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ABSTRACT

The intricate neurological condition known as epilepsy, which is common across the world, presents considerable difficulties in accurately identifying and differentiating between non-epileptic and epileptic activity using electroencephalograms (EEGs). To customize successful therapies, it is essential to accurately identify the kinds of epileptic activity. Since epilepsy affects about 50 million people worldwide according to latest update of WHO and is typified by spontaneous seizures, early identification and prediction are vital in enabling people to minimize possible harm.

This report provides a brief overview of the report on epilepsy diagnosis and classification analysis, which includes various machine learning algorithms such as K-Nearest Neighbour (KNN), Logistic Regression, Naive Bayes, Random Forest, Support Vector Machine (SVM) and Decision Trees. This report explores the evolving field of epilepsy diagnosis and reviews the various machine learning algorithms, datasets, and computational techniques currently in use.

To identify small patterns in EEG data, this study combines cutting edge technologies, like Long Short-Term Memory (LSTM) and 1D-CNN (Convolutional Neural Network) leveraging data from five hundred patients acquired from the UCI Machine Learning Repository. To optimize the 1D-CNN LSTM architecture and hyper-parameters, Bayesian optimization is employed, allowing for efficient exploration of the parameter space. Its effectiveness is not only limited to enhancing the performance metrics of a particular model but also minimizing the computing power required for fine tuning. The research evaluates the effectiveness of the 1D-CNN LSTM-based model, showcasing its potential as a reliable tool for automated epilepsy detection with accuracy of 99.47% (≈ 100%), average sensitivity of 99.45%, and average specificity of 99.57%. This approach, emphasizes the significance of anticipating seizures in advance, attempts to provide epileptics the tools they need to control and avoid seizures in advance, so ultimately enhancing their quality of life for patients.

Keywords: Epilepsy, Seizures, 1D-CNN, LSTM, Bayesian Optimization, electroencephalogram

I. INTRODUCTION

I discovered at the outset of this research that it would be quite helpful to clarify a few things. To provide them a brief overview of what they will read about in the next chapters, as well as the nature of the examination’s subject and the solution’s structure. I will concentrate on identifying epileptic seizures in electroencephalogram (EEG) data. All users are welcome to utilize this information, which was gathered at the German university of Bonn. Several well-known machine learning techniques that have been suggested in the literature for comparable tasks will be used in the identification procedure. To evaluate them, seven different measures will be applied. Python 3.7 was used to implement the whole procedure. The objective is to contrast some of the approaches put out in the literature and expand them from patient-specific to datasets with numerous cases.

The current seizure prediction methods lack, with particular emphasis on their limited performance on small training datasets and their disregard for time-series data. It is a mental disorder characterized by seizures and uncertainty, remains a significant medical problem. Timely and accurate detection of epilepsy is very important for diagnosis, treatment, and patient management. Considering that seizures can occur suddenly and without warning, it is important to have a system that can detect seizures. A comprehensive review of the electroencephalogram (EEG) recording is required to accurately identify these seizures. In recent years, the intersection of machine learning and medicine has shown promise in improving the diagnosis and classification of epilepsy.

Epilepsy is a mental disorder characterized by sudden and unpredictable events that affects millions of people worldwide. These seizures are caused by electrical malfunctions in the brain and often present with symptoms that vary in intensity and duration.[1] Epilepsy is a chronic brain disorder affecting nerves cell activity for an individual of all ages. It has an impact over 50 millions of worldwide population, positioning it as one of the most prevalent neurological conditions. Almost 80% of epileptics belongs to blue collar class, if given the right diagnosis and care in early stages, there are chances of making up to 70% of epileptics enjoy a seizure free life. Individuals with epilepsy have a threefold increased risk of dying young compared to a healthy human being. In developing or underdeveloped nations, 75% of epileptic patients do not undergo proper treatment and many may die undiagnosed. People suffering from epilepsy along with their families and relatives must face stigma and prejudice in many parts of the world.

As per WHO [2] in India, the average incidence of epilepsy is 5.59–10 per 1,000 individuals. In India, there are more than ten million epileptic sufferers, or more than 1% of the total population. The incidence is higher in rural areas 1.9% in contrast to urban areas 0.6%. Since 2015, February's second Monday has been marked as International Epilepsy Day (IED), an internationally recognized healthcare event aimed at uniting epileptic patients and fostering a community where knowledge of the condition's epidemiological profile, diagnosis, and treatment options is exchanged. [3] Electroencephalogram (EEG) is one of the most common diagnostic measures used in medical industry to diagnose epilepsy which is a highly intricate disease. This condition is so complex that it makes understanding EEG signals or results very difficult. Integration of such techniques with machine learning is important in differentiating epileptic seizures from other types and identifying particular forms of epileptic activity.

The optimal treatment and management of epilepsy requires its diagnosis to be accurate and within the golden time period i.e. before I can see the external symptoms of epilepsy like staring, jerking movements of the arms and legs or stiffening of the body. Medical applications for machine learning have been growing rapidly, providing a wide range of opportunities for the analysis, diagnosis and classification of epilepsy. With this integration comes a new way of enhancing diagnostic accuracy, predicting epilepsy occurrences as well as coming up with personalized and customized treatment plans. This comprehensive report encompasses various topics on machine learning for classification of epileptic and non-epileptic signals, stressing on the significance of artificial intelligence (AI) in unravelling complex medical conditions. However, traditional epilepsy diagnosis relied entirely on neurologist clinical observations, physical examinations, and electroencephalography (EEG) data analyses that are all human dependent and are prone to be mistaken thus chances of detection of epilepsy within golden hour is very much reduced, but incorporating Machine Learning techniques such as K-Nearest Neighbour (KNN) or logistic regression is expected to offer a much more precise and efficient way to diagnose the disease.

Both the search and classification scenario can be modified by various machine learning and deep learning algorithms. These algorithms help us distinguish seizures from other conditions, predict the frequency of seizures, and use data from big, complex datasets from pattern recognition and data analytics to develop customized treatment plans for everyone.

I will examine the state of the art models in epilepsy detection and classification in this report, focusing on the many types of system mastery algorithms employed as well as the statistical and computational techniques. I want to get a better understanding of these algorithms efficacy in identifying epilepsy and forecasting seizures by analysing their advantages and disadvantages.

I want to see the potential of machine learning and deep learning, including algorithms like logistic regression and CNN, in classification as I further explore the merger of technology and health. Readers will have a better grasp of the field's present status, upcoming difficulties, and usefulness for machine and deep learning to enhance patient care by having an epilepsy management method from the information in this report.

