Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Advanced Ocular Artifact Removal In EEG For Enhanced Schizophrenia Diagnosis Using Wavelet Shrinkage And LSTM Deep Learning Techniques

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Schizophrenia is a potentially life-threatening mental disease. It is distinguished by deficiencies in cognition, affect, and conduct. Countless individuals worldwide are affected by it. Accurate diagnosis can be achieved by analyzing EEG data. Researchers can non-invasively measure brain activity by using an electroencephalogram (EEG). Blinking of the eyes results in the production of an electrooculogram, which is defined by a robust electrical potential that envelops the eyes. The electrooculogram derives its name from this potential. The EEG data might become corrupted when cortical activity spreads across the scalp. Visual distortions of this nature are commonly known as ocular artifacts (OAs). The device is a commonly seen form of interference that can occur in electroencephalogram (EEG) research. Prior to processing EEG data, it is crucial to eliminate or minimize ocular artifacts (OAs). In order to eliminate the typical ocular artifacts (OAs) that occur naturally, it is essential to perform either two electrooculograms (EOGs) or a multichannel electroencephalogram (EEG). Our study has led us to develop a consistent method by combining EEMD with Fejer-Korovkin filtering. The first stage of the method involved noise decomposition. One great way to apply is with the Empirical Mode Decomposition (EEMD) methodology. We can find several components of the IMFs by means of a comparison between the original signal with the decomposed intrinsic mode functions (IMFs). Then, by means of denoising technique applied on the intrinsic mode function (IMF) components employing fejer-korovkin filtering techniques, the undesired artifacts (OAs) seen in the EEG are erased. Reconstruction of EEG signals is best accomplished by first obtaining artifact-free samples (OAs) and then training a deep learning network (DLN) using the obtained data from those samples with long short-term memory (LSTM). By means of real-time spectrum analysis on data gathered from several channels of electroencephalograms, this approach exactly identifies persons with schizophrenia. A good deep learning network will automatically remove artifacts (OAs) from the contaminated EEG data to retrieve information on the high-order statistical moments from the electroencephalogram (EEG). Analyzing the collected EEG data helps the PSO naïve Bayes classifier to increase the accuracy of differentiating individuals with schizophrenia. The proposed method substitutes a limited set of electroencephalogram (EEG) channels for a great number of electroencephalogram (EOG) reference signals. This guarantees generalizability while yet increasing time efficiency. Using EEG data acquired from both individuals in a laboratory environment and a publically available database, we do a comparison analysis of the proposed strategy with kurtosis-ICA (K-ICA), standard independent component analysis (ICA), and other approaches.

Keywords: EEG, EEMD, PS, naive bayes classifier, IMF

I INTRODUCTION

Schizophrenia affects over 21 million people worldwide and is the most common persistent mental illness [1-2]. Disturbances in the areas of cognition, perception, and behavior are symptoms of this disorder. People who suffer from schizophrenia frequently have auditory hallucinations and delusions. They may also appear detached from reality. Disabling symptoms of this mental disease could make it hard for a person to function in daily life, including attending school or working. Although the majority of people experience symptoms in their late teens or early twenties, they often manifest around the ages of 16 and 17. The death risk is two to three times higher than the usual population for 69% of people diagnosed with schizophrenia, due to the severe lack of appropriate treatment available to them. They have obstacles in accessing mental health treatment because they primarily reside in nations with low or moderate incomes. Electroencephalography (EEG) is a method that records the brain's electrical activity over a set period of time by means of electrodes that are applied to the scalp. The technology used is completely noninvasive. sections 3–4. The most significant biological factor that can disrupt EEG signals is tracking eye movements, which electro oculograms do. Ocular artifacts have substantially larger amplitudes than EEG signals. One can acquire a better grasp of the situation by separating the EEG data from the EOG signals.

Ocular artifacts (OAs) are EEG signals that originate from eye movement and are among the most problematic types of artifact signals [5-6]. A visible or automated blockage of the EEG signal by an overactive bladder (OA) could make data collection and processing more difficult. Additionally, OAs lower the accuracy of BCI labeling, according to studies. In EEG data, there may be several OA episodes. The individual taking the EEG readings will inevitably blink and make other eye movements. Electroocular graphs (EOGs) are spike-like signal waveforms that are produced when the eyes blink. In its short 200–400 ms duration, this waveform contains peaks as high as 800 V. These impulses are referred to as electrooculograms (EOG). Electric fields on the brain's and eyes' cortical surfaces are altered by these movements. The scalp EEG electrode picks up on these movements, which causes OAs and EEG signals to overlap. Short duration and spike-like pattern in low-frequency zones are two of the distinguishing features of EOG signals, which are also shared with OAs [7].

