IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

SPECIAL SECTION ON DEEP LEARNING ALGORITHMS FOR INTERNET OF MEDICAL THINGS

Received July 22, 2020, accepted August 7, 2020, date of publication August 13, 2020, date of current version September 9, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3016481

PGMM–Pre-Trained Gaussian Mixture Model Based Convolution Neural Network for Electroencephalography Imagery Analysis

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ABSTRACT Electroencephalography (EEG) signal processing through imagery inputs using intelligent computation methods are practiced in the recent years for improving the accuracy of detecting neural disorders. Classification and analysis of the input imagery requires prior training and assisted error detection to improve the accuracy. In this article, pre-trained Gaussian mixture model (PGMM) is introduced for improving the accuracy of EEG signal imagery analysis. The proposed model relies on deep learning classifiers for analyzing the imagery using pixel based segmentation through pre-training models. The errors in classification are identified through recurrent convolution neural network training process as aided by the extracted features. Based on the pre-trained feature assessment, the false positive errors are mitigated to achieve a better accuracy (92%) under controlled classification time and high true positives.

INDEX TERMS Convolutional neural network, EEG, feature extraction, imagery analysis, learning classifier.

I. INTRODUCTION

Electroencephalography (EEG) is useful in understanding the neural vitals observed within the human brain. This medical technique is capable of sensing brain functions and converts the pulses into electronic signals for diagnosing and treating neural problems [1]. The recent advances in communication technology have led to ease of observation of such signals from the human body. This is facilitated using handheld devices along with radio communication technologies. The devices observe the EEG vitals through sensors placed on the head of human beings that transmits periodic sensed observation to the hand-held device [2]. From the hand-held device, the observed information is relayed to the diagnosis center such as hospitals/ medical laboratories for further analysis. Epileptic and neural phenomenon changes are the prime focus for diagnosis in this EEG application [3], [4]. EEG signals are stationary and discrete with respect to time and the human activity. The signal vitals changes over time from which the useful information is to be classified for precise analysis. Spatial and temporal representations of the signals/ electrical vitals require sophisticated processing method as the input is expressed through tensor images or infra-red spectroscopy. With the more sophisticated integration of communication technology and intelligent processing methods, processing harmless EEG signals is prominent in the recent years in several applications including brain computer interface, activity monitoring, living assistance, artificial thinking, etc. [5], [6].

Epilepsy is a kind of neural syndrome occurring at irregular time intervals for humans resulting in nervous and paralysis problems. The uncontrollable movement and loss of consciousness lead to serious injuries and sometimes death [4], [6]. The electroencephalogram (EEG) is relatively cost affordable to monitor the brain state. The EEG is recorded with the electrodes which are placed on the scalp used to find the wave with different attributes. EEG signal analysis is used to finds the neuron disorder and also to diagnosis epileptic seizures. Detecting and treating of epilepsy in forehand helps to prevent unnecessary life risks, as human life is valuable [7]. With the integration of computational intelligence and information communication technologies,

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wei.

and portable smart wearable devices, solutions for neural analysis and syndromes are presented in the modern medical world. EEG signal processing or imagery analysis is a common procedure followed in the recent years for predicting the occurrence of neural problems and to provide concurrent diagnosis measures [8], [9].

Computational and artificial intelligence based solutions for EEG imagery processing is devised in the past through linear and discrete analysis. In the methods proposed for classifying EEG imagery over the discrete and varying terminal observations, machine learning and artificial intelligence are exploited in a large scale manner [10]. This kind of learning and processing methods are reliable in identifying the near to accurate diagnosis by mitigating the computation errors. In particular, classification of the features in a less time and non-approximated estimation of precise input signals helps to improve the diagnosis accuracy. In such cases, the precision of classification and the extracted feature are the deciding factors for detection and analysis accuracy [11]. Therefore, the training and classification of such features from the previous output states are required for improving the precision of detection methods. Machine learning and artificial intelligence based processing methods aid the lack of discrete solutions and false positives in the training process [12].

The structure of the proposed work is described as follows: Section 2 discusses about the earlier works and section 3 discusses about the proposed work and section 4 discusses about the results and section 5 concludes the proposed work.

II. RELATED WORKS

Liu [13], proposed a motor imagery EEG on neural networks. The author developed a non-linear function for mapping the traditional back propagation (BP) neural network. It is also based on the small weight by adding the particle swarm filter algorithm to enhance the filtering for the BP algorithm.

Deep Gaussian Mixture-Hidden Markov Model for EEG signal is introduced by Wang *et al.* [14]. A non-stationary EEG signal is been classified by means of two modules. The first one is used for the automatic feature extraction and the other is for the EEG signal classification for extracting the features.