In this light, artificial intelligence intersects [4] with medical research as promising pathways towards advancing the comprehension and handling of epilepsy. With regards to machine learning, recurrent neural networks particularly those involving Long- Short Term Memory (LSTM) [5] networks have shown potential in decoding complex patterns within time series data. This improves accuracy and efficiency in detection and prediction of epileptic seizure A significant obstacle in the earlier research on seizure prediction is the insufficient analysis of time-series data. One kind of neural network that retains information from earlier instances is the Recurrent Neural Network (RNN), which uses past outputs as inputs [6]. RNNs have been more popular recently in studies on speech recognition and natural language processing. Normally RNN faces the gradient vanishing problem which is not an issue with LSTM, one of the RNN designs, which makes it easier to learn long-term relationships in time series data [7].

T. Sainath et al. [8] improved the performance metrics of the DNNs by making an ensemble model of RNN and CNN into a convolutional neural network. In some large problems, this led to a 4 to 6% relative improvement over independent implementation of LSTMs. Numerous studies that have looked at the combination of CNN and LSTM to extract temporal and spatial properties have shown how successful this approach could be by giving prominent outputs in classification. [9]

This report highlights the need of using 1D-CNN LSTM ensembled (our suggested final model based on deep learning algorithms) networks in order to understand the temporal dynamics found in EEG data. Because these networks are designed to detect long term correlations in sequential data, they are perfect for exposing minute patterns that are suggestive of impending epileptic activity. Also Bayesian optimization is used to optimize the performance of the suggested ensemble model. This is a useful technique for adjusting hyper-parameters. The model is ensured to attain optimal configurations that optimize projected accuracy while utilizing the least amount of processing resources that is achieved by employing Bayesian optimization. Interestingly, 500 patients EEG recordings were made available by the UCI Machine Learning Repository, each file contained 4097 data points over a 23.5-seconds period. [10]

II. Related Work

The extension of machine learning in epilepsy-focused sectors, including seizure detection and monitoring, has been the subject of numerous studies. By utilizing methods such as multilayer artificial neural networks, support vector machine (SVM), and deep learning, machine learning shows potential in enhancing the ability to handle and evaluate EEG and imaging data that was once considered too complex for experts. Furthermore, in this paper Abbasi, Bardia and Goldenholz, Daniel M [11] supports applying machine learning techniques to optimize medication selection, improve the precision of clinical outcome predictions, and streamline surgical planning. Predictive models produced by machine learning are a source of concern for the authors due to the limited number of validation studies published. It's worth considering the applicability and generalizability of these models in light of this deficiency. Broader datasets that take into account greater diversity are recommended by the authors in order to fill this void. Furthermore, the expected increase in investment in external validation studies to make the application of machine learning in medicine, particularly in epilepsy, more reliable was highlighted.

Amin, Ushtar, and Benbadis, Selim R [12], highlight the complexity involved in reversing an epilepsy diagnosis, emphasizing the necessity of examining "unusual" EEG patterns, which can pose challenges. A major factor contributing to misinterpretation of regular EEGs as abnormal is the lack of practical experience in neurology residency programs. They argue against prioritizing tests like EEG over medical expertise, as certain seizure types may evade detection, complicating epilepsy identification. For instance, hypermotor seizures in the frontal lobe might be mistaken for psychogenic episodes, while focal unaware cognitive seizures in older adults could be misdiagnosed as dementia. Additionally, epilepsies affecting the frontal and temporal lobes may manifest as psychotic symptoms, leading to misdiagnosis as primary mental disorders. Diagnostic errors are common across medical specialties, carrying significant consequences for both patients and physicians. In neurology, errors often stem from an overemphasis on assessments rather than considering the clinical context. Epilepsy diagnosis typically relies on clinical evaluation and medical history, with overdiagnosis being more prevalent than underdiagnosis. Lack of adequate medical background and atypical EEG findings can contribute to erroneous epilepsy diagnoses. Patients previously diagnosed with epilepsy may fail to improve with antiepileptic medications if they do not truly have the condition. In reality, many individuals receiving incorrect epilepsy diagnoses ultimately experience syncope or psychogenic nonepileptic events.

Chen, Hai and Koubeissi, Mohamad Z reviewed how electroencephalogram (EEG) is linked to Epileptic seizures and provided physiologic basis of EEG and intracranial EEG studies. They talked about pointed contoured waveforms or complexes that are different from background waves and mimic those observed in a part of human people with epileptic diseases are referred to as interictal epileptiform discharges. The most extensively studied interictal epileptiform discharges consist of spikes and sharp waves [13]. They elaborated on rhythmic discharges, which usually need to persist for a minimum of 10 seconds to be classified as an electrographic seizure. BIRDs (Brief Potentially Ictal Rhythmic Discharges) are described as "Concisely, this refers to short bursts of rhythmic brain activity exceeding 4 Hz, which may appear abruptly and do not match any recognized normal or harmless patterns" Their research frequently identifies interictal or ictal abnormalities, and how EEG is still an essential tool for diagnosis of epilepsy. However, the absence of interictal epileptiform discharges or ictal symptoms does not necessarily exclude epilepsy. Seizures can manifest in two forms: focal or generalized. Electrographic patterns may vary, and ictal activity typically evolves over the course of a seizure. For accurate diagnosis and treatment of nonconvulsive status epilepticus (NCSE)—a condition characterized by continuous seizure activity lasting at least 30 minutes, accompanied by cognitive or behavioural alterations—continuous EEG monitoring plays a vital role. When scalp EEG findings are inconclusive, intracranial EEG monitoring proves invaluable, especially in surgical planning, as it often enables earlier detection of seizures and offers superior spatial resolution compared to scalp recordings.

Mesraoua et al. indicated how EEG in comparison to the conventional method of eye assessment alone, scalp electroencephalography has the potential to provide additional spatial and temporal information. Fortunately, this information is easier to acquire because to contemporary digital EEG technology and computer-assisted analysis. A potential method to enhance non-invasive EEG localisation in focal epilepsies is to look at the spike voltage topography of interictal spikes [14]. Another additional method for locating the epileptogenic zone in individuals who are candidates for epilepsy surgery is electrical source imaging. Quantitative EEG offers a simplified and a static visualization of the extensive amount of data contained in continuous EEG. In recent times scalp EEG analysis has improved significantly with the use of computer assisted techniques and technological advancements. Scalp EEG recordings have been enhanced by including spike voltage topography, electrical source imaging and quantitative EEG to offer more consistent spatial and temporal information especially in epilepsy. Modern digital EEG equipment and sophisticated computer algorithms have provided neurologists with additional information to aid in the accurate diagnosis and therapy of epilepsy. This study to maximize the use of scalp EEG in epilepsy demonstrates the necessity of encouraging technological advancements identification and treatment.

All components of the seizure prediction scheme are pre-processing, feature extraction and classification of EEG data. A number of academicians have proposed a variety of deep learning and machine learning techniques to exploit EEG scalp signals which are recorded by installing electrodes on patients' heads in order to detect epilepsy. Several scholars have recently presented strategies for predicting seizures involving epilepsy using scalp EEG data. Preictal and interictal state categorization, feature identification, and EEG data processing comprise the three fundamental stages of all these methods.