We start by taking a look at the various artifacts that have been discovered, as well as the distinct features of the EEG signal. What follows is an analysis of the benefits and drawbacks of the most common methods of trash collection. Afterwards, a comparison based on specific criteria is shown in a juxtaposition. Based on the data we have, we can guarantee that you will discover a workable method of elimination. The level of the substance is shown by it. It is possible to investigate these tactics by grouping them into four broad categories. Reducing noise is EEG data should be prioritized, as has already been demonstrated. For this specific purpose, we have created a robust noise-cancelling technology. Integrating fejer-korovkin filtering and the empirical mode of the ensemble (EEMD) is the way that has been proposed to break down noisy signals. Utilizing the comparison between the initial signal and the deconstructing IMFs, we uncover multiple facets of the intrinsic mode function (IMF). Fejer-Korovkin filtering is done after the IMF components have been noise reduced. The ERP signal can be rebuilt with the use of de-noised IMFs. Using this method, we were able to filter out background noise from EEG recordings. To replicate electroencephalogram (EEG) signals, the suggested simulation approach recommends collecting data devoid of ocular artifacts (OAs) and then constructing an LSTM model using a deep learning network (DLN). This technique reliably identifies schizophrenia patients by real-time spectral analysis of data from many EEG channels. The high-order statistical moment information can be retrieved from the corrupted EEG data by automatically detecting outliers (OAs) using a trained deep learning network. By enhancing the acquired EEG data, the PSO naive bayes classifier improves the ability to distinguish between schizophrenia patients. The proposed approach improves efficiency without compromising adaptability by using a small number of channels of the EEG rather than broad EOG reference signals. The feature extraction procedure extracts spectral properties from these bands, including mean spectral amplitude, spectral power, and the Activity, Mobility, and Complexity Hjorth descriptors. Many modern classification models use these traits, such as CNN-SF and LSTM. Also, the models for classifying raw time-domain and frequency domain EEG segments, known as spectrum convolutional neural networks (CNN-S) and temporal convolutional neural networks (CNN-T), are identical in this study. The CNN-SF model, which relies on spectral characteristics, is superior at accurately identifying schizophrenia patients in real-time, according to all models' evaluations based on numerous performance criteria.

A synopsis of the main points and structure of this book is provided in the following sections. In Section 2, we look at comparable papers using the existing strategy. An extensive discussion of the suggested DLN LSTM architecture is presented in Section 3. The fourth and fifth sections provide more details on the findings and evaluations.

II RELATED WORKS

The most often occurring chronic mental disorder worldwide, schizophrenia affects about 21 million persons [1-2]. Symptoms of this condition are disturbances in the spheres of thinking, feeling, and acting. Those with schizophrenia often have delusions and auditory hallucinations. They could also seem cut off from reality. Disabling symptoms of this mental illness could make daily life difficult for a person, including their attendance in classes or their employment. Though most people have symptoms in their late teens or early twenties, they might show up at the ages of 16 and 17. For 69% of those diagnosed with schizophrenia, the death risk is two to three times higher than the average population because of the extreme shortage of suitable therapy accessible to them. Their main countries are low- or moderate-income countries, hence they have difficulties getting mental health therapy. Electroencephalography (EEG) is a technique whereby electrodes placed on the scalp capture the electrical activity of the brain over a designated period of time. The applied technology is entirely noninvasive. sections three and four. Tracking eye movements—which electro oculograms do—is the most important biological element that can interfere with EEG signals.

Amplitudes of ocular artifacts are much higher than those of EEG waves. Separating the EEG data from the EOG signals helps one to understand the scenario.

Among the most troublesome kind of artifact signals, ocular artifacts (OAs) are EEG signals derived from eye movement [5–6]. An overactive bladder (OA) could cause a visible or automatic obstruction of the EEG signal, therefore complicating data collecting and processing. Studies also show OAs reduce the accuracy of BCI labeling. There can be many OA events in EEG data. The person recording the EEG will surely blink and move their eyes. Blinking of the eyes generates spike-like signal waveforms known as electroocular graphs (EOGs). Over its brief 200–400 ms, this waveform has peaks as high as 800 V. We call these impulses electrooculograms (EOG). These motions change the electric fields found on the cortical surfaces of the brain and eyes. OAs and EEG signals overlap when the scalp EEG electrode detects these motions. Two defining characteristics of EOG signals—also shared with OAs—are short duration and spike-like pattern in low-frequency zones. Eliminating contamination from EEG signals is already a difficult chore since organic compounds (OAs) cannot be measured. OAs have a far higher amplitude than electroencephalograms (EEGs), hence their eradication has great potential to be revolutionized. Reliable EEG data interpretation and appropriate neurophysiological monitoring depend on the elimination of ocular artifacts (OAs). Over the past few years, a flood of studies on several methods to remove artifacts and restore signals has been published. Manual elimination of all OA-affected segments of data used to be routine procedure, which caused a notable data loss [7].

Given this, we set out to create a thorough review of the most often used methods of removing previously captured EEG artifacts. We first review the several unearthed relics as well as the unique characteristics of the EEG signal. The advantages and disadvantages of the most often used approaches of garbage collecting are examined here. Following that, a juxtaposition shows a comparison grounded on particular criteria. We can promise you, based on the facts, that you will find a practical approach of elimination. Its level indicates the degree of the drug. Grouping these strategies into four main groups helps one to investigate them. As already shown, reducing noise in EEG data ought to be given first priority. We have developed strong noise-cancelling technology especially for this aim. Proposed to break down noisy signals is integrating fejer-korovkin filtering and the empirical mode of the ensemble (EEMD). We expose several aspects of the intrinsic mode function (IMF) by means of a comparison between the original signal and the deconstructed IMFs. Fejer-Korovkin filtering follows the reduction of IMF component noise. De-noised IMFs help one to rebuild the ERP signal. We filtered background noise from EEG records using this approach. The proposed simulation method suggests gathering data free of ocular artifacts (OAs) then building an LSTM model using a deep learning network (DLN), so replicating electroencephalogram (EEG) signals. By real-time spectral analysis of data from several EEG channels, this method consistently detects schizophrenia patients. Automatically identifying outliers (OAs) using a trained deep learning network allows one to obtain the high-order statistical moment information from the distorted EEG data. Improving the collected EEG data helps the PSO naive bayes classifier to discriminate between schizophrenia patients. Using a limited number of channels of the EEG instead of wide EOG reference signals enhances efficiency without sacrificing adaptability. Mean spectral amplitude, spectral power, and the Activity, Mobility, and Complexity Hjorth descriptors are among the spectral characteristics obtained by the feature extraction process from these bands. CNN-SF and LSTM are two of the many contemporary classification models that draw on these features. Furthermore, in this work the models for categorizing raw time-domain and frequency domain EEG segments are identical: spectrum convolutional neural networks (CNN-S) and temporal convolutional neural networks (CNN-T). Based on evaluations based on many performance criteria, the CNN-SF model—which depends on spectral characteristics—is better than all other models at precisely identifying schizophrenia patients in real-time.