A subject-Independent EEG Signal Analysis is modeled by Zhang, *et al* [15] for efficient EEG signal investigation. The Convolutional Recurrent Attention Model (CRAM) is used to encode the high-level illustration of the EEG signal. The dynamic part of the EEG signals aims at the temporal periods.

Support Matrix Machine is presented by Zheng *et al.* [16] for single-trial EEG classification. The proposed method is reliable for the EEG signal with high correlation and the EEG matrix is used for the ranging of the low-rank clean matrix in addition to the sparse noise matrix.

Samanta *et al.* [17], observed a cross-subject motor imagery for the EEG signal. The author presented a multiplex weighted visibility graph (MWVG) that is used for uni-variate in the bases of the time series, which is used to enhance the multivariate EEG. It is designed to improve the required generalization feature of EEG.

Zheng, *et al* [18], introduced Deep Learning for Automated Visual Classification using long short-term memory based on bagging theory (LSTMS-B). The EEG signals are used to direct the classification performance. The method decreases the gradient and also optimizes the training process it extracts the category dependent on the EEG signal.

A dynamic and self-adaptive classification algorithm (DSAA) for the EEG signal is designed by Belwafi *et al.* [19]. The method is used to extract the feature and classification algorithm at the time of the training system done on online testing. It also ensures the strength of the chosen couple and sustains the system accuracy.

Tang *et al.* [20], developed a qualified optimization empirical mode decomposition and multi-scale CNN. Conditional empirical mode decomposition (CEMD) is used to eliminate the noise in the EEG to encode the event connected to both the synchronization and de-synchronization. CEMD is based on one-dimensional multi-scale convolutional neural network (1DCNN).

Aydemir *et al.* [21], proposed a Tunable-Q Wavelet Transform and Quadruple, for diagnosing brain disease using EEG signals. The author presented a multi-level machine learning algorithm to identify epilepsy diseases. It is detected by pre-processing extracting the features and finally classifies the phases.

Deep learning feature recognition of motor imaging EEG signals is developed by Shi *et al.* [22]. The brain-computer is designed for the emergency practical value under the mechanism of EEG signal acquisition. In this work, the irregular samples are removed and extract the desired frequency in EEG imaging.

EEG signal decomposition methods in classification are compared with the BCI is addressed by Mohammed *et al.* [23]. The binary limb movements are been classified for the upcoming direction of BCI. They are based on the time-frequency for enhancing accuracy.

Choubey and Pandey [24], introduced an EEG signal processing from the extraction and classification for analyzing the epileptic seizure. It is done by Masking and Check-in based Feature Extraction Technique (MCFET) compared with K-means along with the K-nearest neighbor classification to check whether it is normal or abnormal.

Alyasseri *et al.* [25] implemented the metaheuristic algorithm to find efficiently adapted WT parameters for denouncing EEG signals that involve harmony search (HS). This is the first analysis utilizing optimization techniques in the configuration of WT parameters. This paper discusses which efficient MSE algorithm and the best WT parameter configuration was achieved.

Alyasseri *et al.* [26] introduced a new method for extracting EEG characteristics by multi - objective flower pollination algorithm and transforming the wavelet. The method proposed was tested in two EEG signal decomposition instances to extract unique characteristics from the original signals.

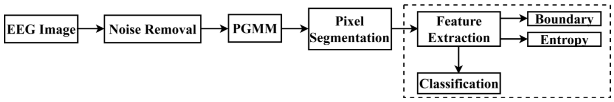


FIGURE 1. Process flow representation.

III. PRE-TRAINED GAUSSIAN MIXTURE MODEL (PGMM) FOR EEG ANALYSIS

PGMM has a finite model to fuse segmentation and classification schemes based on different factors for classification. To improve the EEG image accuracy by segmentation the pixel segmentation model is used. Thus, it focuses to extract the information from the EEG sensed vital more accurately. Then the classification is done with the help of deep convolution neural networks. In Figure 1, the process flow of the proposed method is presented.

PGMM consists of two main processes namely pre-training model and pixel segmentation. These processes are assimilated for classification using deep learning classifier in through the convolutional neural network. The deep learning classifier is responsible for improving the accuracy by analyzing the segmented image. The false positives that are identified in the process are mitigated in this classifier by identifying the nearest possible range of training models. In the following sections, pre-training model and pixel segmentation process of PGMM is discussed along with deep learning classifier.