The process known as Bayesian optimization is an effective way to optimize objective functions that take hours or even minutes to examine [15].In function evaluations, it can tolerate stochastic noise; it is best appropriate for optimization over constant domains with fewer than 20 dimensions. Using an acquisition function derived from the surrogate, it establishes an objective surrogate and uses a Bayesian machine learning technique known as Gaussian process regression to assess the unpredictability in the surrogate. 12 Bayesian optimization stands out as a potent method for optimizing objective functions that are both computationally intensive and subject to stochastic noise. This instructional guide delves deeply into Bayesian optimization, offering an extensive examination of its principles, methodologies, and diverse applications across various fields. Covering fundamental concepts as well as advanced techniques, the tutorial furnishes researchers and practitioners with a comprehensive toolkit for effectively harnessing Bayesian optimization in diverse optimization endeavours. Additionally, it underscores the tutorial's contributions to refining and formalizing acquisition functions, highlighting its pivotal role in advancing optimization methodologies. Concluding with insights into available Bayesian optimization software and future research directions, the tutorial stresses the imperative of advancing Bayesian optimization methodologies to tackle evolving challenges and opportunities within optimization and machine learning spheres. It elucidates the foundational principles of Bayesian optimization, particularly its applicability in optimizing objective functions within high-dimensional continuous domains with limited evaluations. The tutorial introduces Gaussian process regression as a surrogate model for objective functions, facilitating uncertainty quantification and informed decision-making processes.

25 Tinu Theckel Joy, Santu Rana, Sunil Gupta, Svetha Venkatesh [16] gave a detailed and mathematical explanation of the Optimization algorithm, they indicated the efficiency of this algorithm through several bench marked datasets and explained its application on various sate of art technologies. They concluded a test error of less than 0.2% on a CNN algorithm. The authors of the paper introduce an innovative Bayesian optimization framework tailored for hyperparameter tuning, drawing inspiration from principles rooted in statistical learning theory. By employing insights from PAC learning theory, the framework initially optimizes hyperparameters on small subsets of data and then progresses to explore more intricate models using the entire dataset, resulting in enhanced classifier performance. Furthermore, the framework's effectiveness is further reinforced by the deliberate addition of directional derivative signals to the hyperparameter search field. This study incorporates learning theory notions into optimization, which makes a substantial contribution to the progress of hyperparameter tuning approaches. The authors demonstrate the usefulness of their suggested approach in hyperparameter tweaking, which eventually results in the enhanced classifier performance that they explained through experimental validation across a range of machine learning methods. The innovation that they showed by using the directional derivative signs is a remarkable feature of their suggested framework as when I place them in the hyper parameter search, it enables the exploration of more complex models that are consistent with learning theory, insights, which further guide the hyper parameter tuning.

Belhadj S, Attia A, Adnane AB, Ahmed-Foitih Z, and Taleb AA [17] introduced an unsupervised clustering approach for epilepsy identification, employing potential-based hierarchical agglomerative clustering alongside empirical mode decomposition. Together with the Kolmogorov distance using the Bhattacharya distance, the Euclidean distance between the intrinsic mode functions (IMFs) was computed and supplied as input for the clustering method. They reported an accuracy of 98.84% in categorization with this strategy utilizing the CHB-MIT epileptic database. They created a seizure detection processor with wavelet energy as a parameter by utilizing an SVM classifier. Under the direction of knowledgeable neurologists examined two forms of epileptic seizures: partial epilepsy and primary generalized epileptic disease. Using a multi-layer perceptron neural network classifier and a radial basis function neural network classifier, they obtained 95.2% and 89.2% accuracy, respectively. They classified EEG signals into normal, interictal, and ictal forms of epilepsy using the Largest Lyapunov Exponent parameter for both feed-forward and recurrent neural networks. More encouraging outcomes were obtained by the recurrent neural network, which achieved a 96% classification accuracy overall, 97.38% specificity, and 96% classification sensitivity.

A Douglas–Peucker algorithm (DP)-based methodology for epilepsy identification from raw EEG data was suggested by Zarei R, He J, Siuly S, Huang G, Zhang Y [18]. In order to minimize dimensionality and find uncorrelated variables, principal component analysis, or PCA, was utilized. The University of Bonn's epileptic EEG patient database was used for the experiments, and four machine learning classifiers decision tree, k-NN, random forest (RF) and SVM classifiers were used to assess performance. Larger EEG signal data volumes cause this framework's computing complexity to grow, which is a disadvantage.

III. METHODOLOGY

I have applied two domains of artificial intelligence that are machine learning and deep learning in this report. I have used several machine learning and algorithms on the freely available dataset our goal is to find the best machine learning algorithm to detect epileptic signals in the real time and at the end of the report, I conclude that decision tree is the best algorithm in the domain of machine learning for detecting the epileptic brain signals, a table with multiple factors of evaluation is shown in the results part that provides us with the accuracy of different machine learning algorithms. Further I have also use deep learning algorithms so that I can read the epileptic signals more deeply, though it will require a significant use of extensive hardware, but the results provided by the deep learning algorithms would be also significantly much better that I can also see the conclusion table 5.1, I have used an ensemble technique that combines one dimensional convolutional neural network along with a long short term memory, deep learning algorithm.

The goal of the suggested architecture is to create deep learning model that is accurate and reliable in identifying epileptic episodes. This is made possible by the separation of two types of brain states into interictal and ictal. The model proposed in this study is an ensemble model, which is combination of 1D-CNN followed by LSTM. Prior to the introduction of the 1D-CNN and LSTM, initially a pre-processing of the raw EEG is necessary. Next, the 1D-CNN LSTM model is created and used to identify epileptic seizures. The initial data set was pre-processed and reorganized by a UCI official, as explained more in section below “Freely Accessible Dataset” Therefore, a normalization of the EEG signal data is done in the pre-processing step which is acquired from the UCI dataset set before feeding it to the suggested model.

A. Freely Acessible Datasets

The utilization of dataset is crucial for data scientists and academics to evaluate the success of the models they have presented. The detection of a tumour should similarly pick up on our brain signals. The most popular way to track brain activity is through EEG recordings. These recordings are crucial for machine learning classifications that investigate novel techniques for detecting tumours in a variety of ways, including early tumours detection, quick tumour detection, patient tumour detection, and tumour localization. Data sets that are accessible to the general public are crucial for analysis, comparison, and inference. I will go through the well-known dataset frequently utilized in epilepsy "UCI Machine Learning Dataset"

Figure 3.1 UCI Machine Learning Repository[10]

Each of the five folders in the original dataset [10] has one hundred files, each of which represents a particular topic or individual. Every file contains a 23.6-second observation of neural activity. Data points totalling 4097 are collected from the related time-series. The value of the EEG recording at a particular moment in time is represented by each data point. There are five hundred distinct individuals in all, and every one of them having 4097 data points for 23.5 seconds. The 4097 data points were split up into 23 segments, with each segment holding 178 data points in a single second. Each segment had an EEG record value recorded at a distinct time period. Which gives 23 x 500 = 11500 data points in 1 second (column) for each item, and a label with y = 1, 2, 3, 4, and 5 in the last row. Thus, subject from class 2 to 5 are categorized as non-epileptic EEG signals and category 1 belongs to epileptic EEG signals.