The following sections offer an overview of this book's major ideas and organization. Section 2 examines related studies applying the current approach. Section 3 features a thorough review of the proposed DLN LSTM architecture. More specifics on the conclusions and assessments are found in the fourth and fifth parts.

III PROPOSED TECHNIQUE OF FK DLSTM

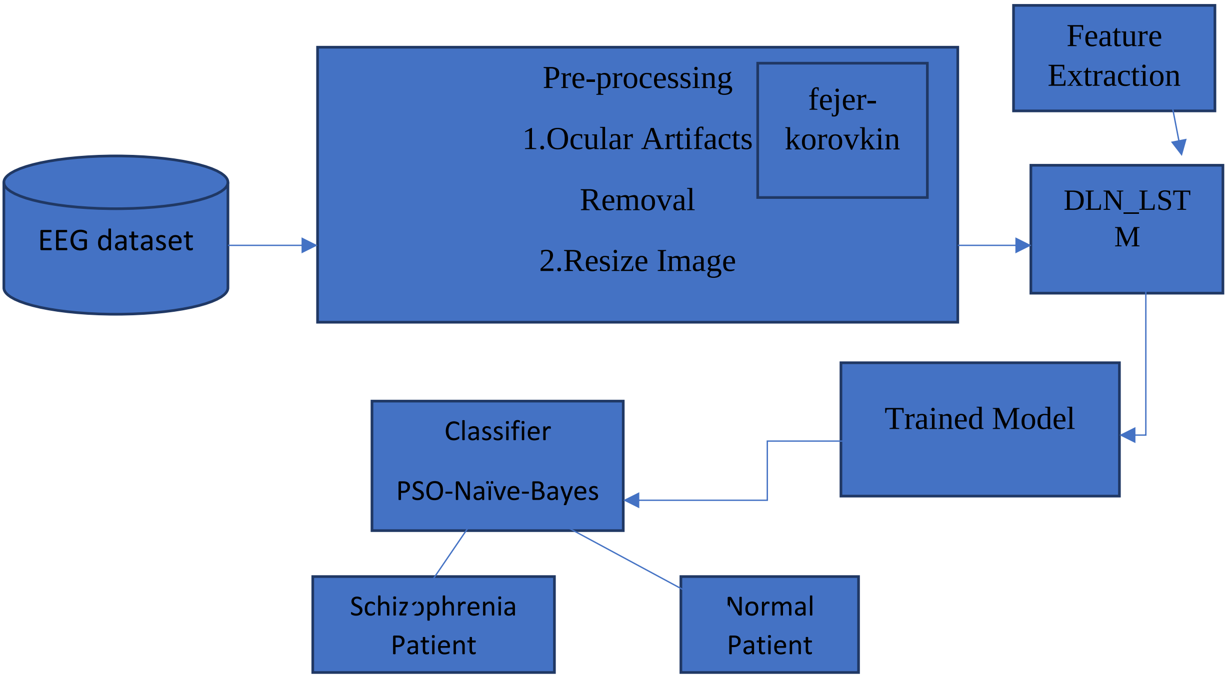

Figure 1: Architecture diagram of the proposed techniques Prop_FK_DLSTM

Figure 1 depicts the proposed architecture of the FK DLSTM system, an acronym for Fejer-Korovkin filtering with deep learning LSTM. The procedure commences with retrieving data from the database and proceeds with pre-processing operations, such as noise reduction and enhancing feature dimensionality using techniques including picture scaling, texture analysis, and color analysis (image descriptors). DLN LSTM is a crucial technique for training a knowledge-based neural network to detect and remove artifacts in fejer-korovkin filtering data. To enhance the precision of the previously trained data and associated images, the utilization of the PSO naive bayes classifier approach is necessary. This function is utilized to generate the categorized output, enabling precise retrieval of the EEG signal. Subsequently, when the task of distinguishing between patients with and without Schizophrenia arises, the categorized output demonstrates superior performance.

3.1 Pre-Processing

An EEG pre-processing block is employed to convert the frequency domain of an EEG signal into the time domain. The following blocks consist of analyzing the EEG, reducing noise using EEMD, and applying “FEJER-KOROVKIN” noise removal.

Figure 1. Pre-processing architecture

Group Empirical Mode Decomposition (EEMD) is a special model that we used to look for mistakes in the way it looked. EMD stands for empirical mode decomposition. It is a way to look at processing series that are not steady or linear.