A. PRE-TRAINING MODEL

The model is pre-trained from the image intensity on the previous processing of the medical images. The image is in the form of the pixel based on a matrix that has a pixel as the elements. The image here is the EEG signal of the brain. Let $\boldsymbol{I}$ will be a random variable that takes the value of the image. The Gaussian mixture model for $\boldsymbol{I}$ is been formulated as below:

$$g_x = H_p^V \sum\nolimits_{p=1}^{R} \left[Y \,|\alpha, \beta_p^2 \right] \tag{1a}$$

In the above equation, R is the region in number and H_p^V must be greater than zero where the weights are defined such as $\sum_{p=1}^{R} Y = 1$ and

$$Y\,|\alpha, \beta_p^2 = \frac{1}{\mu\sqrt{2\rho}^{exp}} \frac{-\left[(Y-\alpha)\right]^2}{\left[\sqrt{\mu_p}\right]^2} \tag{1b}$$

where $\boldsymbol{\alpha}, \boldsymbol{\beta}$ are said to be the standard deviation of the class $\boldsymbol{p}$. By taking the given input image as I, for the particular image, it has the lattice data are the values of the pixels and the PGMM is the pixel-based model. Where the parameter is represented as $\delta = \{Y^1, \ldots .Y^V, \alpha^1, \ldots \alpha^V$ is the number region in GMM denoted by the histogram of lattice data. The input image is classified based on the identified feature space where the weights are defined. Therefore, g_x is simplified to its least utilizing form such as the vector $\boldsymbol{Y}$ denotes both the error and the Gaussian mixture model as

$$\left.\begin{array}{c} Y = \alpha^1 g_{x_1} + \alpha^2 g_{x_2} + \ldots + \alpha^n g_{x_n} \\ where \\ e = 1 - \sum_{k=1}^{R} \frac{H_i(\mu_i)}{R} \end{array}\right\} \tag{2a}$$

In the above equation, the error is identified as the cumulative mean error of all $\boldsymbol{R}$ in the region excluded from $\boldsymbol{Y}$ i.e. $(\boldsymbol{Y} - \boldsymbol{\alpha})$. This validation is expected to improve the training of the model in the feature classification process. This classification is aided by CNN over the audio and image signals. The above distinguished region segregates the image from the audio and hence the deviations are different from the original image. The CNN on EEG includes the two ideas for leaning a particular task one is based on the natural signal which includes images and audio signals. These are often having an inherent hierarchical structure, where the images are typical consists of edges which are gathered as larger complex shapes. The CNN uses the pooling layers to create a coarser intermediate feature representation.

The pooling layer is constructed as a disjoint point between all the features that are extracted and is represented. The hierarchical structure of the edges (as determined by the images) is constructed based on the disjoint point of $(\boldsymbol{Y})$ given by

$$\left.\begin{array}{l} \rho\,(Y) = \rho(Y=p)^i \rho(Y=p)^{i+1} \ldots \rho(Y=p)^R \\ \quad = \prod_{i \in R} \rho(Y=p)^i \end{array}\right\} \tag{2b}$$

The above $\boldsymbol{\rho}(\boldsymbol{Y})$ forms the disjoint edges of all the extracted image points to retain the constituents of the pooling layer. Therefore, the input in a $\boldsymbol{n} \times \boldsymbol{n}$ matrix from which a simplest $\boldsymbol{n} \times \boldsymbol{n}$ matrix is extracted (refer Figure 2) as per the product of $\boldsymbol{\rho}(\boldsymbol{Y})$. The intermediate features boundary and entropy are expressed as $[I_{a,b}]_g$ and I_i respectively. These features are the hidden layer analysis constraints in determining the classification instances. If the classification is appropriate, then $\boldsymbol{\delta}$ is the sequential derivative of the input without errors.

In this work, the frequency domain is used for detecting EEG seizures. Here, both the Fourier transform magnitude and phase are been used for detection. It depends on the Index Segmentation (IS) for multi-channel EEG signal. By considering cross-spectrum such as X_a^V *and* X_b^V is formulated as below:

$$[I_{a,b}]_g = \left(\left[X_a^V\right]_g - \left[X_b^V\right]_g \right) \tag{3}$$

where, $[X_a^V]_g$ *and* $[X_b^V]_g$ are the Fourier transform of X_a^V *and* X_b^V. Thus the coherence of the complex is calculated as:

$$H_{a,b}^g = \frac{[I_{a,b}]_g}{\sqrt{[I_{a,b}]_g}} \tag{4}$$

When comes to IS the complex coherence is formulated as:

$$\gamma_{ab} = \left[\sum\nolimits_{g \in G} \left(H_{a,b}^g\right)_g^* H_{a,b}^g (g + \rho g) \right] \tag{5}$$