TABLE 3.1 SUMMARY OF UCI DATASET

Subject Category	**Subject State**	**Epileptic/Not Epileptic**
1	*Epileptic Patient*	*Epileptic*
2	*Brain With Tumour*	*Not Epileptic*
3	*Healthy Brain*	*Not Epileptic*
4	*Eyes Closed*	*Not Epileptic*
5	*Eyes Open*	*Not Epileptic*

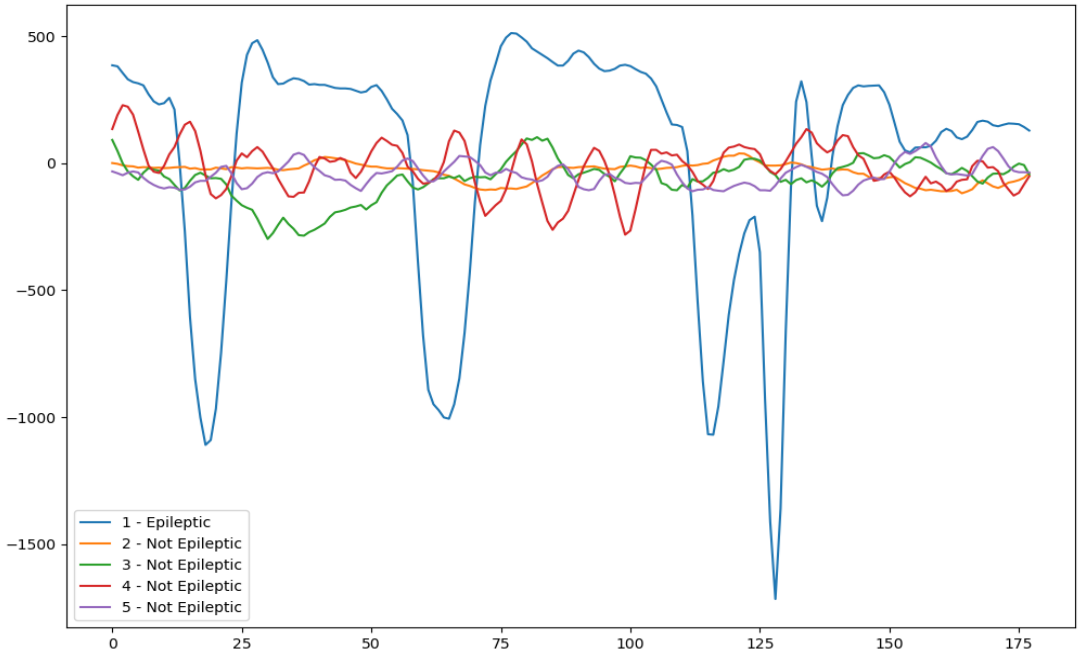

Figure 3.2 The raw EEG signal waveform of four healthy subjects and one epileptic subject.

B. 10-20 Electrode System

A 10-20 electrode arrangement serves as a standardized technique for the strategic placement of electrodes on the human scalp, primarily for electroencephalography (EEG) measurements as shown in Fig 3.3 It divides the scalp into defined zones and positions electrodes at precise coordinates relative to anatomical landmarks. The nomenclature "10-20" signifies that the separation between these landmarks are uniformly either 10% or 20% of the total measurements from right to left or front to back on the skull. This approach offers a consistent methodology for capturing brainwave activity and finds extensive application in clinical and scientific investigations, supporting the examination and exploration of neurological conditions and brain functioning.

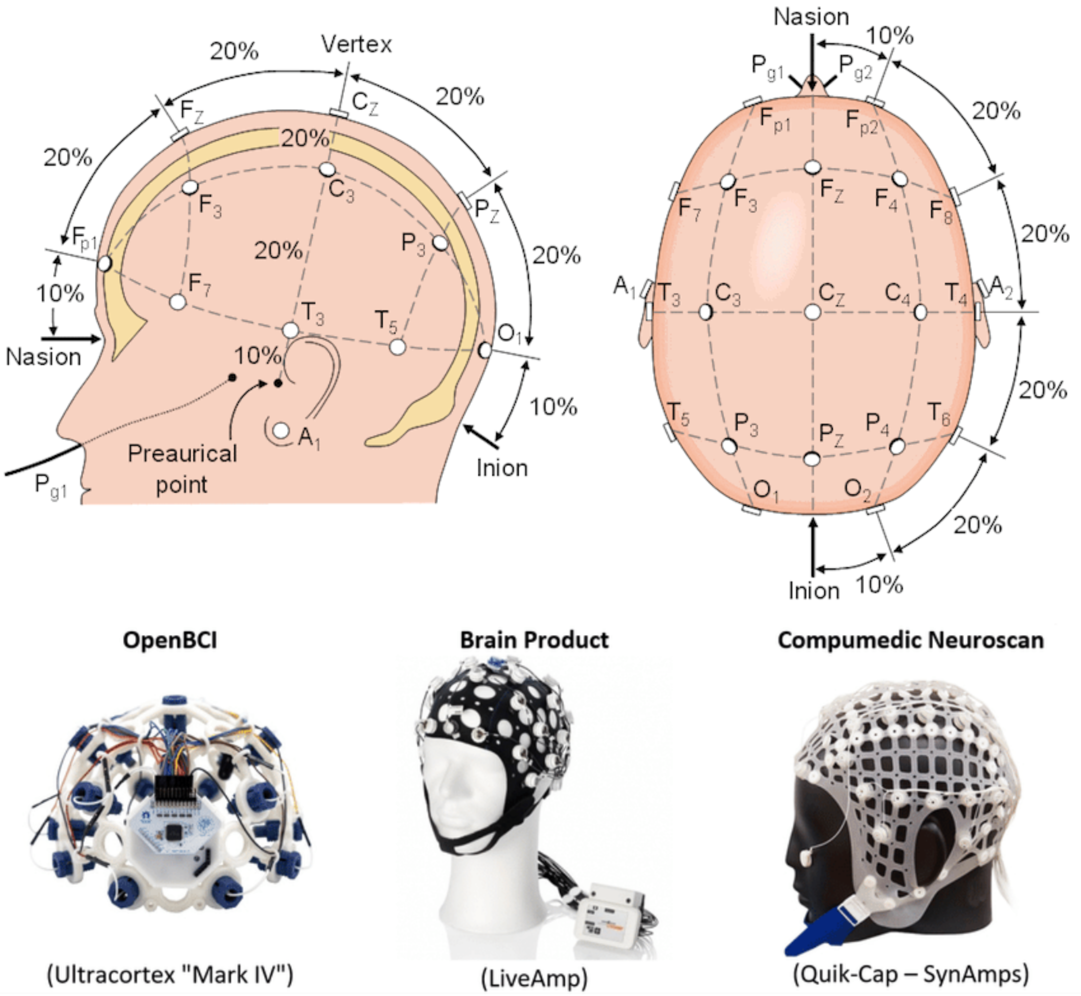

Figure 3.3 The 10-20 system with front-back (nasion to inion) 10% and 20% electrode separation [22]

The 10-20 electrode system is a standardized method used for the placement of electrodes on the scalp for electroencephalography (EEG) recordings. Figure 3.4 shows the equipment which is used to measure the brain's electrical activity in a non-invasive manner, it is used very commonly by the neurologist in their clinics to understand the functioning of the brain in real time.