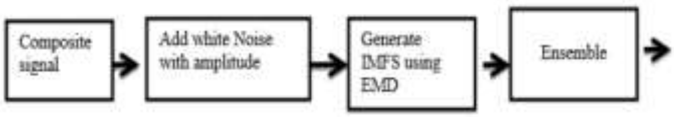

Figure 2. EEMD block diagram

Figure 2 displays the EEMD architecture. The original EEG signal is utilized to identify and utilize biological abnormalities, such as eye movements captured using electrooculograms, in order to construct intrinsic mode functions. After gathering these inherent mode functions, a direct method that relies on thresholds is employed to combine them. The sifting algorithm is an iterative procedure employed by the Empirical Mode Decomposition (EMD) technique to extract Intrinsic Mode Functions (IMFs).

$$S(x) = rn\ (x) + ci + ci\ (x) \qquad (1)$$

Given that rn(x) is the residual of n extracted intrinsic mode functions (IMFs) of x, the IMF in this particular scenario is denoted as ci. In order to utilize the IMF, two prerequisites must be fulfilled. (1) Only one feature can be associated with one component or one mode of oscillation with one frequency at any given time. Both of them exhibit an equivalent number of extreme points and points where the function crosses the x-axis. (2) The average value of both the upper and lower envelopes is zero. In order to produce a fraction that meets the previously stated criteria, the signal undergoes a repetitive process of filtering to remove the IMF components.

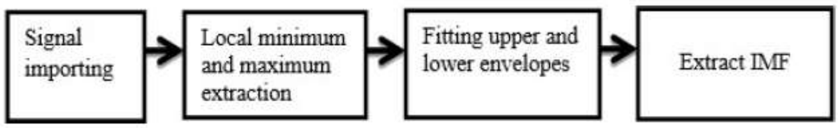

Figure 3: EMD Architecture

Figure 3: The EMD Design. The following steps describe how to transform the signal's IMF format:

(i) Recognize the original signal's highest and lowest points.
(ii) The bottom and upper envelopes are built using the cubic spline form technique.
(iii) Calculate the average value by connecting the upper and lower envelopes (blue).
(iv) Subtract the mean from the original signal while creating the first intrinsic mode feature of type IMF1.
(v) Subtract IMF1 from the original signal to get the first residual part. For the purposes of determining the next IMFF, this information should be considered new.
(vi) If a monotonic function remains as the last residual component, no further IMFs need to be eliminated.
(vii) Figure 4 shows how to use EMD to rebuild the two sinus waves that were overlaid in the original signal.

A high- and low-frequency component of the original data vector has been created. The ideal original signal is obtained by adding all of them together.

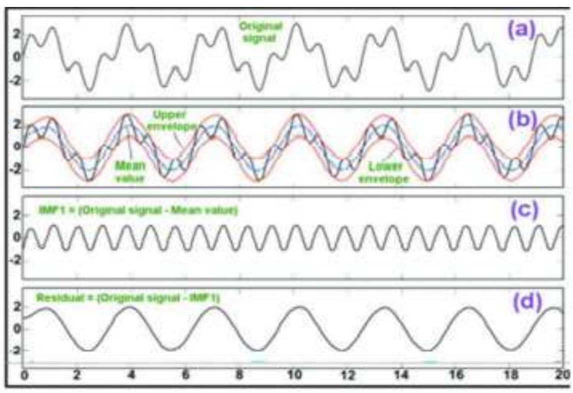

Figure 4: The EMD two-wave signal decomposition includes the following components: (a) the sum of two waves, (b) the lower and upper envelopes represented in red, together with their mean in blue, (c) the first intrinsic mode function (IMF), and (d) the first residual envelopes in red.

3.2 De-Noising of EEG Signal using FEJER KOROVKIN

The "stationary wavelet transformations" (SWTs) are utilized to extract two components of periodicity from the data. These components are produced from the Fejer-Korovkin wavelet filter and consist of a high frequency component and an inter-annual periodicity component. Convolution kernels are used to construct families of quadrature filters with excellent frequency resolution, namely those that are ordered and ideal. In order to get the optimal upper bound for EEG, it is necessary to utilize the lower bound for all filter lengths of 2N.

3.3 Identifying Ocular Artifact Spike Zones:

At each successive level of decomposition of the EEG signal, the 'detail' portion is taken into account This "approximation" portion may be kept for signal reconstruction[18-20], however. The coefficient of variation for each spike zone is computed using the spike zone coefficients (d_(j-1),d_j,d_(j+1)). The greater values of the coefficient of variation must be chosen. due to the fact that a higher coefficient of variation implies a lower level of accuracy or a higher level of noise loudness. For example, look at figure 5, which depicts an EOG-contaminated EEG epoch recorded at a rate of 128 samples per second, where the EOG artefacts may be seen at intervals of 0.3-0.7 seconds and 2.0 to2.2 seconds.

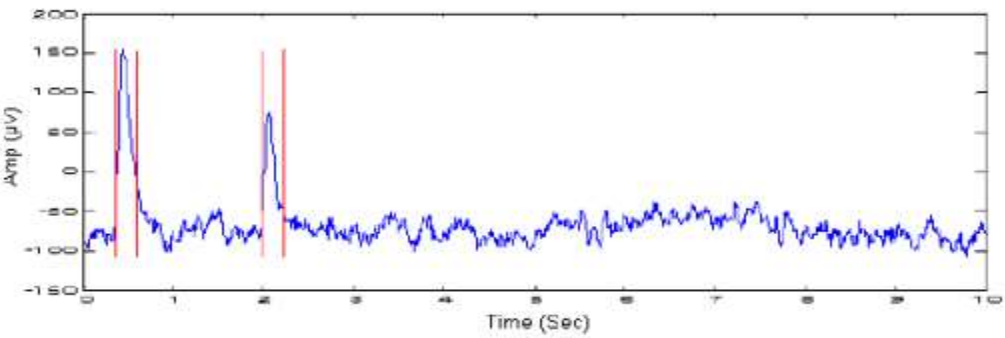

Figure 5. Identification of artifact zones

3.4 DLN_LSTM to reconstruct the Feature extracted EEG data:

New learning techniques such as deep learning (DLN) use a multilayered structure to represent data well, with each layer reflecting a different level of data feature abstraction.