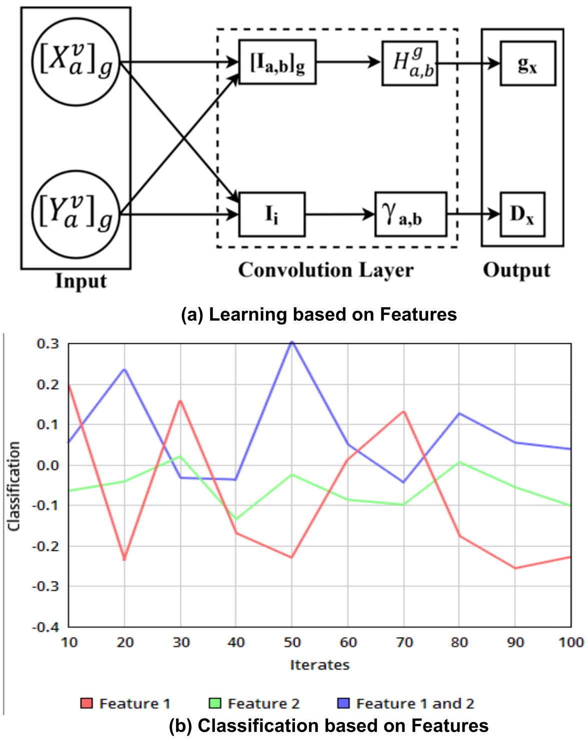


FIGURE 2. **(a) Learning based on features. (b) Classification based on features.**

In the above equation, ρg represents the frequency resolution and G is the frequency band of interest, and γ_{ab} is used to measure the weighted sum of the IS lies between X_a^V *and* X_b^V. The IS is used to measure whether it is seizure or normal by using the above formula.

B. PIXEL SEGMENTATION

The Pixel segmentation is used for classification of the CNN for EEG signal image; it consists of a standard architecture for image classification tasks. The images are been segmented by its areas i.e., the mask is generated to separate a single EEG image to the many classes. Thus, the network is trained in an end-to-end fashion; it is mostly used to segment the image which is in the higher resolution and process in a less amount of time.

The Pixel segmentation is mainly used for the biomedical images, for reducing the dimension of the EEG signal image through CNN, i.e., the Pooling layer. It reduces the height and width of the information by keeps its channel as constant input. The output is based on precise segmented information. The padding is important for concerning the Pixel segmentation to the large set of images. The initial step of Pixel segmentation is to crop the feature map obtained from the encoding unit which is given to the decoding unit. The modeled Pixel segmentation is used under many advantages for the segmentation task. It provides end-to-end processing for the whole image where it forwards the segmentation map.

The input is the image has the $n \times n$ matrix and then it is reduced to the matrix filter $m \times m$ which is said to be the feature map. The input images are been trained in the network for the gradient descent. From the padded value, there is some of the unpadded value in the convolution, where the output images are smaller than the input by the effect of border width is stable. The pixel-wise computation is used for the final feature map extraction process and thus it causes the entropy loss function. Thus, the cross-entropy is been positioned as:

$$I_i = E(w)\left[log_x D_x\right] \tag{6}$$

Based on the above features, the initial learning using the convolution layer is illustrated in Figure 2(a).

The process illustrated in Figure 2(a) considers the chances of boundary, entropy or both for the validation of optimal g_x and D_x. This is the initial classification of the input image based on the feature conditions wherein the following classification and learning process is imposed using different metrics over the above.

In equation (6), I_i is the input EEG signal image, $E(w)$ is the energy function for the feature map, and x is the pixel of the image. D_x is the predicted segmentation.

For the given input image the grayscale is been obtained and thus it produces the binary mask of 1s and 0s, where 1 denotes the pixel cell and 0 represents the background which lies between the borders and the cells. Thus, the semantic segmentation is done on the cell by receiving the same label. In this paper, the different label differentiates the image between the different individual's pixel thus the instance segmentation is done. In Figure 2(b), the classification process of the features is presented.

The consideration of the different features varies the change in classification rate irrespective of the time and segment factors. The classification is optimal with the consideration of both the features, whereas considering only one feature, results in non-optimal classification (negative values). Here, the first feature is the boundary and the second is the entropy.

Instead of a fully trained model, the given input image generates the binary segmentation mask that is 0 or 1. In this, it predicts the segmented mask and also compares the predicted mask to the mask in the ground-truth. It also used to ensure the updates of the model which are used to segment the upcoming training in the network.