The 10-20 electrode ensures that there is similar placement of the equipment for all the patients, this method is medically proven. Its name is derived from the percentage percentages of certain cranial lens that are used to quantify the relative distance is between the reference points as shown on the scalp of the statue in figure 3.4.

The 10-20 electrode system defines the nasion and the inion as the primary point of the reference for all the distance or the percentages. The outward bump at the base of this skull is called inion and the nose, where the frontal and the nasal bones meet is called nasion. These two points are the primary reference point for this system that could be understood by any researcher of this field.

10% and 20% respectively refers to the distance between the nasion, inion and distance along the sides of the skull (mastoid). The setting of the electrode placement is done in respect to these percentages, such as if the distance between the nasion, inion is of 10 equal segments. Then the electrodes are positioned at a specific percentage along the line.

C. Experimental Setup

The hardware used here is of an apple MacBook Air with M1 chipset having an integrated graphic card that consist of 8 cores, it is an integrated part of the recently developed chip named as M1 SoC by Apple. I have used Keras version 2.12.0 and Python version 3.7 and Streamlit version 1.32.0 for all the algorithms applied are hardware or version of the library used hasn't changed.

A 90-10 train test split on the data is performed throughout the experiment. The number of training epochs for the CNN, 1D convolutional LSTM, and deep neural network (DNN) models is 100. The suggested method also employs the dropout strategy to enhance the generalization performance and prevent the issue of overfitting. Distribution of the data in a random manner is done before training, and then subsequently forwarded to the network. Furthermore, checkpoints are incorporated into the training process. During training, the model's accuracy for each epoch's training data set and test data set shall be calculated, that at the end of each epoch to allow us to assess whether that model is overfitted or in order to verify its generalization potential. Should the model's capacity to generalize not increase after ten training cycles, the learning rate will be reconciled.

D. Streamlit Integration

With the help of Streamlit, an open-source Python framework, one may quickly and easily create unique web apps for machine learning and data science projects. The in-depth procedures and factors that need to be taken into account when integrating Streamlit into an epilepsy detection system that uses machine learning are covered in this study. The goal is to provide an interactive and intuitive front-end interface that enables users to upload and examine EEG data in order to identify seizures associated with epilepsy.

Advantages:

- Uploading EEG data files is one of the Streamlit App's primary features.
- Data visualization: Users may examine the data by seeing the EEG waves using the app.
- Real-Time Analysis: The application performs real-time or almost real-time processing on the uploaded data. In order to identify possible seizures, the machine learning model examines the EEG segments.
- Results Display: The app shows the analysis's findings, emphasizing the sections where seizures were found.
- User comments and Interaction: Over time, users may assist the model get better by offering comments on the detection findings. Users can change settings and do the analysis again using interactive components
- Configuring the Environment: Install the required libraries, such as TensorFlow/PyTorch, NumPy, Pandas, Streamlit, etc.
- Preparing data: Put in place the functionalities needed to load and prepare EEG data. Ascertain that the data is formatted correctly for model input

- Streamlined Application Development: Use Streamlit to write the primary application script.

- Provide elements for uploading data, visualizing it, and displaying the results.

- Connect the app's user interface to the model inference.

- Testing and Deployment: To verify functioning, test the app using a variety of EEG data samples. Install the application on a local server or cloud platform so that users may access it.

It offers statistical data on the detection, including the quantity and duration of detected occurrences. When Streamlit is combined with a machine learning model for epilepsy diagnosis, researchers and medical practitioners have access to a potent and intuitive tool. This method makes it possible to analyze EEG data effectively, which makes it easier to identify epileptic seizures in a fast and precise manner. Because of its interactive characteristics, Streamlit is an application that is easy to use and accessible in a variety of clinical and research contexts. Using Streamlit provides a reliable way to implement machine learning models in an interactive and user-friendly way while developing an epilepsy detection system's front end. The technology improves the capacity to identify and interpret epileptic convulsions, offering researchers and medical professionals a useful resource. Future developments may boost the accuracy of the model, add more features to the app, and connect it with medical record systems to make it more widely used in clinical settings.

Figure 3.4 Streamlit Frontend

E. Classifiers Theory

1) Decision Tree

A decision tree approach could be useful in detecting the availability as it is a good classifier by recursively dividing the data. According to the distant qualities, I can create a tree like structure which can further be used to identify whether the patient is epileptic or non-epileptic based on the distinct characteristics shown by the data in the training phase, this approach makes the use of internal structure tree as a tool for the decision making. Epilepsy may be diagnosed using EEG using a decision tree approach, which is frequently used for classification tasks. A tree like structure is produced by recursively splitting the data based on unique attributes, and this structure is utilized to determine the class labels of individual instances. This method functions by exploiting the internal structure as a decision making tool. In order to create a decision tree, the recursive process involves determining which characteristic to use to separate the data at each node.

In order to get homogeneous subsets, it is necessary to decrease the disorder and impurity in the data, which may be done with the criterion measure. Until every sample in a node has the same class label, the recursive process goes on for every subset. It then finally stops until a stopping condition such as the maximum depth or the minimum number of samples per leaf is met. The epileptic or non-epileptic status of fresh EEG data may be determined by moving up the decision tree from the root node to a leaf node. This is the mathematical justification for the classification procedure that follows decision tree construction as shown in equation 2.

$$Entropy(S) = \sum_{i=1}^{N} p_i \log_2 p_i \qquad (1)$$

N = count of unique class values

Pi = event probability

2) K-Nearest Neighbours

KNN is k-nearest neighbours algorithm otherwise known as a supervised learner with nonparametric characteristics. This involves determining an approximate class or value of a data point by comparing it to other data points. It is applicable in both regression and classification purposes but the general use of clustering similar points makes this tool mainly a classifier. “K” in KNN stands for the number of nearest neighbours, which is taken into account in case of a certain record classification. Choice of ‘K’ depends upon various parameters of the input data. Most of such data generally benefit from a higher ‘K’ value. For a classification technique, it’s usually advisable to use one ‘K’ value for this purpose; besides, some cross validation methods can help choose the best ‘K’ for a dataset.

