Memory Storage and Retrieval) network used in this study. The method involves preprocessing EEG data using nonlinear filters to extract attributes such as spike amplitude and occurrence frequency, which are then fed into the LAMSTAR ANN for training and diagnosis. This approach demonstrated high accuracy in distinguishing epileptic signals from normal ones.

Epileptic seizures leave distinctive patterns in EEG, categorized as ictal (seizure period) and inter-ictal (between seizures). The inter-ictal phase often exhibits spikes that are critical for epilepsy diagnosis. Traditional statistical methods failed to generalize effectively to unseen data, which prompted the shift toward ANN-based solutions. The LAMSTAR network, characterized by its ability to handle fuzzy and incomplete data, was chosen for its flexibility and adaptability. This network employs multiple self-organizing maps (SOMs) to process individual problem attributes independently, making decisions based on their combined responses.

The study utilized EEG segments from normal and epileptic subjects for training and testing the LAMSTAR ANN. Preprocessing steps included segmentation, filtering, and thresholding to enhance spike features. Key attributes were quantized to streamline training, and the network was trained on these inputs to classify segments as epileptic or non-epileptic. This system continued learning during operation, improving performance without requiring reprogramming. Testing revealed an overall accuracy of 97.2%, with a miss rate of 1.6%. These results underscore the system's efficacy in detecting epilepsy while emphasizing the importance of careful data preprocessing.

The study also highlights the potential for further enhancements. Incorporating additional attributes, including patient history and other non-EEG data, could improve diagnostic robustness. Moreover, integrating correlation links within the LAMSTAR network might enhance its ability to capture complex relationships between attributes, further boosting accuracy. The authors suggest that alternative preprocessing methods, such as wavelet analysis, might also simplify and expedite the detection process, paving the way for real-time applications.

The LAMSTAR-based detection system represents a significant advancement in automated epilepsy diagnosis, offering high accuracy and adaptability. By leveraging the network's capacity to learn from diverse and incomplete data, the study addresses a critical clinical need. However, the authors acknowledge the need for further research to optimize preprocessing, integrate additional diagnostic features, and validate the system's performance in broader clinical settings.

5.2 A good example of CNN for epilepsy detection

This article from 2008 [7] 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 nonlinear 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.

This 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.

5.3 In the middle of the CNN craze

A more recent article [9] 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 CNN architecture 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.

5.4 What 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 [15] that had come out during 2018, when the use of LTSMs and other RNNs was 'fashionable' in our field of research.

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.

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

The study [20] tries to detect epileptic seizures from EEGs, taking into consideration the multimodality [18] of EEG data, 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 dataset used in this study was the Bonn Epilepsy EEG dataset, which contained EEG recordings from healthy individuals and epilepsy patients during different states (non-seizure, interictal, and seizure). A kNN algorithm was used to categorize non-seizure signals, ensuring that those similar to seizure patterns (boundary signals) were identified separately. Then, a GAN was employed to generate pseudo-samples from the safe non-seizure signals to create a reference representation. By measuring the distance between real EEG signals and this generated reference, the GAN helped further distinguish hidden boundary signals that could have confused a standard classifier.

Once the boundary signals were identified, the main classification task was carried out using a deep learning model based on the VGG-16 (Visual Geometry Group) convolutional neural network. This CNN, originally designed for image classification, was adapted for EEG-based seizure detection using time-frequency diagrams as input. Transfer learning was applied to optimize the CNN, allowing it to effectively classify seizure and non-seizure signals even with a relatively small training dataset. The modified VGG-16 architecture was trained with the extracted features from both the boundary signals and standard non-seizure/seizure data, leading to improved classification accuracy.

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.

5.6 Reviews and surveys through the years

The begining of the DL in epilepsy boom - year 2019

The goal of this study [12] 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 requires 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. In 2019, CNN and LTSM were the two most prominent DL methods used for this task, while SVM was the most used linear classifier.

Recently, LSTM has been used in seizure prediction. A 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 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 literature review [10] done in 2020 focuses on the use of machine learning in the detection of epileptic seizures. The authors 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 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)	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	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 file)	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 ML and 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 for these issues.

How does the field look like today?

This review [11] 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

6.1 The dataset we worked with

We used the BONN epilepsy dataset -an open source dataset- for all of our experiments:

- SET A in directory Z.zip containing Z000.txt - Z100.txt
- SET B in directory O.zip containing O000.txt - O100.txt
- SET C in directory N.zip containing N000.txt - N100.txt
- SET D in directory F.zip containing F000.txt - F100.txt
- SET E in directory S.zip containing S000.txt - S100.txt

The dataset consists of five sets, each containing 100 single-channel EEG segments of 23.6-second duration.

