A PROTOTYPE FOR EPILEPSY SEIZURE DETECTION BASED ON ARTIFICIAL INTELLIGENCE

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Abstract—*The enhanced Artificial Intelligence paved a path for rapid diagnosing in medical field. Artificial Intelligence has rapidly developed and been used widely in numerous sectors during the past 20 years. Electroencephalography (EEG) is one of the most important tools that can identify most precisely the epileptoid cortex. Numerous epilepsy ailments have distinguishing EEG characteristics. In recent years, it has been noted that AI is widely being used in medicine. The literature review presents different Artificial Intelligence methods for EEG signal processing in epilepsy research, with particular emphasis on applications for automated seizure identification, prediction, and orientation. Because an EEG signal is non- stationary and has a significant degree of time variation, it can be analyzed using non-linear methods. Therefore, we have used the discrete wavelet transform (DWT) which is used to extract the frequency components of the EEG. And we have proposed a prototype with better hybrid algorithm for detection includes Water Cycle algorithm and Enhanced Learning Model.*

Keywords*—Epilepsy, EEG, Artificial Intelligence, Discrete Wavelet Transform (DWT), MWCA, ELM.*

I. INTRODUCTION

The brain's abnormal physiological reaction known as epilepsy may or may not be linked to a visibly obvious anatomical problem. Epileptic seizures can range from brief, barely perceptible episodes to protracted tremors because of abnormal electrical activity in the brain. Physical injuries may be sustained as a direct result of these incidents, such as shattered bones, or indirectly by creating accidents. Seizures associated with epilepsy frequently recur and may not have a clear underlying cause.

It may be possible to avoid epilepsy that develops as a result of other problems. About 69% of the time, seizures may be controlled with medicine, and there are frequently affordable anti-seizure options available. Surgery, neurostimulation, or dietary changes may be considered when medication fails to control seizures. Not all epilepsy cases are permanent, and many people get better to the point where they no longer require treatment.

Convulsive seizures are the most prevalent form (60%) and involve uncontrollable muscle spasms. One-third of these start off as generalised seizures from the beginning, affecting the left and right hemispheres of the brain and disrupting consciousness[1]. One hemisphere of the brain is only affected by two-thirds of seizures, which can progress to generalised seizures. The remaining 40% of seizures are non- convulsive seizures[2]. This kind includes the absence seizure, which lasts about 10 seconds and causes a decreased level of consciousness.

Auras, which are specific feelings, frequently come before focal seizures. Depending on whatever area of the brain is affected, the seizures can include sensory (visual, auditory, or olfactory), psychological, autonomic, and motor symptoms. A Jacksonian march is the term for when muscle jerks originate in one muscle group and extend to neighbouring muscle groups. Autism, which are unintentionally formed behaviours, can happen. They can be more complex behaviours like attempting to pick up something or more basic ones like smacking the lips repeatedly.

Artificial intelligence, has advanced significantly over the past 20 years. Identification and diagnosis of diseases and conditions that would otherwise be difficult to diagnose is one of the main uses of machine learning in healthcare. This can range from various hereditary illnesses to tumours that are difficult to detect in their early stages. A good illustration of how combining cognitive computing with genome-based tumour sequencing might aid in reaching a quick diagnosis is IBM Watson Genomics. Berg, the industry giant in biopharma, is using AI to create therapeutic treatments in fields like oncology. Predicting Response to Depression Treatment, or P1vital PReDicT, aims to create a commercially viable method of diagnosing and treating common clinical conditions.

By processing vast amounts of data, AI technology can help healthcare professionals create precise pharmaceutical regimens that are matched to individual traits [3]. AI employs algorithms to methodically reveal the hidden characteristics and underlying relationships of data by combining statistical and computer science principles. In several domains, AI is used extensively (For instance, autopilot, web search, spam mail screening, visual pattern recognition, and speech recognition). AI improves prognosis evaluation, disease identification, and prognosis prediction accuracy in medicine. AI produces objective, automatic, and principled algorithms for complex, high- dimensional biomedical data[4].