3) Naïve Bayes

Naïve Bayes is an easy-to-use probabilistic classification technique for simple applications. The latter relies on the Bayes theorem and provides the probability for a point to belong to a specific class. The naive assumption is that every attribute is independent and makes calculation easier, but this notion does not hold true in real cases. While it is somewhat oversimplified, still many techniques applied in the text classification of spam and opinion mining lose against naive Bayes. This particular algorithm is specifically ideal for high dimensional datasets that have just enough labelled data. Naive Bayes is of considerable importance because of the capability of handling multiple classifications as well as the ease with which it can be trained and implemented for machine learning and many natural language processing applications.

$$P\left(\frac{C}{X}\right) = \frac{P\left(\frac{X}{C}\right) \times P(C)}{P(X)} \tag{2}$$

P(C/X) = Posterior Probability

P(X/C) = Likelihood

P(C) = Class Prior Probability

P(X) = Predictor Prior Probability

4) 1D-CNN

In order to obtain representations and effective features from 1D time series convolution sequence data, a 1D-CNN may perform 1D operations with different filters. Fig 3.5 shows the technicalities of the 1D-CNN process. To confirm to the single dimensional nature of the raw EEG signal data, the feature maps and convolutional filters of the 1DCNNs used in this work are entirely one dimensional. By increasing the number of convolutional layers, CNN is capable of progressively generating higher level features for epileptic seizure detection tasks which are resistant and discriminable.

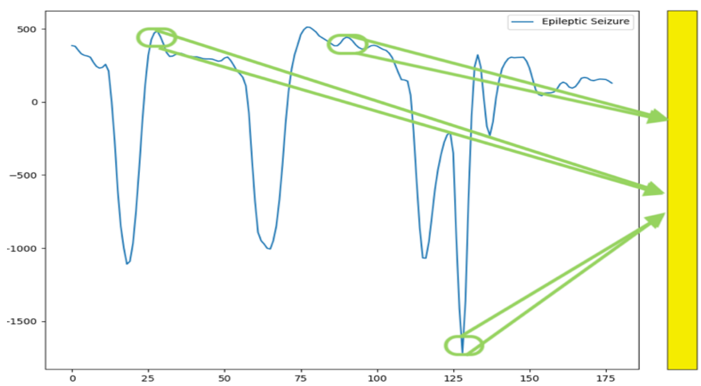

Figure 3.5 1D Convolution operation

5) *LSTM*

The standard LSTM block structure is shown in Fig 3.6 The LSTM block consists of four gates: input gate zi, here, a sigmoid function receives the input states the previous hidden state and the current input state and determines which values should be updated by converting them to a range of 0 to 1. One indicates importance, whereas zero indicates not much; forget gate z^f, this gate determines what data should be retained or discarded. The sigmoid function processes data from the present input as well as data from the prior hidden state; gate z in the cell state that retains the data throughout time; and output gate zo, which determines the value of the subsequent hidden state keeping in mind that information about prior inputs is contained in the concealed state and predictions are also made using the concealed state.

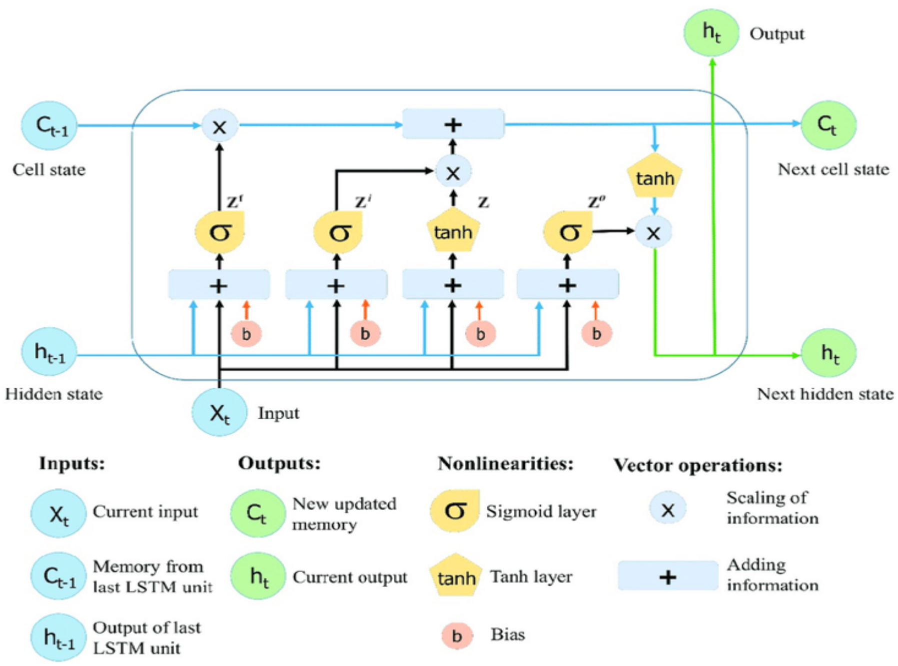

Figure 3.6 LSTM Block Structure [20]

6) *1D-CNN LSTM*

4 convolutional layers, 2 LSTM layers, 1 input layer, 1 pooling layer, 4 fully connected (FC) layers, and a SoftMax output layer make up the suggested ensemble model. First, as the data source for the proposed model, the 45 X 1 form of the one-

dimensional EEG signal data is used after that, to extract abstraction features from the raw signal data, input data is transmitted through an initial convolution layer composed of 64 one dimensional convolution kernels with a shape of 3 X 1 and a length of 1, respectively. A ReLU (Rectified Linear Unit) activation layer comes after this convolutional layer, which adds non-linearity to the suggested model. Here, the one-dimensional convolutional operation and the ReLU activation are defined mathematically as follows:

$$y_i^k = \sigma\left(\sum_{j=1}^{N_{k-1}} b_i^k + \mathrm{conv1D}\left(w_{j,i}^k , x_j^{k-1} \right) \right) \tag{3}$$

In the kth layer is the i^{th} feature map; the activation function ReLU, which can assist prevent over fitting, is represented by $\sigma()$; $w_{j,i}^k$ is the trainable convolutional kernel; In the $(k-1)^{th}$ layer x_j^{k-1} is the jth feature map; where N^{k-1} depicts how many feature maps are there in the $(k-1)^{th}$ layer; Since conv1D is a representation of the one-dimensional convolution process without zero-padding, the size of feature map in the kth layer is smaller than its corresponding dimension in the $(k-1)^{th}$ layer.

After the convolution and activation, (45 X 1) sized 64 feature maps are produced. Subsequently, a max-pooling layer receives the output of convolutional layer 1. The following is a description of the one-dimensional max-pooling operation's mathematical definition:

$$p_i^a = \max\,(p_i^{a'} : a < a' < (a+s) \tag{4}$$

Here "s" represents pooling window size; max pooling action leads to pai which represents the a^{th} neuron; before that $p_i^{a'}$ represents a'^{th} neuron in the i^{th} feature map. Both the size and the stride of the pooling windows in the Pooling Layer one are 2. It can speed up the training process and drastically lower the overall training parameters in the suggested model. 21 × 64 is the size of 64 feature maps produced after pooling. Subsequently, 3 convolutional layers are employed to additionally extract advanced characteristics that may aid in categorization. ReLU is also used for convolution procedure and the non-linear activation.