The idea behind the Pixel segmentation is that it obtains the lower-dimensional representation of the image in which it consoles the traditional Convolutional neural network and thus the up sampling is done on the low-dimensional representation to obtain the final set of segmented output as the map. Two types of the path are associated with the Pixel segmentation:

C. CONTRACTING PATH AND EXPANSIVE PATH

The contracting path is used to generate the low-dimensional representation of the EEG signal image, whereas, the expansive path is used for the up sample representation in order to get the final output segmentation map. The contracting path defined for D_x based on the $E(W)$ and $O(R)$ conditions as

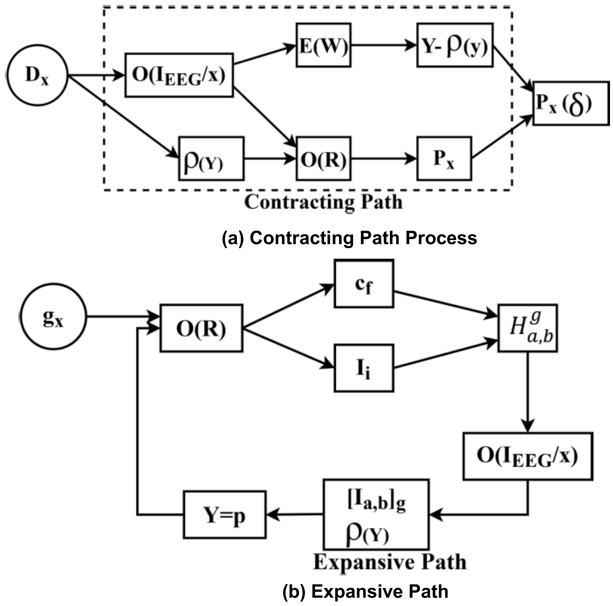


FIGURE 3. (a) Contracting path process. (b) Expansive path.

in Figure 3(a). The mediate output of $\boldsymbol{P_x}$ with respect to the sequence $\boldsymbol{\delta}$ is estimated in the contracting path process.

Similarly, in Figure 3(b), the Expansive path process is illustrated.

Different from the expansive path, the conditional assessment and processing of the normalized g_x follows the entropy condition to mitigate the initial error. This is in accordance with the initial classification error as in equation (2a). In this expansive path processing the output $H^g_{a,b}$ determines the dimensions of $n \times n$ matrix for retaining the optimal output that is different from the output of the initial learning process as in Figure 2(a)

After the Gaussian mixture model, the gray images are having the lower resolution feature maps from that the Pixel segmentation extent the high-resolution feature maps by using the contracting path. Thus, the expansive path does the processing in an easy way by copying the concatenated feature maps.

In the above equation 6, E(w) is used for pre-computation based on the correct segmentation. The morphological image processing is applied to the correct segment border of the pixel, and then the weights are created to map the thin border by separating its high weights. The weighted map is forward to the cross-entropy by means of Pixel segmentation.

D. DEEP LEARNING CLASSIFIER (DLC)

After the pixels are been segmented the deep learning classifier is used to classify the image for easy determination. Let the input EEG image are in the size of an array pixel. If the image is in the size of $250 \times 250 \times 3$, in this 250 is the width and 250 is the height and 3 is the RGB value of the channel. Basically, the RGB is ranged from 0-255. The pre-pixel classification model is used in this DLC for analyzing the segmented images.

The classifier is used to identify whether the patients are having a seizure or not. To classify the image each element are to be in the binary classifier and produce the result. Thus, the given input image is I and R is the realization which has the current information of the image such as $O(I_{EEG}\,|x) = O(I_{EEG}\,|R)$. Thus, the probability is calculated as follows:

$$O\left(I_{EEG}\,\middle|\,x\right) = \frac{O(R\,|x = I_{EEG})}{O(R)} \tag{7}$$

O(R) is the normalization factor for the image. O is the probability. The contrast between the images is finding out by the dichotomies.

$$C_f = \arg^{x}_{max} \sum\nolimits_{b_x \in b_g} O(I_{EEG}\,|x) = O(I_{EEG}\,|R) \tag{8}$$

C_f is the classifier b_x is the binary value and b_g represents a highly correlated function for the dichotomies it is considered as $b_x \in b_g$.

Based on spectral information the classifier is used to classify the pixels. The main objective work of this is the images have an allocated specific pixel of classes. The particular image is been classified as

The classes are defined in the initial step, i.e., in which location the classes are located.

Then the features are been selected by means of the preprocessing where it identifies the relevant features in the EEG signal image and also it removes the irrelevant information.

Training the sampling image by decreases the continuous-time of the signal which falls on the x-axis and y-axis.

Based on steps 2 and 3 the classification is done on the image and the results are been verified.

E. PRE-PIXEL CLASSIFICATION

The per-pixel classifier is used as the traditional spectra for all the sets of training pixels it is the aim of the deep learning classifier for a given feature image. Per-pixel classification is based on the parametric or non-parametric which are used in the distributed pixel image which includes the mean vector and covariance matrix obtained from the training samples.

