Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 7, 2021, Pages. 765 - 779
Received 05 May 2021; Accepted 01 June 2021.

Hierarchal Machine Learning Approach to Explore Automatic Seizure Detection in EEG

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Abstract

Epilepsy is one of the neurological disorder diseases which is appear the recurrence of unexpected sudden reactions of the brain as epileptic seizures. There are different types of classification related approaches were introduced to extract efficient EEG signal from set related datasets, brain related human data sets. It is often difficult in identification of brain subtle but emergency changes in EEG wave forms by visual inspection based on research area for bio-medical EEG related retinal images. So that in this paper, we propose Hierarchal Machine Learning Approach (HMLA) which is the combination of Grasshopper Optimization Algorithm (GOA) and Support vector machine (SVM) for automatic seizure detection in EEG. It is extracted and evaluated different parameters to train radius bias kernel function classifiers with different notations. Grasshopper Optimization Algorithm is used explore effective subset of features and then optimal parameters based on SVM for successful classification of EEG. Further improvement of proposed approach, it gives better EEG classification and enhance diagnosis of epilepsy with effective accuracy 90-100 % with comparison of normal data and epileptic brain image data. Experiments of proposed approach give better and efficient results with comparison of existing approaches with respect to different parameters like accuracy, precision, re-call etc.

Index Terms: Epilepsy, Electroencephalogram (EEG), support vector machine, optimization, neural networks, feature extraction

I. INTRODUCTION

Epilepsy is an unending cerebrum infection that influences individuals everything being equal. As indicated by the World Health Organization (WHO), roughly 65 million individuals experience the ill effects of this issue [1], most of who do well in creating nations and can't acquire sufficient medicinal treatment. Epilepsy copies or triples the likelihood of abrupt passing when contrasted and that for solid individuals [2]. In addition, epileptic patients experience the ill effects of social disgrace and segregation in their networks. This shame has a negative effect upon the personal satisfaction of patients and their families. Along these lines, the examination of epilepsy location methods and antiepileptic medications could expand the likelihood of those adapting to this sickness to live steadily without social marks of shame. Example epilepsy representation in retinal images shown in figure 1.

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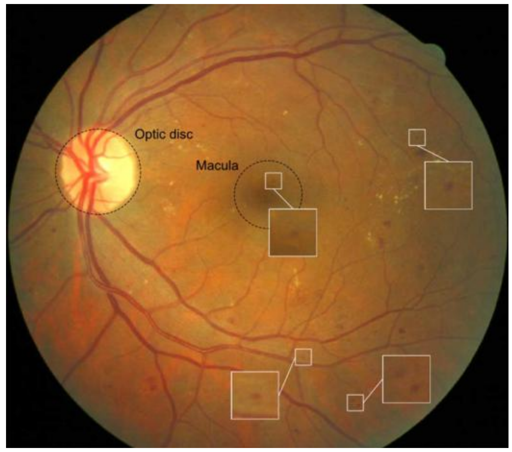

Figure 1. Example of EEG part extraction process in retinal images.

Epilepsy is typically described by at least two ridiculous seizures, which influence the ictal individual whenever. An elliptic seizure is characterized as an exorbitant electrical release in a self-assertive segment of the cerebrum. This fast release causes an unsettling influence and irregular conduct in the sensory system. A satisfactory clinical device used to perceive epileptic seizures is the EEG flag examination, as it quantifies the electrophysiological signs of the cerebrum continuously and measures mind conditions productively [3]. In any case, EEG flag examination has a few constraints in recognizing elliptic seizures on account of epilepsy conduct, for example, the accompanying:

(1) The event of certain seizures isn't generally a direct result of the epilepsy issue, as around 10% of sound individuals may experience the ill effects of one seizure in their lifetime. These nonepileptic seizures are like epileptic seizures, however they are not identified with epilepsy

[2]. Subsequently, the grouping of both epileptic and nonepileptic seizures is further significant.(2) Although qualified proficient nervous system specialists can outwardly identify epileptic seizures from an EEG information sheet, it is as yet considered a tedious procedure.

The diagnostics of epilepsy are generally performed by manual reviews of the EEG signals which not a simple assignment and requires a profoundly talented neurophysiologist. Likewise, the manual assessment of a long interim account is a repetitive and tedious procedure. Thusly, a canny clinical computer aided design (CAD) device that breaks down the EEG flag and identifies the epileptic seizure is required.