The discrete wavelet transform is used in many areas of science, engineering, mathematics, and computer science. The most notable use is signal coding, which represents a discrete signal in a more redundant form and is frequently used as a prerequisite for data compression [5]. The signal processing of accelerations has numerous other practical applications, such as image processing, digital communications, and gait analysis. It is shown that discrete wavelet transforms—discrete in scale and shift and continuous in time—are successfully applied as an analogue filter bank in biomedical signal processing for the development of low-power pacemakers and for ultra- wideband (UWB) wireless communications.

AI is used to identify unexplored territory and forecast some future events. The computational feature of AI generates a hypothesis from training data (or examples) given by mathematical algorithms. Generally speaking, supervised and unsupervised operations fall under the umbrella of AI [6].The former converges to the optimal classifier from prelabelled inputs using an algorithm that has been "trained" for the classification of unlabelled data. After comparing the commonalities among unlabelled inputs to find patterns, subgroups, or outliers, mathematical models are created. Unsupervised techniques (such as clustering and dimensionality reduction approaches) are referred to as the process in contrast to the supervised approach. Semi- supervised learning, which combines the concepts of supervised learning and unsupervised learning to construct a classifier, involves learning a combination of a sizable number of unlabelled datasets and a small number of tagged datasets (or model function).It can sometimes result in a significant boost in learning accuracy. One of the most cutting-edge methods for dynamical systems (such as evolving, time-varying, and power systems) that automatically learns the best control strategies is reinforcement learning. "Reinforcement" suggests that in order to get closer to an ideal strategy, good deeds are positively reinforced while bad ones are negatively degraded.

EEG monitoring of brain activity has developed into a fascinating tool in recent years for the automatic detection of epilepsy, without the need for neurological consultation, and epileptic seizures, which can help save patients' lives. The electroencephalogram (EEG) of a person can show excessive and aberrant neuronal activity in the cortex of the brain, which is the fundamental mechanism of epileptic seizures [7]. Most epilepsy cases are idiopathic, meaning they have no known cause; however, epileptogenesis, a process that can develop from brain trauma, stroke, brain tumours, infections of the brain, or birth defects, can also cause some cases. Only a small percentage of cases have been explicitly connected to known genetic alterations. In order to make a diagnosis, it is necessary to rule out other illnesses that could result in symptoms similar to fainting as well as to look for additional seizure triggers including alcohol withdrawal or electrolyte imbalances. Blood testing and brain imaging may also be used to partially achieve this. A normal test does not rule out epilepsy, but an EEG can frequently confirm the diagnosis.

Following then, other study fields are created, vying with one another to establish a superior technique for determining brain state and establish the best computer-aided diagnostic. Due to the frightening nature of their symptoms, people with epilepsy may receive variable levels of medical care and societal stigma around the world.

On one hand, the nature of EEG, which is regarded as non-stationary signals, nonlinear, and irregular, is related to the definition of those models. To use those systems in real time while maintaining high accuracy, we must get past their run-time, memory, and software complexity constraints [8].

A survey of the literature indicates that there are three processes in the processing of EEG signals for epilepsy monitoring. First, noise and artefact removal during signal preparation. The second step is feature extraction, which takes the most important information from signals and eliminates the unnecessary ones. Lastly, classification to determine the patient's mental state We compare our findings in this work with the previous research work on the same database.

The difficult biomedical problem of identifying epileptic seizures has received a lot of attention from AI algorithms during the past 20 years. The exact identification of epileptic seizures using EEG data is covered in a synopsis of pertinent and current studies. Most researchers have suggested using different artificial neural network algorithms, such as adaptive structure neural network, learning vector quantization, self-organising maps, radial basis function, cellular neural networks, multilayer perceptron neural networks, and recurrent neural networks, to recognise epileptic seizures.. To define various classifier systems, such as the support vector machine (SVM), the adaptive neuro-fuzzy inference system (ANFIS), and the time-frequency analysis, numerous studies have been offered in the literature to address this issue.