- **Sets A and B:** These were taken from surface EEG recordings of five *healthy* volunteers using a standardized electrode placement scheme.
  - **Set A (Directory Z):** Recorded while the subject had their eyes open.
  - **Set B (Directory O):** Recorded while the subject had their eyes closed.
- **Sets C, D and E:** These are intracranial EEGs acquired from *epileptic* patients.
  - **Set D (Directory F):** Recorded during the inter-ictal period (when the patient is not undergoing a seizure).
  - **Set C (Directory N):** Recorded during the inter-ictal period.
  - **Set E (Directory S):** Recorded during the ictal period (when the patient is experiencing a seizure).

This dataset structure allows for its use in supervised learning models.

This EEG data was recorded using the international 10-20 system for EEG electrode placement and is also monopolar (has only one channel). An advantage of the monopolar channel is that it provides a more comprehensive brain activity measurement, but this comes with the risk of having more noise interfering with the data. All EEG signals were recorded with system, using an average common reference omitting electrodes containing pathological activity (C, D, and E) or strong eye movement artifacts (A and B) [5].

Each file from this directory represents a time series. Each time series contains 1500 elements. The data points represent voltage fluctuations over time, corresponding to the brain's neural activity.

6.2 A more complex classification

We chose to implement an algorithm from the 2022 paper we discussed above [20]. 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.

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`

6.3 The value of preprocessing data in an experiment

Using [8] as inspiration, we once again used the BONN dataset for our experiments in epilepsy classification.

Two sets of EEG data files were selected. One set consisted of time series of EEG from normal subjects during wakefulness with eyes open, which we correlated with our directory Z. The other set consisted of time series of epileptic

EEG that was recorded during the occurrence of epileptic seizures in subjects suffering from epilepsy, which we substituted with our directory S.

The first step was preprocessing the data according to the paper:

a) Divide the EEG time series into small segments of duration 1 second. EEG is considered to be stationary for an interval of 1 second. Segmentation into smaller blocks helps in the analysis of local phenomena.
b) Apply a median filter of suitable length to each segment. The filter length should be chosen to smooth the epileptic spikes. Since spike duration is normally between 70 and 100 milliseconds, a median filter over 15 milliseconds is chosen for smoothing. Subsequently, subtract the median-filtered signal from the original EEG segment to yield a difference signal. The difference signal emphasizes epileptic spikes, if any are present, while very low-amplitude spikes remain in normal segments.
c) Further enhance the epileptic spikes in the difference signal by applying nonlinearity, such as raising the difference signal to an odd power. This also reduces noise effects.
d) Apply thresholding to the enhanced epileptic spikes. In this study, the threshold was set to 50% of the maximum spike amplitude in the segment. This step distinguishes spikes from any residual noise.
e) Store the maximum spike amplitude and calculate the number of spikes in a particular segment.
f) Quantize the spike amplitude and spike occurrence frequency. Both variables are quantized into five bits each.
g) Combine the quantized attributes to form a comprehensive word to be fed into the LAMSTAR neural network.
h) Train the LAMSTAR using the word formed in the previous step.

The peak-occurrence frequency and maximum amplitude peak occurrence for a particular segment were quantized before feeding into the LAMSTAR. Quantization shortens the size of input words and subwords by coding the data in fewer bits. Also, it renders slightly dissimilar subwords similar, to decrease the number of training/testing patterns. For quantization, the maximum epileptic spike amplitude was rounded to the nearest multiple of 100 and then divided by 100. Hence, a spike of 345 microvolt yields 3. Note that five bit binary coding of 345 is 00011. Spike-occurrence frequency is not quantized since it is a small number. Also, errors in spike occurrence frequency greatly affect diagnosis.

The LAMSTAR was built according to figure :

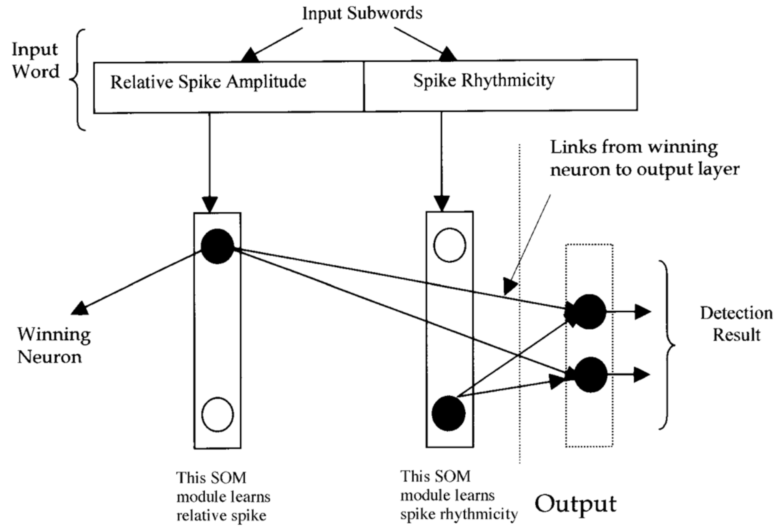


Figure 4: The LAMSTAR NN

Fig. 2. The architecture of the LAMSTAR network

Unfortunately, the results of the experiment are less than desirable: the model classifies all signals as epileptic. Despite using denoising techniques, performing training amongst several thousand epochs and tuning the model, the result remained the same.