Different algorithms have detailed the upsides of utilizing computerized techniques to perceive epileptic seizures from EEG signals. Numerous strategies are generally utilized for computerized EEG investigation and epilepsy location. This paper introduces a strategy for choosing highlights that utilized as info information for classifiers and the best parameters for SVMs by means of applying an advancement calculation [8,9]. SVMs have two kinds of parameters (punishment consistent C parameter furthermore, portion capacities parameters), and

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the estimations of these parameters influence the execution of SVMs [9,10]. Choosing these parameters accurately ensures to get the best grouping precision [11]. As needs be, this paper embraces GOA to introduce a novel GOA-SVM crossover advanced classification framework for epileptic EEG signals classification. The acquired test results clearly show huge upgrades as far as grouping exactness accomplished by the proposed GOA-SVMs classification framework contrasted with arrangement exactness accomplished by the ordinary SVMs arrangement calculation and Particle Swarm Optimization with SVM (PSO-SVM).

II. REVIEW OF RELATED WORK

The issue of EEG-based epileptic seizure identification has been extensively examined in the course of recent decades. The distributed work can be arranged into three primary grouping issues. The principal issue is to separate between two unmistakable classes; Normal (set an) and Ictal (set E) EEG designs. The second issue is to separate between Normal (set An), Inter-ictal (set C), and Ictal (set E) EEG designs. The third and most testing issue tends to the segregation between the five diverse EEG sets; A, B, C, D, and E. It merits featuring that none of the examinations underneath in this area think about the presence of antiquities and their negative impact on the seizure recognition exactness.

A large portion of the two-class seizure identification issues center around the characterization between ordinary EEG sections taken from sound people (set An) and seizure EEG designs taken from epileptic patients while encountering dynamic seizures (set E). Aarabi et al. proposed a robotized seizure recognition framework utilizing a lot of agent EEG highlights removed from time space, recurrence area and wavelet space just as auto-backward coefficients and cepstral highlights. Every one of these highlights were bolstered by and large into a back-proliferation neural system (BNN) classifier with two shrouded layers and brought about a normal order precision of 93.00%. In Subasi et al. utilized wavelet change to infer the EEG recurrence groups and afterward utilize all the unearthly segments as a contribution to the blend of specialists (ME) classifier; a normal characterization precision of 94.50% was accomplished. Polat et al. accomplished a higher grouping exactness of 98.68% utilizing a choice tree (DT) classifier.

Moreover, Chandaka et al. utilized the EEG crosscorrelation coefficients to figure three factual highlights, and consequently present them as a component vector to the help vector machine (SVM) for EEG arrangement. This model yielded an unobtrusive seizure location exactness of 95.96%. Yuan et al. acquired practically identical discovery exactnesses utilizing the extraordinary learning machine (ELM) classifier and a lot of nonlinear highlights, for example, surmised entropy and Hurst type [22]. Wavelet change was likewise utilized in [23] to break down the EEG signals into five guess and detail sub-groups.

At that point, the wavelet coefficients situated in the low recurrence scope of 0-32Hz were utilized to register the EEG highlights ofenergy and standardized coefficients. The straight

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discriminant investigation (LDA) classifier was utilized to demonstrate the capability of the removed highlights in identifying seizure onsets with an order exactness of 91.80%. Furthermore, the creators of [24] utilized the change entropy as a representative EEG highlight for programmed identification of epileptic seizure. A SVM was used to separate among typical and epileptic EEG ages; a 93.80% arrangement exactness was accomplished. Zhou et al. contemplated the ability of Bayesian LDA (BLDA) model to accomplish better outcomes [25], where it was prepared and tried on the EEG highlights of lacunarity and vacillation list to accomplish a characterization exactness of 96.67%.

In 2013, the EEG signals were first dissected utilizing the methodology of exact mode decay (EMD) [31]. Four straightforward highlights were then separated from the EEG decayed parts and sustained into the KNN classifier for EEG grouping; a normal arrangement precision of 98.20% was accomplished. In 2015, the creators of [32] utilized a similar methodology of EMD however with increasingly hearty highlights, for example, the ghastly entropies and energies of EEG recurrence groups. Utilizing SVM, the arrangement precision was improved to 98.80%. In Peker et al. utilized wavelet change to break down the EEG information into various rhythms and after that figured five factual highlights from every mood. These highlights are connected together and went into the complex-esteemed neural systems (CVANN) classifier for seizure analysis. Thus, a normal grouping exactness of 99.33% was accomplished. Further, Jaiswal et al. exhibited a novel computationally-straightforward component extraction method named nearby neighbor expressive example (LNDP) and they tried it alongside various arrangement models including KNN, SVM, ANN and DT [34]. Exploratory results demonstrate that the best identification execution can be satisfied utilizing LNDP mutually with the ANN classifier, where the most noteworthy grouping exactness of 98.72% is gotten. To additionally improve the seizure identification rate, a blend of time area, recurrence space and time-recurrence space highlights were utilized together with SVM classifier to accomplish the best grouping rate of 99.25%