Our research seeks to lower the price of epilepsy diagnosis in this article. On the other hand, it can lessen the workload of medical professionals, assist them in improving the accuracy of diagnosis, and decrease the likelihood of misdiagnosis, allowing patients to obtain early and efficient treatment and lessening the strain on both medical professionals and patients [4]. We suggested a new epilepsy classification method with two components to address the aforementioned issues: processing the EEG signal using a wavelet transform and Modified Water Cycle Algorithm WCA classifier. The wavelet coefficient is employed in this study to identify epileptic episodes in EEG recordings. The MWCA method is then used with these coefficients.

II. STATE-OF-ART VS PROPOSED METHOD VIA MWCA ON SAME DATABASE

At present, the work on epilepsy detection has already been addressed by many researchers. But the selection of the significant features which plays an important role in detection. Therefore there are hybrid methods which have been used in this field like SVM(Support-vector-classifier) and it provides promising results [5]. The work of WMCA algorithm has been extended in this field by using our own proposed hybrid WMCA-ELM algorithm giving higher accuracy on this dataset proposed before..

III. LITERATURE REVIEW

Researchers have been working on the identification of epileptic seizures for many years in an effort to develop automatic diagnosis systems that would relieve physicians of their laborious tasks. Numerous research papers are released in this area to help identify epileptic seizures. It is challenging to provide a thorough analysis of all of this literature. Consequently, efforts have been made to review and improve the detection of an epileptic seizure on this dataset in this paper. The literature review also reveals that different EEG dataset conditions require different levels of pattern recognition in order to detect epileptic seizures. This is primarily caused by the fact that EEG detected under various circumstances has different properties. To effectively distinguish EEG epileptic data from other types of EEG data, it is then necessary to identify a pattern recognition technique.

A new technique for variable mode decomposition based on kurtosis was presented in [1]. After extracting bandwidth and spectral characteristics, they choose the most significant one using the Kruskal Wallis test, and then they compare various classifiers for the classification stage. Using Discrete Wavelet Transform, they separated the signals into five sub bands and retrieved 11 characteristics. The researcher gave the number of features utilised and the calculation time in seconds for the used features. The researcher obtained accuracy for all classification situations using various combinations of subsets. Additionally, they have created an intriguing model that, when compared to published works that are state of the art, allows us to obtain great accuracy with a basic model that only requires a few elements and has a short run time.

Yang Si's CNN [2] (Convolutional Neural Network) demonstrated excellent seizure prediction sensitivity rates and low false prediction rates of 0.11-0.02 false alarms per hour. Deep learning, a subset of AI techniques, is based on representation learning, a system that automatically learns and discovers patterns for a classifier using multiple layers of input data. In contrast to the supervised method, the process of developing mathematical models after examining the similarities among unlabelled inputs to find trends, subgroups, or outliers is referred to as "unsupervised algorithms". It has been determined that the potential of AI as an emerging technology, which automatically and objectively renders principles and complicated data in high dimensions, can be managed.

The author in [3] presents a thorough analysis of previous research on the topic of epileptic seizure detection using a variety of deep learning techniques, including CNNs and RNNs. Deep learning has been used since 2016 to identify epileptic seizures, making it one of the most sophisticated techniques. AI has used traditional techniques to diagnose epileptic episodes. In order to diagnose epileptic seizures, a number of deep learning models have been employed. Deep learning methods were compared to the most popular 2D- CNN and 1D-CNN models for detecting epileptic episodes.