To enhance the performance of the model, we implemented a LAMSTAR network with a multi-layer architecture, allowing for adjustable layers and neurons per layer to accommodate various data complexities. We incorporated flexible subword dimensions and configurable output neurons to optimize adaptability for different datasets. Additionally, for comparison, we designed a feedforward deep learning model with two hidden layers, utilizing ReLU activation functions for the hidden layers and a sigmoid activation function in the output layer for binary classification tasks. The model was trained using the Adam optimizer and binary cross-entropy loss to ensure robust convergence and effective performance in the classification task.

The model demonstrates moderate performance in classifying epileptic signals, with an overall accuracy of 61% and a strong recall of 88%, indicating its effectiveness in identifying most epileptic cases. However, the precision of 56% highlights a significant issue with false positives, as the model incorrectly identifies many non-epileptic signals as epileptic, which could lead to unnecessary interventions or alarms. This imbalance between recall and precision is further reflected in the F1 score of 0.69, showing that while the model is sensitive to detecting epileptic signals, it lacks specificity. The confusion matrix reveals that

392 epileptic signals are correctly classified, but 303 non-epileptic signals are misclassified, alongside 53 missed epileptic cases. To improve, the model could benefit from optimizing its decision threshold, employing more complex architectures better suited for time-series data, enhancing feature extraction techniques, or addressing potential data imbalances. While it performs well in avoiding false negatives, critical for medical applications, the high false-positive rate limits its practical utility.

The implementation can be found in github: `https://github.com/dianajianuuvt/Classifying-epilepsy-from-spike-count-and-amplitude-from-EEG-data`.

6.4 A very simple experiment

As seen in the paragraphs above, we have taken a look at a multitude of papers that each proposes very complex solutions to what can essentially be boiled down to a simple classification problem. As such, it makes us wonder what would happen if we take the same dataset we have used before and use two much simpler methods: a neural network with one hidden layer and an MLPClassifier with two hidden layers. We once again used two directories each consisting of 100 time series from EEG data recordings, one from an epileptic patient and one from a healthy control.

Let's first take a look at the neural network. We built it in keras -a simple interface for working with complex deep learning algorithms- with one hidden layer with 16 neurons and one output layer consisting of 1 neuron. We used a sigmoid activation function for the output layer, as this is generally used in binary classification. We load the data, pads it to make sure all time series have the same length (we chose a maximum length of 1500, based on the length of our time series), and split the data into training and testing sets. It creates the output as a probability value between 0 and 1, which can be interpreted as the probability of the input belonging to one of our two classes: healthy or epileptic, with 0 representing 'healthy' and 1 'epileptic'. After fine-tuning the parameters, we managed to obtain as the best accuracy 72.5%. A surprisingly high value for such a simple classifier.

Here is a resulting confusion matrix:

True Negative (TN)	**False Positive (FP)**
15	4
False Negative (FN)	**True Positive (TP)**
7	14

- The **top-left** cell (15) represents the **true negatives (TN)**, which are the healthy samples correctly classified as healthy.
- The **top-right** cell (4) represents the **false positives (FP)**, which are the healthy samples incorrectly classified as epileptic.
- The **bottom-left** cell (7) represents the **false negatives (FN)**, which are the epileptic samples incorrectly classified as healthy.

– The **bottom-right** cell (14) represents the **true positives (TP)**, which are the epileptic samples correctly classified as epileptic.

Next we took inspiration from [13] to use an MLPclassifier to perform the same binary classification task. An MLPClassifier (Multi-Layer Perceptron Classifier) is a type of artificial neural network used for classification, regression, and pattern recognition. When it comes to classification, it is useful for tasks like image recognition, medical diagnosis, and EEG signal classification. MLPs are excellent for a variety of classification problems because they are able to simulate complicated, non-linear relationships between features and target classes. The dataset is then processed 100 times to evaluate model consistency. In each iteration, the data is split into training (80%) and testing (20%) sets, and a MinMax scaler is applied to normalize the input. A MLP classifier with two hidden layer (each of 16 neurons) and a single output neuron using the tanh activation function is trained on the scaled data. MLPClassifier is a shallow neural network, not deep learning, unless it has multiple hidden layers, as such we chose the lowest number of 2 hidden layers. The process is repeated 100 times, and the average accuracy is computed, allowing an assessment of the model's reliability and performance on our dataset.