After passing through each of the one-dimensional convolution layers, the resulting 1024 feature maps, each measuring 43 X 64, will be fed into a single 256 neuron FC layer, after which a dropout of 0.3 will be applied to the FC's output. With aim of fitting the results of LSTM layers, FC Layer 1 can integrate the results of the convolution layers, minimize the size of feature maps, and, to some degree, mitigate the overfitting problems through dropout.

In order to prevent the prolonged dependence of the conventional RNN, the output features are sent to the LSTM layers after going across the FC layer1. There are 4 gates in the LSTM cell: forget, input data, output logic and cell state gate. In order to protect the earlier data and to increase the capacity to obtain meaningful incites from the EEG time series data, they can cooperate. Both the LSTM layers 1 and 2 have 64 neurons each.

After their passage by the LSTM layers, result characteristics shall be supplied at three FC levels. Lastly, a layer of SoftMax output is applied in the ensemble model for better results. In line with the specific results produced by Bayesian hyperparameter optimization, the proposed model's more detailed structure has been modified. The architecture depicted in Fig. 3.7 [21] is employed, when the recommended model has been successfully built and trained, to recognize epileptic seizure activity.

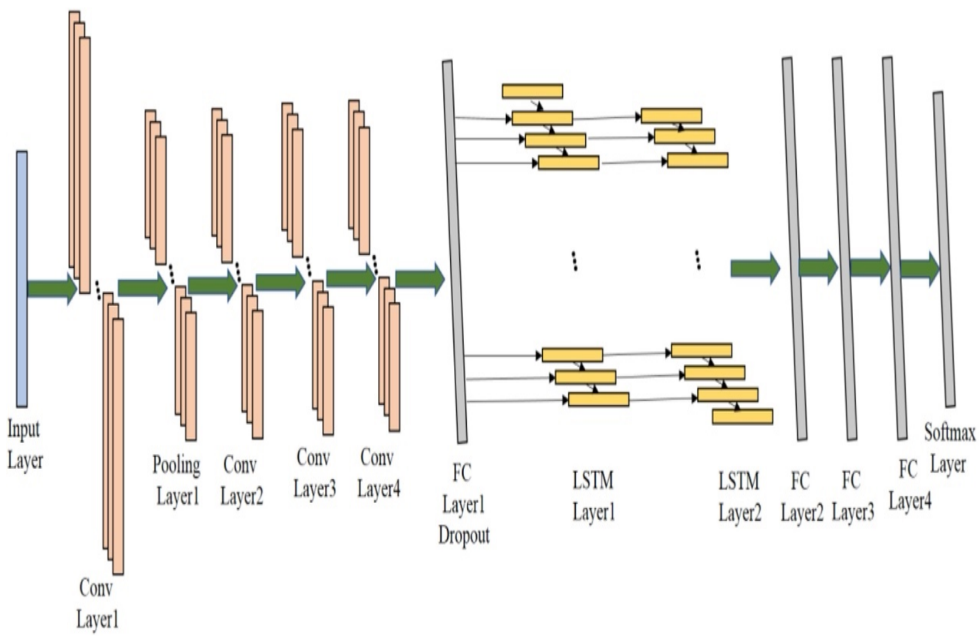

Figure 3.7 1D-CNN LSTM Model [21]

Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are two potent deep learning architectures that are combined in a 1D-CNN LSTM ensemble model to handle sequential and temporal data processing tasks. It uses a group of CNN layers to capture the special information and then uses the current layers to collect the temporal information and then utilize the advantages of both CNN and LSTM. A deep explanation is given below:

a) 1D Convolutional Neural Networks (CNNs):

One dimensional filter is used to extract the features from the input sequence when I are working with one dimensional data like in the case of epileptic signals, these filters uses the convolution operation to capture the local changes in the patterns when they move over the data. This is the reason it is mostly suited for the tasks like classification. It has an exceptional ability to recognize the special patterns in the data which is most important in capturing the special or the temporal differences between the signals. Pooling layers, such as Maxpooling is used to down sample the features to control the computational complexity.

b) Long Short Term Memory (LSTM) Networks:

LS team is an advanced version of an RNA that is a neural network, which is crafted, specially to capture the long-range relationships and the temporal nuance contained in special sequential data. The idea to use an LSTM is because of its memory cells and getting mechanisms which are designed to control the information flow within the network, making it the best algorithm available for the classification of sequential data. Because of its unique architectural design, it is able to efficiently store the important data for a long period of time compare to other algorithms where I face the issue of vanishing gradient.

This special feature of maintaining the memory over such a long period of time is one of the most astonishing feature of the LSTM this makes time series forecasting very easy, which helps in understanding temporary relationships within the data. This is why LSTM are the most important part of a deep learning algorithm, providing it the unmatched efficacy in the task that involve sequential data interpretation or classification.

c) Ensemble Approach:

The objective of a 1D-CNN LSTM ensemble model is to enhance prediction performance by merging the complementing advantages of CNNs and LSTMs. This is accomplished by utilizing the same input data to train independent CNN and LSTM models and then finally combining their predictions using an ensemble approach (e.g. weighted combination or average).

7) Workflow of 1D-CNN-LSTM Ensemble Model:

a) Input Data Preparation

Pre-processing and model training are done on the input data, which might be temporal or sequential data represented as one-dimensional signals. Normalization, feature extraction, and segmentation could be required for this.

b) CNN Model Training

The input data is then processed into a CNN model, which consists of pooling layers after one or more convolutional layers as shown in figure 3.7 then through convolution and pooling processes the CNN gains the ability to extract spatial characteristics from the input sequence. The CNN model finally generates a series of feature maps collecting relevant patterns in the data.

c) LSTM Model Training

In parallel, an LSTM network is trained to recognize long-range patterns and temporal relationships in sequential data by running the same input data through it. By adjusting its internal state in response to both the current input and earlier states, the LSTM model iteratively processes the input sequence.

d) Ensemble Combination

Following training, an ensemble technique is used to integrate the predictions of the CNN and LSTM models. A weighted combination depending on each model's performance on validation data could be used, or the predictions from the two models might be averaged.

e) Evaluation and Prediction

To measure the performance of the ensemble model, an independent test dataset is used. After that it may be used to forecast fresh or unknown data utilizing the complementary abilities of LSTMs and CNNs to provide predictions that are more reliable and accurate.

In conclusion, a 1D-CNN LSTM ensemble model combines the temporal modelling or complementing skills of LSTMs with the spatial feature extraction capabilities of CNNs to produce a potent framework for the analysis of sequential and temporal data. The ensemble strategy takes advantage of the complimentary characteristics of both models to enhance overall predictive performance by integrating their forecasts.