A method for analysing EEG signals to identify epileptic seizures is described in [4]. The proposed approach combines AI and multi-wavelet change. To calculate the anomalies present in EEG data, the rough Time and frequency domain calculation is updated and given the name Improved Approximate Time and frequency domain. In order to compare the author's methodology with other approaches, affectability, specificity, and exactness aspects were taken into consideration. It has been noted that precision is at about 93%. The primary goal of this study was to use AI algorithms to classify EEG signals as epileptic or non-epileptic for the diagnosis of epilepsy. Ten different patients were chosen to participate in the study. In the research project, a single patient recording lasts for 7.2 seconds and contains roughly 7200 samples, captured at a rate of 1000 samples per second. The outcomes demonstrate that SVM (Support Vector Machine) classifiers may be trained to accurately categorise the data as epileptic or non- epileptic.

The idea of code converters is described in [5], but the categorization outcomes were unsatisfactory. Adaboost Classifier helped refine it even further.

According to the results, utilising Adaboost Classifier as a post classifier produces average perfect classification rates of about 94.58%, classification accuracy averages of about 97.29%, performance averages of about 94.51%, and average quality values of around 21.82. As a result, it is anticipated that changes will be made to the code converters technique in the future for improved epilepsy categorization.

The model put forth in [6] offers trustworthy pre-processing and feature extraction techniques. The model offers a higher true positive rate and predicts epileptic episodes with enough foresight before they begin. They employed empirical mode decomposition to get the data ready for pre-processing and to extract time and frequency domain variables for training a prediction model (EMD). In order to distinguish between the preictal state and the interictal state, Support Vector Machine has been utilised as a classifier (Fig. 1). On the scalp EEG CHB-MIT dataset, which consists of recordings from 22 subjects and is a dataset of EEG recordings from paediatric subjects with intractable seizures, the proposed model outperforms conventional methods at detecting the start of the preictal state, which is the state that begins a few minutes before the onset of the seizure. The largest amount of time spent anticipating is 33 minutes, while the average amount of time is 23.6 minutes.

Sr.No.	Stage	Characteristics
1	preictal stage	the time before the seizure.
2	ictal stage	the actual seizure.
3	postictal stage	the period after the seizure, lasting usually between 5 and 60 minutes.
4	interictal stage	characterised by normal brain activity, is the time between seizures (postictal to preictal stage).

Fig. 1. Stages Of EEG Recording

The authors suggest a novel, energy-efficient method for non-invasive EEG seizure detection using wireless body sensor networks [7]. This innovative approach is based on the extraction of local features from the segmented EEG data using the Haar wavelet transform. An alert is then sent to a distant server if the epilepsy seizure is found. The design of this scheme is covered in the paper. Additionally discussed is the performance study for epilepsy detection and its energy effectiveness when applied to sensors. The results show that compared to full streaming of the raw EEG data to a remote server, the suggested technique uses 46% less sensor energy and has a sensitivity of 97% for 10 second segments.

The study provides a brief overview of techniques that have been proposed and used to identify seizures in EEG recorded data [8]. The research is divided into three categories: a study on feature extraction AI methods, a review