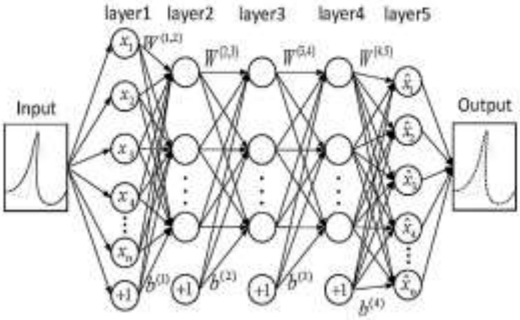

Figure 6. Structure of DLN

Figure 6 depicts a DLN with 3 hidden levels concealed from sight. In this case, let's assume that x is input data to the DLN and xˆ is its output data. So it utilises x = xˆ, where the inputs to the DLN are represented by the n-dimensional column vectors x and xˆ, respectively. There are five layers: one input layer, two –four hidden layers, and layer 5 is the output layer. Bias units are the "+1" circles, and they correlate to the intercept terms. Neurons are the "other" circles. An individual "neuron" is shown in Figure 6. Figure 7 shows the connection weights (W1–W3).

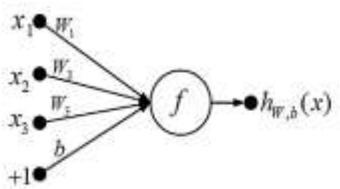

Figure 7. A single “neuron”.

The "neuron" is an arithmetic unit that takes as inputs x1–x3 and b. It's possible to output it in the following way:

$$h_{w,b}(x) = f(W^{\top}x) = f\left(\sum_{3}^{f-1} W_i x_i + b\right) \qquad (2)$$

where the activation value is hw,b (x) and the activation function is f (•). The activation function used in this study is the sigmoid function, which is:

$$f(z) = \frac{1}{1+exp\,(-z)} \qquad (3)$$

where f(z) is in the range of 0 to 1. W(l,l+1) is the parameter matrix, often known as the weight matrix, that corresponds to layers l and l + 1. The values for l are 1, 2, 3, and 4. The bias associated with layer l and layer l plus 1 is similarly represented by the symbol b(l). Intercept words and weights are used to connect adjacent layers.

An DLN is trained using EEG data devoid of OAs[21-24]. One of the benefits of the suggested approach is that it avoids the usage of EOG signals by performing this step. This paper's most important phase is determining how to intercept the best training samples. To start, you'll need EEG segments that don't have any OAs. OA-free segments are abbreviated as NOEs and NOE (no-OA-electroencephalogram segment).

Kurtosis is a fourth-order cumulant of a random variable. Kurtosis is defined by

$$Kur = cm_4 - 3cm_2^2 \qquad (4)$$

where cmj (j = 2, 4) is the j th order central moment with the following form:

$$cm_j = E\{[s - E(s)\hat{Y}\} \quad (5)$$

where s is a random variable, and E is its statistical expectation, The greater the kurtosis value, the steeper a signal's slope will be. As a result, detecting OAs may be accomplished using the kurtosis.

We snoop on NOEs to get the training samples. Suppose a window has length Lw, and a NOE has length L. In this case, let Lw and n have an integral multiple connection with an assumption that the duration of the training sample is n. Because the parameter is a positive real number, all of the intercepted segments have the same length. The intercepted segment's alignment allows researchers to make full use of the EEG segment, which aids in the investigation. The connection between Lw and n must fulfil the following conditions in order to fully use the chosen NOEs:

$$L_w = \alpha n(\alpha \in N_+) \quad (6)$$

DLN training is one of the essential components of this technique. At first, the utilization of NOEs for training involves collecting a set of m training samples, denoted as x(1),..., x(m). The inputs of DLN are represented by the n-dimensional column vectors (x(a)), where a belongs to the set of positive natural numbers and m is less than or equal to the minimum value of m. Prior to commencing training, it is necessary to normalize each training sample. Prior to commencing any training, it is necessary to standardize each training sample. Evaluation of the optimal parameter configuration. This further demonstrates that these experiments have identified specific attributes of EEG signals. Prior to the elimination of OAs, it is necessary to do online adjustment of the contaminated EEG signal.

3.6 PSO_naive bayes classifier:

The primary objective of enhancing the underlying algorithm is to expedite the identification of the global optimum. Consequently, the PSO algorithm was updated in the subsequent manners. The inertia weight (λ) is typically presumed to be constant between generations. As the number of generations (or iterations) increases, you have the option to systematically decrease λ. As the number of generations increases, the search space for the global optimum may become restricted. After each generation, the most superior particle from the previous generation takes the place of the least superior particle from the current generation. Scientists have developed multiple approaches for selecting the suitable course of action. This study included both linear and non-linear selection approaches for inertia weight in order to compare their respective effects. When employing linear selection, the value of λ should fall rapidly at the optimal point and gradually in its vicinity. Mathematically, this is how it appears.

Define g1 as the number of generations required for linear selection and g2 as the number of generations needed for non-linear selection. In linear selection, λ0 represents the initial point, whereas λ1 represents the final point. The inertia weight for Particle Swarm Optimization (PSO) will be determined using the provided approach for a range of generations from 1 to g1.

$$\lambda_1 = \lambda_0 - \left((\lambda_1/g1) * i\right), \text{ where } i = 1,2,3, \dots, g1 \quad (7)$$

The inertia weight of PSO will be computed using equation for generations g1 to g2.

$\lambda_1 = (\lambda_0 - \lambda_1) * exp\ (((g1 + 1) - i)/i)$, where $i = g1 \ldots g2$ (8)

For empirical studies, the values of g1 and g2 are often used. We took 100 generations into account while conducting our study. 50 percent of the total generations are selected using linear and non-linear methods of determining the inertia weight.