It's important to notice that there was no preprocessing done on this data, nor any fine tuning for the models. And yet, the first model produced accuracies rivaling the ones computed from far more complex models. Meanwhile, while the second model did not perform well, it is still relevant.

Predicted/ Actual	**Healthy (Z)**	**Epileptic (S)**
Healthy (Z)	967 (True Negatives)	1059 (False Positives)
Epileptic (S)	951 (False Negatives)	1023 (True Positives)

Table 3. Confusion Matrix Breakdown

The model makes a high number of mistakes, especially predicting healthy (Z) as epileptic (S) and vice versa. The False Positive Rate (FP) and False Negative Rate (FN) are quite high, indicating the model struggles to distinguish between the two classes.

The implementation can be found in github: `https://github.com/dianajianuuvt/Classification-epilepsy`.

7 Conclusions

In this study, we analyzed various deep learning architectures for predicting and classifying epileptic seizures using EEG datasets. Through an extensive literature review, we examined the evolution of seizure prediction models, from traditional machine learning methods such as k-Nearest Neigbors and Support Vector Machines to advanced deep learning techniques like CNNs, RNNs, and GANs. We observed that while CNNs excel in feature extraction and classification, RNN-based architectures, particularly LSTM networks, are well-suited for processing sequential EEG data. Additionally, GANs offer a promising avenue for generating synthetic EEG signals to augment imbalanced datasets.

Our implementation of a kNN-GAN-based approach aimed to identify nonictal signals that mimic seizure patterns, referred to as boundary signals. While the kNN classifier successfully categorized EEG signals into safe, boundary, and noise classes, its accuracy was hindered by data imbalance. This limitation, in turn, affected the GAN's ability to generate realistic boundary signals. In a separate experiment, we applied a LAMSTAR neural network for epilepsy detection, following an approach inspired by prior studies. However, our model struggled with overclassification, misidentifying many normal signals as epileptic, which highlights the challenges of designing robust classifiers for this task.

Additionally, we explored a simplified classification approach using a neural network with one hidden layer and an MLPClassifier with two hidden layers. Surprisingly, the simple neural network achieved a relatively high accuracy, demonstrating that even basic architectures can yield competitive results when applied to well-preprocessed EEG data. This shows the importance of data quality and preprocessing techniques in achieving high accuracy, sometimes even rivaling more complex DL architectures. The results suggest that while sophisticated models offer potential improvements, simpler methods should not be overlooked, especially when computational efficiency is a concern.

Our findings also highlight several challenges in seizure prediction, including data imbalance, interpretability of deep learning models, and the need for reliable real-time implementations. While GANs provide a means to augment datasets, further research is needed to refine their ability to generate realistic EEG signals that meaningfully contribute to classification performance. Furthermore, the choice of an appropriate classifier remains crucial, as different architectures exhibit varying strengths and weaknesses in handling EEG data.

8 Future work

There are several directions of research that can be pursued in the future, considering how vast our area of research is. Building upon the findings of this study, several avenues for future research can be explored to enhance the accuracy, generalizability, and clinical applicability of deep learning models for epileptic seizure prediction and classification.

One immediate area of improvement is the optimization of the kNN classifier and GAN model to improve boundary signal detection. It would be interesting to see how the models perform on another dataset.

A more extensive comparative analysis of different DL architectures, including transformer-based models, could provide insights into their potential for handling EEG time-series data. Transformers, which have demonstrated remarkable success in sequential data processing tasks, may offer an advantage over traditional RNN-based models like LSTMs by addressing vanishing gradient issues and capturing long-range dependencies more effectively.

Furthermore, expanding the dataset to include multimodal data—such as EEG combined with functional magnetic resonance imaging (fMRI) or other physiological signals like heart rate variability —could improve the robustness of seizure prediction models. Multimodal learning approaches can leverage complementary information from different physiological sources, potentially leading to more accurate and early detection of seizures. Future studies could also explore transfer learning techniques, where models pre-trained on large EEG datasets can be fine-tuned for specific patient data, improving personalization and adaptability.

Finally, ethical considerations and patient privacy must be addressed when designing real-world implementations of DL-based seizure detection systems. Developing federated learning approaches, where models are trained locally on patient devices without transferring sensitive EEG data to centralized servers, could enhance data security while maintaining model performance. Collaboration with neurologists and clinicians will be essential to ensure that these AI-driven approaches align with medical needs and regulatory requirements, ultimately contributing to more effective epilepsy diagnosis and treatment strategies.

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