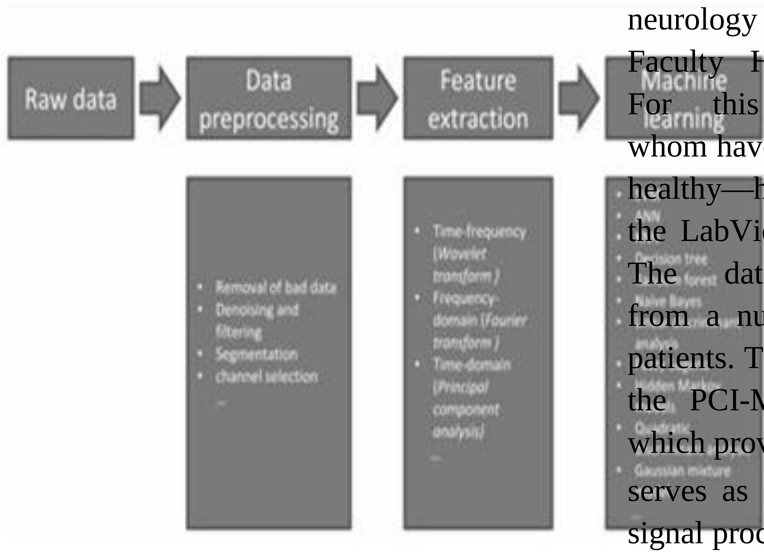

Fig. 2. EEG Extraction Process

on artificial neural network-based detection methods, and a study on deep learning-based detection methods. The degree to which the identified output and the ground truth are similar was assessed using SI or DICE performance indicators. The most frequently utilised features, according to the authors, are energy, skewness, and entropy; nevertheless, in order to lighten the load on the classifier and maintain accurate results, the feature vector must be optimised. And the results demonstrate that the random forest classifier produces the best seizure detection accuracy results.

IV. METHODOLOGY

A. EEG Data Recording

EEG signals offer a variety of frequency components and are divided into four spectral components: 1, 2, and 3. The following four frequency bands make up the majority of the distinctive waveforms found in the EEG spectrum: (0.5-4 Hz), (4-8 Hz), (8-13 Hz), and (13- 30 Hz). In this study, the EEG data set was collected from individuals of various ages. They are known epileptics with uncontrolled seizures who have been admitted to the neurology department of the Medical Faculty Hospital of Dicle University. For this system, 400 people—200 of whom have epilepsy and 200 of whom are healthy—had their EEGs analysed using the LabView programming language. The data collection includes signals from a number of healthy and epileptic patients. The EEG signals are contained in the PCI-MIO 16E DAQ card system, which provides real-time processing and

serves as a data highway for computers, signal processors, and personal computers. It normally takes 8 to 10 hours to capture EEG signals, which are utilised to guarantee the accuracy of disease diagnosis. Section employs EEG waves

to communicate a notion lasting 23.6 seconds at a sampling rate of 173 Hz (Fig.2).The EEG in the presence of clinical interest for focusing range is provided using an international

10-to-20 electrode placement technique and 12-bit analog-to- digital conversion after the samples are captured. Data can then be passed via a filter with a bandpass range of 0.53 to 40 Hz. The EEG data for our investigation were obtained from 24-hour EEG recordings of epileptic patients and healthy subjects. To be examined were the bipolar EEG channels F7- C3, F8-C4, T5-O1, and T6-O2. To assess the performance of the classifier, we used 500 EEG segments with spike and wave complex, artefacts, and background normal EEG.

B. Discrete Wavelet Transform

The wavelet transform is a better spectrum analysis method than other spectral analysis methods for non-stationary data[4]. The wavelet transform method's large low-frequency and constrained high-frequency changes have an impact on the window size. As a result, over the entire frequency range, the best time-frequency resolution is possible. It is challenging and time-consuming to vary parameters due to continuous wavelet coefficients for each scale when analysing continuous and discrete wavelet transforms. Discrete wavelet transform is used more commonly since these non-stationary signals are less frequent. The wavelet scale is divided into a number of points using the multi resolution decomposition approach, or x[n]. It is essential to choose the correct wavelet decomposition level, detect many signals, then analyse them using wavelet transforms. Since classification performance depends on the type of wavelet, the number of decomposition levels is utilised to identify the main frequency components of data. Wavelet coefficients offer essential information for feature vector extraction from EEG recordings. The following statistical-time frequencies are seen in EEG signal sequences:

1.The arithmetic mean of the coefficients' is the absolute values for each sub-band.

2. Coefficients' highest possible absolute value for each sub-band.

3. Each sub-band's mean force coefficients.

4. Coefficients' standard deviation for each sub-band.

5. The common absolute value of the band-to-band ratio.

6. Breakdown coefficient distribution within each sub- band.

Signal characteristics are in the 1-3 sequence, and the amount of frequency change is in the 4-6 sequence. This multi-layer neural network classification input feature vector of EEG signals is used [5].