Algorithm for PSO_naive bayes classifier

Do this for each particle
Set the location and speed of the particle to zero.
End For
If the conditions for stopping are not met do
Decide whether to use equation 7 or 8 to calculate inertia weight.
Do this for each particle
Determine your level of fitness (Using MSE)
If the fitness value is higher than the highest fitness value ever recorded for a particle (pBest), then
pBest should be used as the current position.
End If
End For
Select the particle with the greatest fitness value on a global scale (gBest)
Do this for each particle
Calculate the velocity of a particle.
Particle position has been updated based on (Center, Spread & Weight)
End For
End While

An unsupervised learning method based on the Bayes theorem is known as the naive Bayes technique. The Bayes' theorem says that for class variable y and dependent feature vectors x through xn:

$(y|x1, \ldots, xn)$ = $Py\ (x1,\ldots,|y)P(x1,\ldots,xn)$ (9)

Using naive independence

$(xi|y,1, \ldots ,xi-1,xi+1,\ldots, xn)$ = P$(xi|y)$ (10)

It is simplified as

$$P(\, y \mid x_1 \ldots \ldots, x_n\,) = \frac{\pi_{i=1}^{n} P(x_i|y)}{P(x_1 \ldots\ldots x_n)} \quad (11)$$

Since $x1$ is constant for given input, it is simplified as

$$P(\, y \mid x_1 \ldots \ldots, x_n\,)\ \alpha\ P(y)\pi_{i=1}^{n} P(\, x_i \mid y\,) \quad (12)$$

$$\hat{y} = arg\, max_y\ P(y)\pi_{i=1}^{n} P(\, x_i \mid y\,) \quad (13)$$

Maximum A Posteriori (MAP) is utilised in the training set to assess P(y) and P(Xi|y). This method relies on the distribution of P(Xi|y) to make assumptions. According to Equation 9, we have a Bayesian Interaction Network. A class label and an attribute value may be represented by two letters, respectively: c and x i. Because of this, we may say that the naïve Bayes distribution is

$$P_r\,(c, x_1, \ldots \ldots, x_m) = P_r\,(c). \prod_{i=1}^{m} P_r\,(x_i \mid c) \qquad (14)$$

Analyze parameters derived from data using MAP of maximum likelihood by taking into account conditional distributions Pr(Xi|C) and class priors Pr(C). When the naïve bayes model is established, we may look at the posterior probability of observations sx1,...,xm to see whether the class label c* is valid.

$$c^* = \operatorname{argmax}_c P_r\,(c \mid x_1, \ldots \ldots, x_m) \qquad (15)$$

Classification is a substantial difficulty in the domains of data mining and machine learning. A learning methodology is utilized to generate training instances with class labels. An attribute value is denoted by a tuple (x1,x2, • • •,xn), where each value xi represents the attribute value Xi. The classification variable C is symbolized by the letter C, whereas the specific value of C is represented by the letter c. Let C be the classification variable, and let c be the value of C. There are precisely two portions. A class that can be categorized as either positive or negative. A classifier is a mathematical function that assigns a specific class label to a given input. A classifier can be used to assign a class identification to a variable. According to Bayes' Rule, the chance that an example E=(x1,x2,• •,xn) belongs to class c can be calculated as follows:

$$p(\,c \mid E\,) = \frac{p(\,E|c\,)p(c)}{p(E)} \qquad (16)$$

E is classified as class C =+ if and only if:

$$f_b(E) = \frac{p(C=+|E)}{p(C=-|E)} \geq 1 \qquad (17)$$

Where fb (E) is known as Bayesian classifier. Consider all attributes which are independent class variable value.

$$f_{nb}(E) = \frac{p(C=+)}{p(C=-)} \prod_{i=1}^{n} \frac{p(x_i|C=+)}{p(x_i|C=-)} \qquad (18)$$

Classifier fnb(E) is also known as classifier nave Bayes, and it is used to classify data (NB). Node has single parent in naive Bayes class. As a Bayesian network, the characteristics of each node are independent of the others. Contextual independence is a term used to describe something that is often wrong in real-world settings. Increasing structure to clearly express dependency in attributes manages its restriction.

IV PERFORMANCE EVALUATION

The following results displays the suggested method's performance analysis. There are four parameters to examine while evaluating the test: accuracy, sensitivity, specificity and F1 score. Using the webpage http://brain.bio.msu.ru/eeg schizophrenia.htm.

4.1 Dataset Description:

The open-access EEG dataset32 was acquired and prepared through a collaboration between researchers from the Laboratory for Neurophysiology and NeuroComputer Interactions, including Professor N.N. Gorbachevskaya of The “Mental Health Research Centre” and Senior Researcher Dr. S.V. Borisov of the Faculty of Biology at M.V. Lomonosov Moscow State University. This dataset comprises two types of resting-state EEG signals: one obtained from a group of healthy individuals (n=39) and another obtained from a group of individuals diagnosed with schizophrenia (n=45). This dataset has a total of sixteen channels, with each EEG signal being unique. The channels included are F7, F3, F4, F8, T3, C3, Cz, C4, T6, O1, and O2. The International 10-20 system is used to implant electrodes in order to gather impulses from the scalps of individuals.Each collected 1-minute EEG data point consists of EEG voltages measured at 7650 millivolts and sampled at a frequency of 128 Hz. Figure 8 illustrates the chronological correlation between the 16-channel EEG data of healthy individuals and the data of individuals with schizophrenia.