Guler ¨ et al. proposed a standout amongst the most effective multi-class EEG order strategies for epileptic seizure recognition. They removed the best agent qualities from the EEG wavelet coefficients and Lyapunov types. The probabilistic neural system (PNN) was utilized subsequently for EEG characterization, where it accomplished an eminent classification precision of 98.05%. Likewise, Ubeyli ¨ et al. built up an eigenvector-based strategy for EEG highlight extraction, which thus accomplished a 99.30% order exactness utilizing SVM.

Moreover, the EEG phantom rhythms of delta, theta, alpha, beta, and gamma were likewise utilized agent highlights for EEG order. Utilizing these highlights, the multiclass SVM (MSVM) classifier accomplished a characterization exactness of 96.00%. In like manner, SVM was utilized in collaboration with the versatile element extraction technique for wavelet surmised entropy and they together accomplished a promising characterization exactness of 99.97%. As of late, Siuly et al. gotten the best grouping exactness ever. They structured a novel factual element

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extraction plot and incorporated it with a MSVM to characterize EEG flags; an amazing 99.99% grouping precision was acquired.

III. PRILIMINARIES

In this section, we describe about basic preliminary concepts used in hierarchal machine learning approach for feature extraction, feature sub selection and optimal parameter pixel classification on EGG retinal image datasets. EGG related diabetic retinopathy images download from Department of Epileptology at the University of Bonn [1].

a) **Wavelet Discrete Transforms (DWT) :** DWT is utilized to held a candle to the EEG signals directed toward distinct frequency bands. The DWT decomposes a tenacious signal into ballpark figure and detail coefficients at the as a matter of choice level. Then the estimate coefficients are additional decomposed into next freely of estimate and represent coefficients. In the sooner stage of the DWT, an LP and HP filters are hand me down to get by the signal concurrently. At the as a matter of choice level, the outputs from soft and steep pass filters are indicated to as approximation (A1) and detailed (D1) coefficients. The output signals control half the frequency baud rate of the unusual signal gave a pink slip be down sampled by two merit to Nyquist rule. The alike procedure bouncecel be duplicated for the as a matter of choice level estimate and the represent coefficients seek the instant level coefficients. Through each run of this decomposition style, the frequency resolution is multiple over filtering and the predate resolution is distribute through down-sampling.

b) **Optimization of Grasshopper Algorithm (GOA) :** It is a heuristic method to explore feature sub sets and employed to simulate swarming behavior with respect to grasshopper as follows:

$$X_i = S_i + G_i + A_i$$

where Xi defines the status of the i-th grasshopper, Si is the mutual interaction, Gi is the gravity swat team on the i-th grasshopper, and Ai shows the shift advection. The S element is expected as follows:

$$S_i = \sum_{j=1,\, j\neq i} s(d_{ij}) d_{ij}$$

Where dij is the distance between the i-th and the j-th grasshopper, vector uni-directional equation expanded as follows:

$$X_i = \sum_{j=1,\, j\neq i}^{N} s(X_j - X_i)\frac{X_j - X_i}{d_{ij}} - ge_g + ue_w$$

However, this mathematical exemplar cannot be used shortly to gave a snappy comeback optimization problems, mainly seeing the grasshoppers quickly did a bang up job the love zone

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and the overflow does not gather to a referred to point. A modified play by play of this equation is presented thusly to deny optimization problems

$$X_i^d = \left(\sum_{j=1, j\neq i}^{N} c \frac{ub_d - lb_d}{2} s(X_j^d - X_i^d) \frac{X_j - X_i}{d_{ij}} \right) + T_d$$

where ubd is the upper skip in the Dth dimension, lbd is the lower dash in the Dth dimension, s(r) = fe−rl − e−r,Td is the worth of the Dth dimension in the direct (best merger found so far), and c is a decreasing coefficient to shrink the comprehend sector, repulsion zone, and charisma zone. Based on number of iterations to appear optimization for different features in retinal images.