In this study, per-pixel based classifier is used, and it is calculated by:

$$P_x = \frac{\delta I - D}{D} \tag{9}$$

P_x is the pixel ranges from 0 to 255, and δ is the initial stage of the image pixel in the block boundary and I is the image and D is the total number of pixels in the images. The initial stage of the pixel is subtracted by the last number of the pixel in the given input image.

The function of this is to assign the pixel vector of x to the single-pixel by pixel in a set of the boundary. Then the supervised classification is done to categorize the set of specific classes by providing its training set. The training areas are referred by the EEG monitor, to find the specific areas which are required for the study. By doing this per-pixel the images are been properly classified.

In this training process, the output of $n \times n$ matrix as classified into $m \times m$ output is analyzed for its normalization. If the normalization is not possible, then the boundary feature needs to be validated for the next pixel and therefore, $x = x + 1$ and $y = y + 1$. In this case, the failed normalization is the error (e) that is estimated for all the iterates of the learning process. This process generates the false positive rate that is computed as

$$\left.\begin{aligned} e_1 &= Y - \rho(Y_1) * \left[1 - O(R)_1\right] \\ e_2 &= Y - \rho(Y_2) * \left[1 - O(R)_2\right] + e_1/\rho(Y_2) \\ e_3 &= Y - \rho(Y_3) * \left[1 - O(R)_3\right] + e_2/\rho(Y_3) \\ &\vdots \\ e_{iterate} &= Y - \rho(Y_{iterate}) * \left[1 - O(R)_{iterate}\right] + \frac{e_{iterate-1}}{\rho(Y_{iterate})} \end{aligned}\right\} \tag{10}$$

The error estimated in equation (2a) is different from that of the above as the classification is based on iterates. The proposed method works in the following bases the input EEG signals image is captured; basically, it has some sort of noise in the original image. It is reduced by the pre-trained Gaussian mixture model to segment the images. Then, the Pixel segmentation framework is used for CNN to segment the pixel of the image obtained from the PGMM.

From the Pixel segmentation the images are extracted in a better resolution because the size of the image is correlated with the RGB values. Then, the images are feed into the CNN in that EEG image is nonlinear and then it forwards to the pooling layers and finally, they are fully connected to the layers and at last, it generates the output.

The convolution layer is done initially then the image matrixes are associated with the pixel values. By reading the image as the input matrix, in which it reads from the top left of the particular image. The smallest matrix is been selected in which it is said to be a filter or neuron in which it generates the convolution that moves along with the input image. The main aim of the filter is to multiply the values of the original pixel values and finally, all the pixels are summed. From the top left corner to the end it performs the operation, thus, the filter is positioned and thus, the matrix is been obtained but it is smaller. In Figure 4(a) and 4(b), the processing of $n \times n$ of the output $H^{g}_{a,b}$ and the sum pooling process is illustrated.

The network consists of the many Convolutional networks with a mixture of nonlinear and pooling layers (Figure 4(b)). When the input passes through the one layer of the convolution the output of the first layer is the input for the second layer. This happens with every further Convolutional layer. The non-linear layer is attached to the convolution operation where the activation function is said to be a non-linear property. The pooling layer tracks the nonlinear layer, where it has the width and height of the image and it associates with the down sampling operation. The resultant image size is been reduced by doing this process. Here, the sum pooling is used for the identification of features that are reliable. If some of the boundaries of the feature are been identified in the previous convolution operation then the specified image will not be any longer needed for the upcoming processing, and it compresses to the less specified image. Followed by this process the series of Convolutional, nonlinear and pooling layers is necessary to the next layer of the fully connected layer. This layer obtains the information from the Convolutional network as the output. The Fully connected layer results in the Z dimensional vector where Z is the number of classes from the where the model chooses the preferred class. Thus, the proposed method is effectively used for the EEG signal image segmentation and classification by means of FCN to analyze the image using PGMM for better accuracy and for pixel-based per-pixel classification is done then the Pixel segmentation is used for the pixel segmentation. Then, the input is the classified image from the Pixel segmentation and then it is given as the input to the FCN to detect the seizure in the patient's EEG signal image.