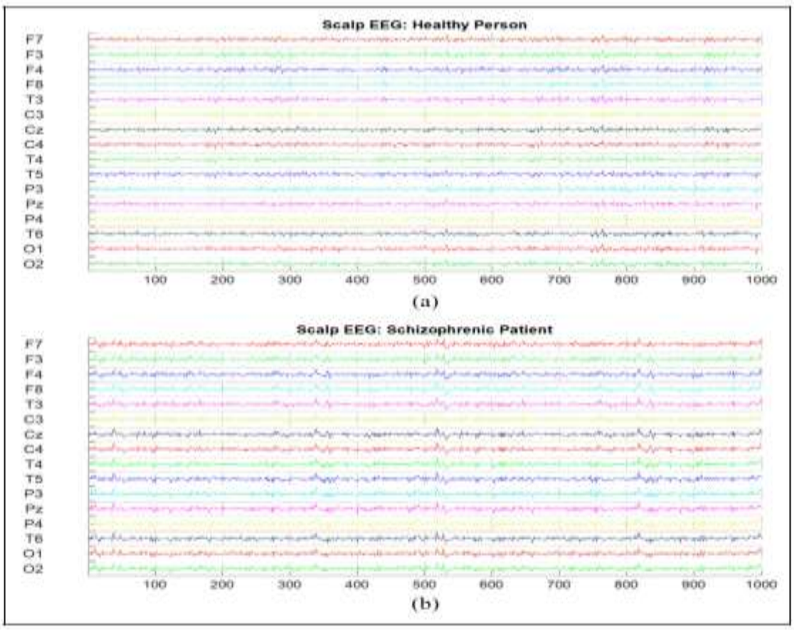

Figure 8. The temporal relationship between healthy people and schizophrenia sufferers' 16-channel EEG data

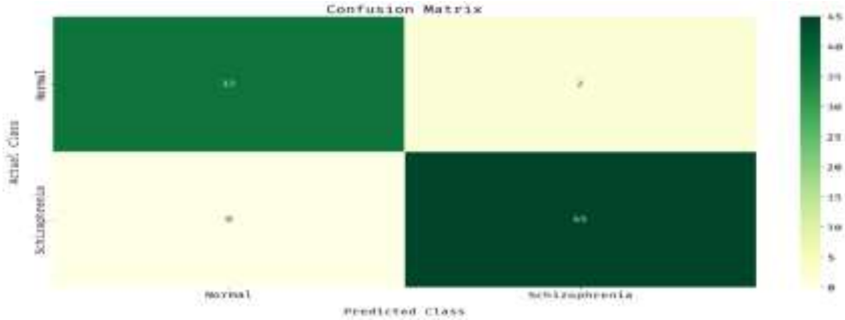

Figure 9. Confusion Matrix of the Proposed FK DLSTM technique

The above figure 9 is the Confusion Matrix of the proposed technique with the two classes to identify that is the Schizophernia and a normal patients.

Table . 1 To detect schizophrenia patients using dataset-I, three CNN models and one LSTM were evaluated for performance.

Measures	CNN-T(%)	CNN-S(%)	CNN-SF(%)	LSTM(%)	Proposed FK DLSTM (%)
Accuracy	71.09	92.38	94.08	76.78	97.62
Sensitivity	70.71	91.98	92.7	80.72	94.87
Specificity	71.35	92.6	95.31	73.18	100
F1-Score	68.71	91.84	93.62	76.06	97.37

The performance of the proposed FK_DLSTM in Table is compared with that of numerous “CNN-T, CNN-S, CNN-SF, and LSTM” techniques. Firstly, the classifier determined the output based on the categorization of instances with similar observations from individuals with schizophrenia. Finally, a comparison was made between the performance measures of many techniques, including “CNN-T, CNN-S, CNN-SF, LSTM, and FK_DLSTM”.

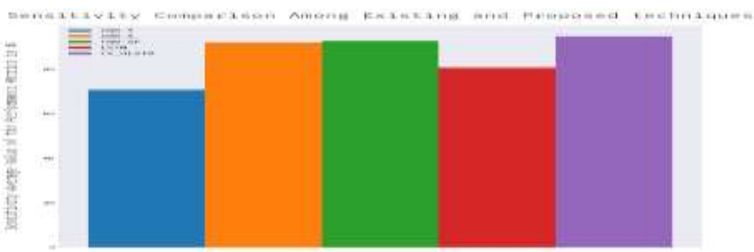

Figure 10:Sensitivity of Comparison of the Existing and Proposed FK DLSTM techniques .

Figure.10 shows the difference between different methods in terms of Sensitivity. It's a study of current and potential methods for EEG databases in terms of Sensitivity. The Proposed

FK_DLSTM achieves Sensitivity with a maximum percentage than current techniques, as seen in the above figure. The CNN-T,CNN-S,CNN-SF, and LSTM, and approaches, on the other hand, generated the worst results, with a minimum Accuracy value at epoch-100 of about 70.71 %, 91.98 %, 92.7, and 80.72% respectively. Finally, when compared to other prototypes, the Proposed FK_DLSTM technique is more effective, achieving a maximum accuracy value of 94.87 %.

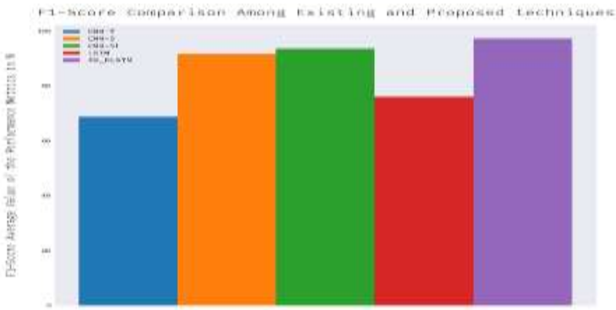

Figure 11. F1-score of Comparison of the Existing and Proposed FK DLSTM techniques.