IV. EXPERIMENTAL RESULTS

In Deep Learning this report shows Validation, Training Loss, and Validation and Training Accuracy of suggested method i.e. 1D-CNN LSTM ensemble model is shown in Fig 4.1 Additionally, 2 deep learning models—a conventional CNN and a DNN—for the identification of epilepsy have been created and may be compared with the proposed model. Finally, Table 4.1 compares and calculates the accuracy, precision, recall, and F1-score metrics to further assess the seizure categorization performance of these three models.

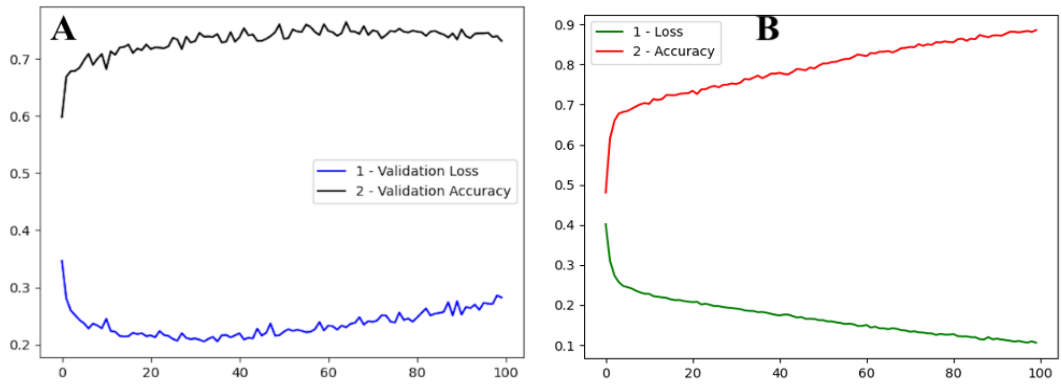

Figure 4.1 Training and Validation Accuracies (A) Validation Loss and Accuracy (B) Training Loss and Accuracy

With a 99.47% accuracy rate, the suggested model outperforms KNN by 7.7%, SVM by 5%, and DT by 2.27% as compared to the machine learning algorithms applied in paper [22]. This drives to the fact that suggested 1D-CNN LSTM ensemble model has great potential in the field of epileptic seizure detection research through EEG signals, as demonstrated by all these results.

TABLE 4.1 PERFORMANCE METRIC OF DEEP LEARNING MODELS

Model	Accuracy	Precesion	Recall	F1-Score
CNN	*97.13%*	*94.24%*	*92.34%*	*0.9328*
DNN	*96.35%*	*95.18%*	*87.50%*	*0.9118*
Suggested 1D-CNN LSTM	*99.47%*	*99%*	*99%*	*0.9959*

V. CONCLUSION

The increasing prevalence of epilepsy underscores the growing importance of accurate detection. A significant challenge lies in effectively identifying seizures from extensive datasets. Given the intricate nature of EEG signals within such datasets, ML classifiers prove to be a fitting solution for precise seizure detection.

This report has conducted a comprehensive examination of machine learning methodologies for seizure detection. Consequently, it is concluded that "non-black-box" classifiers, specifically the decision forest, exhibit superior effectiveness. This choice is motivated by their ability to generate several logical and informative rules while maintaining a higher prediction accuracy. Moreover, decision forests facilitate the exploration of valuable insights, including seizure localization and the investigation of various seizure types.

On the other hand, despite their high predicted accuracy, "black-box" classifiers are unable to provide unambiguous rules. Regarding feature selection, it is recommended to opt for features that yield logical outcomes. Effective knowledge discovery may not be supported by reducing the dataset's dimensionality by using only one or two characteristics, such as line length and energy.

In essence, this report offers fresh insights for data scientists engaged in the domain of epileptic seizure detection through EEG signals. To sum up, this report centres on the assessment of machine learning classifiers and the selection of appropriate features as key factors in enhancing seizure detection methodologies.

A 1D-CNN LSTM ensemble epilepsy seizure detection model is proposed in this study using EEG signal as input. The proposed ensemble model will build an entire network i.e. by combining a LSTM with 1D-CNN, it will be able to distinguish precisely between the ordinary and epileptic seizures EEG data. The LSTM model is successful in identifying and interpreting the individual EEG signals, whereas the 1D-CNN picks out features from EEG data very well. Experiments on one of the popular dataset i.e. UCI epileptic seizure data set validate the effectiveness of the suggested approach. Furthermore, when compared to other approaches such as DNN, CNN, KNN, SVM, and

DT, the suggested model improves accuracy by 3.12%, 2.34%, 7.7%, 5.0%, and 2.27%, respectively. The suggested model has made significant strides toward recognising epileptic seizures but there are still some issues that need to be resolved in the future. The suggested model requires a significant quantity of labelled EEG signal data from a reliable source for its supervised training.

TABLE 5.1 DIFFERENCE BETWEEN DEEP LEARNING AND MACHINE LEARNING MODEL

Model	Accuracy	Precesion
1D-CNN LSTM	*99.47%*	*99%*
Decision Tree	*97.2%*	*96%*
Difference	*2.05%*	*3%*

Table 5.1 shows dominance of suggested deep learning algorithm over the best performing Machine learning algorithm though the suggested model used an extensive hardware and overloaded it, but it also provides a significant rise in the results. As I know that in the real world, it is difficult to get such filtered and clean epileptic signals. So, there is a significant chance of a dip in the accuracy of the model. Thus, I want to achieve as high as possible accuracy in theory so that any robber in the real-time data should cause the least deviation possible from the theoretical accuracy. This signifies the importance in difference of 2.05% accuracy and 3% precision. On theory, these minor differences may not justify the over-utilization of the hardware resources, but in practicality, these can prove as the game changers of our model. As I are dealing with the human health here, so even a 0.1% accuracy is a great step for saving the human lives.

VI. FUTURE PROSPECTS

However, gathering EEG data is a tedious work because it requires sensitive information of patients. The next study will be concentrating on two areas in light of these limitations: first, the transfer learning technique that could have been incorporated into the suggested model to lessen its reliance on labelled signal data; second, the suggested model can be improved more and adjusted further to perform better on increasingly difficult epileptic seizure recognition tasks, which will enhance its capacity to classify data from a variety of sources.

In contemporary research, the adoption of graph-theory methodologies has ushered in novel perspectives in the realm of epilepsy detection through EEG signals, leveraging distinct graph parameters. These graph-theory-based approaches offer valuable insights into the latent dynamics of brain activity and the mapping of brain behaviours. They facilitate a comprehensive understanding of EEG signal dynamics across various scales—microscopic, mesoscopic, and macroscopic—while also establishing meaningful correlations among them. Graph theory serves as a crucial tool in pinpointing anomalies within EEG patterns and extracting significant information regarding the underlying brain connectome through specific topological attributes of the EEG signal network. Statistical features derived from constructing networks from EEG signals furnish indispensable insights into dysfunctions associated with the structural and functional aspects of the brain in epilepsy research.

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