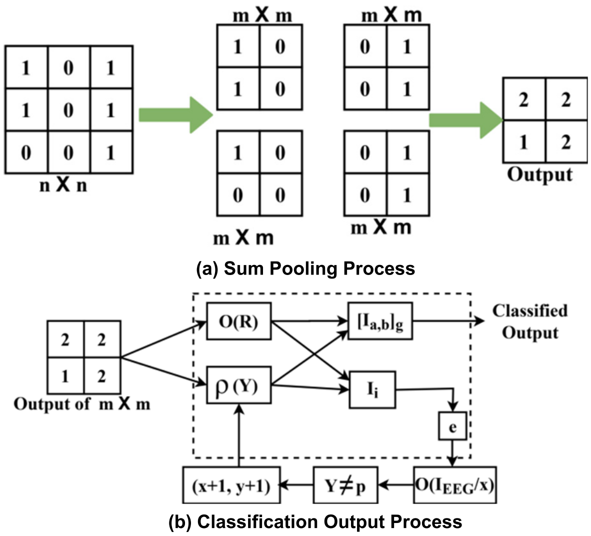


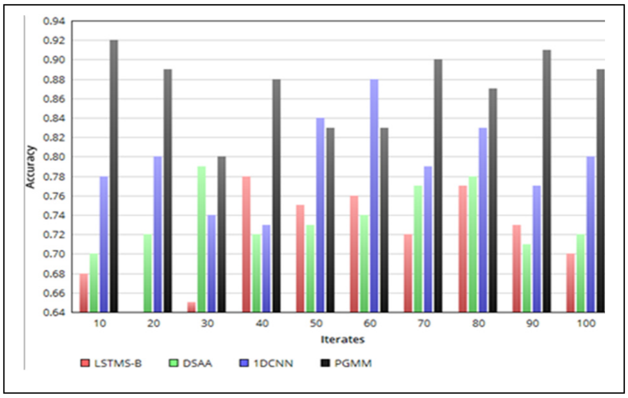
FIGURE 4. (a) Sum pooling process. (b) Classification output process.

IV. RESULTS AND DISCUSSION

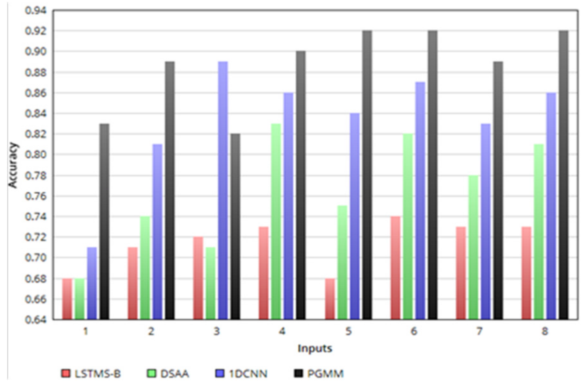
This section discusses the performance of the proposed PGMM that is assessed using MATLAB simulations. In this analysis, the dataset [32] is exploited for 8 inputs observed for three features (boundary, entropy, and both). These inputs are observed at different time intervals for both linear and discrete activities of 4 subjects. The signals imagery varies between 400×120 pixels and 400×150 pixels by size. In this classification and training model, 100 iterates of erroneous classification is considered in the convolution layers. The input signals are obtained from a channel of frequency between 40-180Hz with a sampling of 12Hz. In order to perform a comparative analysis, the existing methods such as LSTMS-B [18], DSAA [19], and 1DCNN [20] are considered. In this analysis, the metrics accuracy, classification time, and true positive rate (TPR) are compared. The comparative study is presented in the following sub-section.

A. ACCURACY

In Figure 5 (a) and 5 (b) the accuracy of the proposed method in accordance to iterate and inputs is presented. The number



(a) Accuracy versus Iterates



(b) Accuracy versus Inputs

FIGURE 5. (a) Accuracy versus iterates. (b) Accuracy versus inputs.

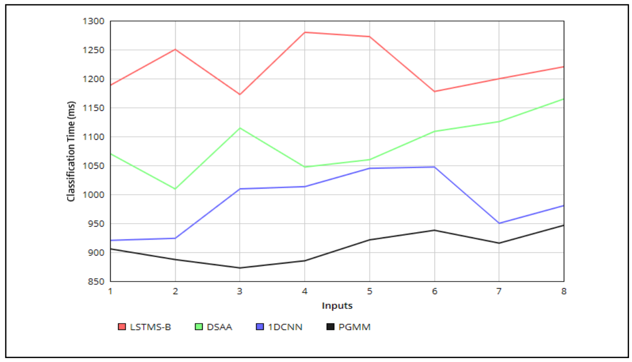


FIGURE 6. Classification time.