Figure 11 shows the difference between different methods in terms of F1-Score. It's a study of current and potential methods for EEG databases in terms of F1-Score. The Proposed FK_DLSTM achieves F1-Score with a maximum percentage than current techniques, as seen in the above figure. The CNN-T,CNN-S,CNN-SF, and LSTM, and approaches, on the other hand, generated the worst results, with a minimum F1-Score value at epoch-100 of about 70.71 %, 91.98 %, 92.7, and 80.72% respectively. Finally, when compared to other prototypes, the Proposed FK_DLSTM technique is more effective, achieving a maximum F1-Score 94.87 %.

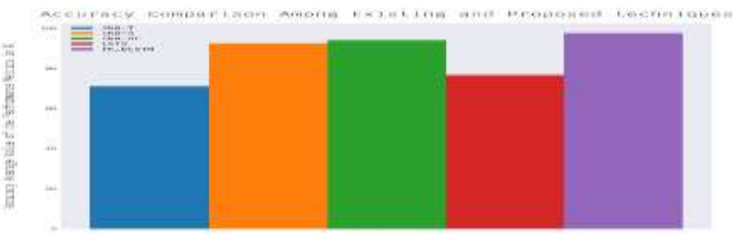

Figure 12. Accuracy of Comparison of the Existing and Proposed FK DLSTM techniques

Figure 12 shows the difference between different methods in terms of Accuracy. It's a study of current and potential methods for EEG databases in terms of Accuracy. The Proposed FK_DLSTM achieves Accuracy with a maximum percentage than current techniques, as seen in the above figure. The CNN-T,CNN-S,CNN-SF, and LSTM, and approaches, on the other hand, generated the worst results, with a minimum Accuracy value at epoch-100 of about 71.09 %, 92.38 %, 94.08, and 76.78% respectively. Finally, when compared to other prototypes, the Proposed FK_DLSTM technique is more effective, achieving a maximum Accuracy 97.62 %.

Figure 13. Specificity of Comparison of the Existing and Proposed FK DLSTM techniques

Figure 13shows the difference between different methods in terms of Specificity. It's a study of current and potential methods for EEG databases in terms of Accuracy. The Proposed FK_DLSTM achieves Specificity with a maximum percentage than current techniques, as seen in the above figure. The CNN-T,CNN-S,CNN-SF, and LSTM, and approaches, on the other hand, generated the worst results, with a minimum Specificity value at epoch-100 of about 71.09 %, 92.38 %, 94.08, and 76.78% respectively. Finally, when compared to other prototypes, the Proposed FK_DLSTM technique is more effective, achieving a maximum Specificity 97.62 %.

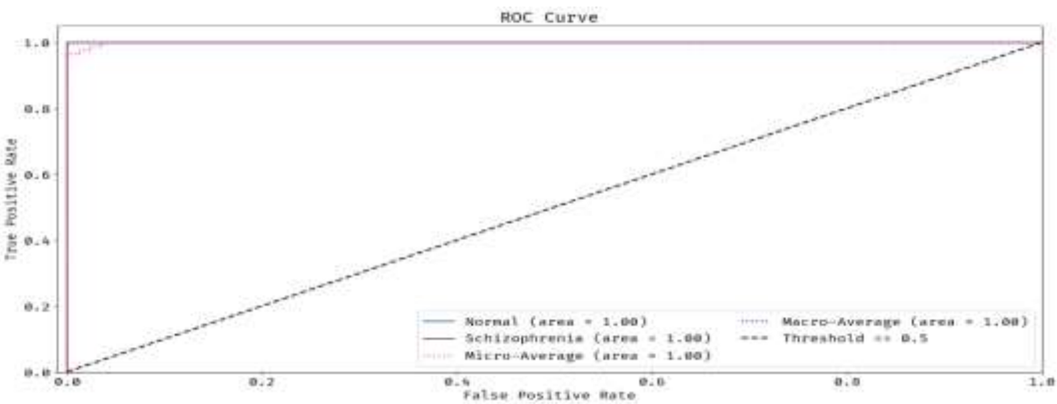

Figure 14. ROC curve with TPR and FPR of the Schizophernia dataset

The above figure is the ROC curve which determines the TPR and FPR of the Schizophernia dataset

V.CONCLUSION

A novel approach is proposed to identify schizophrenia patients using multichannel EEG inputs and an EEG-based FK DLSTM model. This technique identifies several forms of brain activity using the collected EEG data. This study examines the rate at which the sickness impacts the cognitive ability of the patient. This study examines both raw time- and frequency-domain EEG segments, as well as standard methods, to distinguish between persons with good mental health and those with schizophrenia. The LSTM model utilized "raw temporal" and "spectral EEG" segments as input and generated spectral information as output, thereby accomplishing the classification objective. Upon examination and comparison with current works, it is found that the suggested fejer-korovkin filtering with deep learning performs as anticipated for these classification PSO naïve bayes models. The LSTM model is effective for the rapid and precise diagnosis of schizophrenia. The ability of these models to remotely monitor patients in real time would assist neurologists and other medical professionals. The FK DLSTM Model demonstrates superior accuracy compared to the current techniques "CNN-T, CNN-S, CNN-SF, and LSTM" when evaluated on a dataset consisting of schizophrenia patients receiving treatment in a hospital or rehabilitation facility. Additionally.

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