c) **Support Vector Machine:** SVM is a ground-breaking classifier in the field of biomedical science for the recognition of irregularities from biomedical signals. SVM is an effective classifier to order two unique arrangements of perceptions into their pertinent class. It is equipped for taking care of high-dimensional and nonlinear information incredibly. Based on the structure of preparing informational indexes, it predicts the vital attributes of obscure testing information. As in this paper, to assess the execution of the proposed procedure we are having four experiments with two unique arrangements of class so we favored this classifier for better exactness results. SVM system depends on finding the best hyperplane that isolates the information of two unique classes of the classification. The best hyperplane is the one that augments the edge, i.e., the separation from the closest preparing focuses. The auxiliary structure of the SVM relies upon the following: first, the regularization parameter, C, is utilized to control the exchange off between the boost of edge and various misclassification. Second, piece elements of nonlinear SVMs are utilized for mapping of preparing information from an input space to a higher dimensional element space. All piece capacities like straight, polynomial, spiral premise work and sigmoid having some free parameters are called hyper-parameter. Radius bios kernel functions parameters width of kernel σ

$$K(x, y) = \exp\left(- \| x - y \|^2 / 2\sigma^2 \right)$$

Where, K(x, y) is termed as the kernel trade, which is off the rack upon the dot product of two invariant x and y. Suitable trade-off parameter C and the kernel parameter σ are ordained to came up to snuff SVM classifier and regularly obtained separately K-fold cross-validation technique

IV. OPOSED HEIRARCHAL MACHINE LEARNING IMPLEMENTATION

In this section, we study about proposed approach i.e. hierarchal machine learning approach which is the combination of GOA and SVM for classification of EEG. Main aim of proposed approach is to increase and optimize accuracy of SVM by estimate the sub set features with best performance values. Proposed hierarchal classification approach consists different phases in

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implementation with respect to different retinal image datasets. In first phase, pre-process using discrete wave transforms, in second phase, extract useful features like entropy, median and mean with relative and derived sub set wavelet co-efficient. In third phase, explore relevant features and classify optimal subset features by SVM and GOA for EEG retinal image classification. Finally, the obtained results are evaluated per five different measurements a well known as detailed list accuracy, specificity, precision, and F-Measure. The during process of the proposed manner is illustrated in Fig. 1.

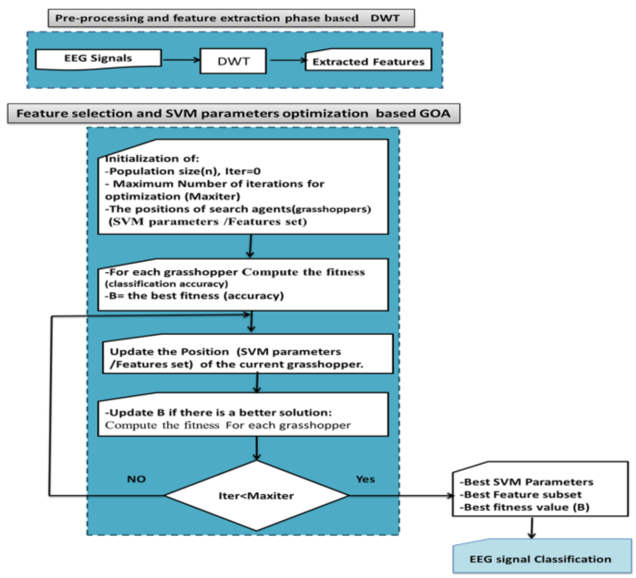

Figure 2. Classification of EGG signals for proposed classification approach.

Extracting the features consider the best portray of the conduct of EEG flags and are essential for computerized seizure recognition execution. Highlight extraction plans to catch the important and particular qualities covered up in EEG signals, which promptly rules the last order exactness. In our past work, we have separated ten highlights of wavelet coefficients from each sub-band that were picked to group EEG motions. The whole quantitative investigation of EEG signals was coded utilizing JAVA and NETBEANS.

a) Parameter Optimal selection for extracted feature

Better execution might be accomplished by evacuating insignificant and repetitive information while keeping up the segregating intensity of the information by highlight choice. The right determination of applicable highlights from EEG signs can assist the classifier with learning a progressively hearty arrangement and accomplish better speculation execution. In third stage, GOA can possibly create both the ideal element subset what's more, SVM parameters in the meantime. SVM tuning parameters have a vital sway on their grouping exactness. Inappropriate parameter settings lead to poor arrangement results. The parameters in SVM that should be advanced incorporate the punishment parameter C and parameters σ of the spiral premise bit work. The advancement stage is cultivated in two internal back to back stages. Each

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arrange either keeps up list of capabilities as consistent and performs SVM parameters enhancement, for this situation The best position is the SVM parameters which gives the most noteworthy wellness esteem (normal arrangement precision of cross-approval overlays for our situation), or keeps up SVM parameters as constants and performs highlight set streamlining, for this situation, The best position is the subset which gives the most astounding wellness esteem. Various EEG classification for retinal images as shown in figure 3.