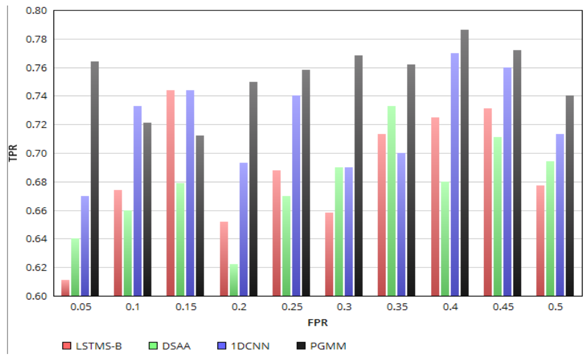


FIGURE 7. True positive rate.

of iterates increases the chances of precise classification, irrespective of the $\left[I_{a,b}\right]_g$ where the coherence $\gamma_{a,b}$ is suppressed by validating the pixels using I_i.The uncondition I_i that belongs false positives are segregated using E(W) in a recurrent manner. This process follows expansive path until $Y = p$ such that $p_x(\delta)$ is the output for both discrete and continuous inputs. On the other hand, if $Y \neq p$, and then $O(I_{EEG}/x)$ follows the expansive path or the learning process to normalize R. This normalization helps to balance the output of the learning either under pixels or entropy for classification. The classification using learning instances over the simplified $m \times m$ achieves normalization and $\rho(Y)$ of all the input process so as to leverage accuracy by differentiating e. If the e is identified in $Y \neq p$ instances, then $\rho(Y + 1)$ is verified for $x + 1$ and $y + 1$ pixels in the segmentation process. This help to reduce the errors in normalization and to improve the accuracy of the classified output.

This method is common for any number of inputs that is classified through $\left[I_{a,b}\right]_g$ and I_i. These classified features are trained for any input of varying size to suppress e and thereby to leverage the accuracy.

B. CLASSIFICATION TIME

Classification time of the proposed PGMM is less compared to the existing methods as in Figure 6. The initial feature extraction and classification using pre-training model and pixel segmentation helps to differentiate g_x and D_x at an earlier stage. Both g_x and D_x are analyzed using O(R) and E(W) respectively to identify $H^g_{a,b}$ or $p_x(\delta)$ in a reliable manner. This estimation helps to train either g_x or D_x irrespective of the I_i based training. Therefore, the classification is performed for g_x or D_x depending on the $Y - \rho\,(Y)\,\forall Y = p$ and $Y \neq p$ cases respectively. In both the process, classification follows either of $Y - \rho(Y)$ or Y in a recurrent manner, improving classification accuracy. Therefore, the classification does not require additional pre-training instances for both normalization and $p_x(\delta)$. Hence in the classification of $H^g_{a,b}$ using g_x, the time required is less, improving the learning rate of the successive features. Instead, in the process of D_x analysis, c_f and I_I are the determining factors to achieve $O(I_{EEG}/x)$ where in the condition is differentiated as $Y = p$ and $Y \neq p$. In this case, $Y \neq p$ forms the e case and $Y = p$ is alone used for classification. Therefore, the time required for $Y = p$ case in D_x is less. The overall process of PGMM requires less classification on time at average for both P_x and D_x respectively.

C. TRUE POSITIVE RATE

In the proposed method, false positive are estimated as $\frac{D_x}{P_x+D_x}$ instances and the true positive are $\frac{P_x}{P_x+D_x}$. As the false positives increase, true positives are suppressed. Therefore, the false positives are to be mitigated by identifying precise a throughout the iterates in the learning process.

TABLE 1. Comparative analysis results.

Metrics	LSTMS-B	DSAA	IDCNN	PGMM
Accuracy vs Iterates	0.7	0.72	0.8	0.89
Accuracy vs inputs	0.73	0.81	0.86	0.92
Classification Time (ms)	1220.44	1164.85	980.59	946.55
True Positive Rate	0.677	0.694	0.713	0.74

The occurrence of e due to $Y \neq p$ case is identified using expensive and $m \times m$ and $H^{g}_{a,b}$ processing. In both the processing models $(I_{i,e})$ and (γ_{a,b,D_x}) pairs are the constraint analyzers for mitigating e. If this e is mitigated then the ratio of $\frac{D_x}{P_x+D_x}$ is reduced, reducing the impact of false positives over the $[I_{a,b}]_g$ for the computed $(I_i, \gamma_{a,b})$. Therefore, the mediate output of g_x and D_x is processed using $Y - \rho(Y)$ constraint and normalization for achieving $P_x(\delta)$. Further processing of $m \times m$ from $P_x(\delta)$ helps to achieve a better classified output with high true positive. In Table 1, the comparative analysis results are tabulated.

V. CONCLUSION

This paper presents pre-trained Gaussian mixture model for improving the analysis accuracy of EEG imagery. In this model, convolutional neural network based feature analysis and pixel based segmentation are jointly employed for reducing the errors in classification. This helps to reduce the false positives and classification time based on different features. The process is recurrent in determining the accuracy of the inputs over various iterates by refining the output based on the probability of occurrence and hence the classification of the input to its simple form generates better accuracy with less classification time and high true positives

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