C. Using AI Algorithms

For testing and training procedures that calculate a prediction model's generalization error, cross validation is used. Extreme AI techniques uses sophisticated mathematical modelling to process data in complex ways. ELM has been applied for the classification of different datasets like brain tumors, breast cancer etc. The MSCA is proposed to optimize the weights of the ELM model to enhance the performance of the conventional ELM model. Epilepsy and normal are the two categories that we have. According to the data mining tool RapidMiner Studio, the result is given with accuracy.

The EEG signals are converted to images by employing Synchro squeezing Fejer-Korovkin Wavelet Transform and the HOG features are extracted. The program is written with tensor flow python programming. After execution of the program it has been saved to MSCA-ELM.h5 file which can run any general python environment. This has been implemented to make user friendly. The completing programming has been enrooted through the ARM Cortex processor to detect and classify the epileptic seizures

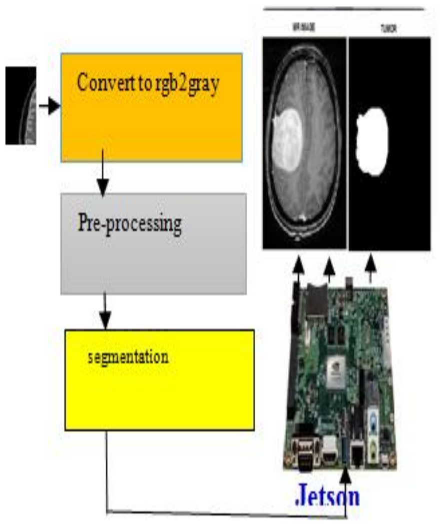

Fig. 3. Prototype

All calculations are postponed until classification and classification continues with local approximations. Consequently, the dataset for training measurements (x, y) and establishing a connection between x and y has labels. In order for h(x) to correctly predict the same output y given an unknown observation x, we must find a function h:x y. Fig. 4

$$P(y=j|X=x)=\frac{1}{K}\sum_{i\in A} I(y^{(i)}=j)$$

Fig. 4. Euclidean Function

Therefore, in this study, cross-validated EEG data is classified by the majority vote of its neighbours, with the object being assigned to the class that is most popular among its k closest neighbours (K=1). The steps in this study's methodology are as follows:

1) EEG samples are used to specify k (k=1).
2) K elements are chosen as input (for DWT = [400X129], for AR = [400X15]).
3) This study model includes 400 examples in 15 dimensions from the epilepsy and normal DWT data classes. The model comprises 400 instances and 129 class dimensions.

V. RESULTS

We show 400 patients' EEG data in our study. The other 200 EEG data are normal, while 200 EEG data are associated with epileptic seizures. Cross validation has been used to choose training and test data. WMCA_ELM techniques are used to extract information from these data. Comparing the results from the previously proposed algorithm.

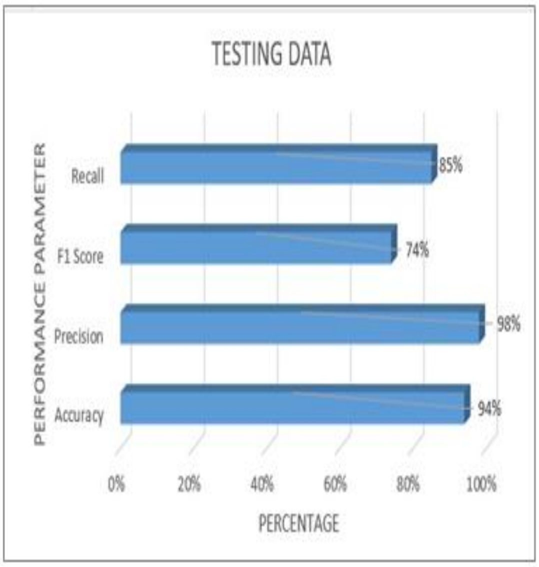

Fig. 5. Training Data Comparison

Comparison on training data : (Fig. 6, Fig. 7)

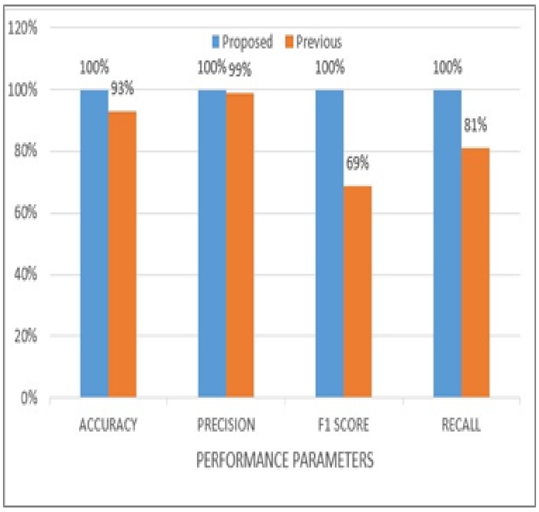

Fig. 6. Training Data Comparison

PARAMETERS	PROPOSED	PREVIOUS
Accuracy	100%	93%
Precision	100%	99%
F1 Score	100%	69%
Recall	100%	81%

Fig. 7. Training Data Comparison Table

On testing data we have achieved : (Fig. 8, Fig. 9)

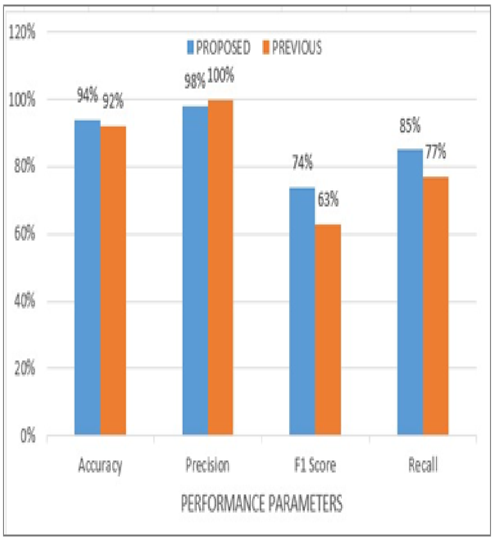

Fig. 8. Testing Data Comparison

PARAMETERS	PROPOSED	PREVIOUS
Accuracy	94%	92%
Precision	98%	100%
F1 Score	74%	63%
Recall	85%	77%

Fig. 9. Testing Data Comparison Table

VI. LIMITATIONS OF RESEARCH

Open access EEG data: The absence of long-term EEG data is one of the key problems with early-stage prediction and analytic studies. According to [9], the prediction warning was created about 91 minutes before the commencement of the ES using individual EEG data. Since then, no one has been able to duplicate these findings using any publicly available EEG data. Open access sharing of EEG databases with comprehensive recordings and code exchange are necessary for reproducible outcomes (using GitHub or other comparable repositories) [3]. Prediction algorithms usually perform badly due to data dropout. The storage device's inability to interface with wearable or implantable devices with limited store space is the cause of many zero or almost zero values in the observed data for a number of different reasons.

VII. CONCLUSION

In contrast to conventional techniques AI, an emerging technology, produces principled, automatic, and objective algorithms for highly dimensioned and complex data. Despite the benefits of ML (such as high sensitivity and low biases in pattern recognition), it is important to take into account the accuracy of the classifiers, the precise features that should be extracted, the quality of the data, and the cost of the computation. Channel selection, for example, can reduce the computational burden on both feature extraction and pattern recognition when certain conditions are met. This is possible for online computation, especially for some wearable or implantable devices in practical applications. A potential alternative is to exchange EEG recordings in real- time by using cloud computing connected by 3G technology. Machine learning is a well-liked approach for image processing when it comes to machine learning techniques, but it is only recently beginning to appear in EEG processing, proving its superiority in EEG pattern recognition.

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