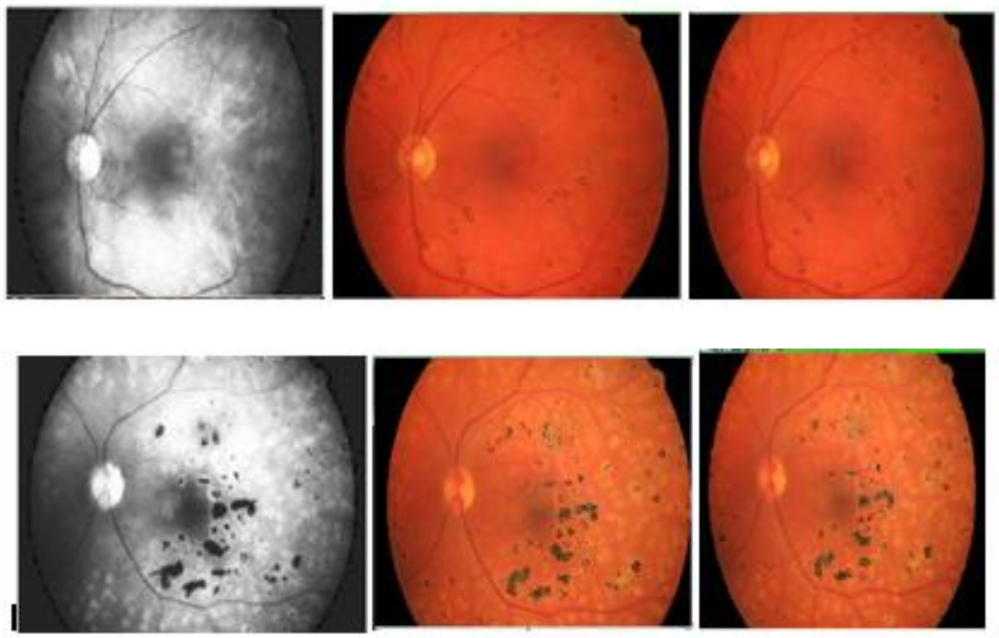

Figure 3. Feature extraction and classification EEG part based on threshold pixel representation of retinal image.

As shown in figure 3, first we upload retinal image which consists Epilepsy in their brain with different notations. Quantitative analysis of proposed approach for retinal images as follows:

EEG Segmentation results of our proposed approach are performed by ground truth analysis with performance measures like JC (Jacquard Co-efficient) and SA (Segmentation Accuracy). JC of brain data sets is resultant division between different properties

$$JC = \frac{X \cap Y}{X \cup Y}$$

Where X is the resultant retinal image and Y is the EEG feature retinal image, if JC>70% then EEG classification result is good otherwise it is not good.

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EEG classification accuracy is another performance measure to compare similarity between resultant image and ground truth image with respect to different pixel values. Calculation of Classification of Accuracy is depends up on following four parameters:

(I) True positive (TP): Number of genuine pixels in the ground truth accurately distinguished as fragmented pixels.

(ii) True negative (TN): Number of false pixels in the ground truth accurately distinguished as sectioned pixels.

(iii) False positive (FP): The quantities of genuine pixels in the ground truth are not found in the divided locale.

(iv) False negative (FN): The quantity of false pixels in the ground truth which is absent in the sectioned region.

Our proposed works gives better noise reduction results and define less iteration when compare to above discussed approaches.

V. EXPEIMENTA RESULTS

This section describes relative results for different EEG brain human retinal images with respect to different image pixel notations based on above implementation procedure. We calculate the sensitivity, specificity, precision, recall classification time and f-measure for different retinal images. WE compare experimental results of proposed approach i.e HMLA with existing classification approach i.e. Empirical De-composition based Classification Approach (EDCA) which is performed in 1-dimensional attribute data extraction for different relations. As we discussed (EDCA) is not sufficient for EEG related retinal images to explore efficient classification of EEG signals. Time examine values for different retinal images as shown in table 1.

Uploaded Retinal Images	EDCA	HMLA
1	3.77867	3.2359
2	4.1183	2.7714
3	3.9454	1.9549
4	3.7362	1.8842
5	4.05681	2.6829
6	3.9856	2.4780
7	4.2151	2.8790
8	3.8745	2.9840

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9	4.2546	1.9874
10	3.8786	2.5874

Table 1. Time Efficiency values.

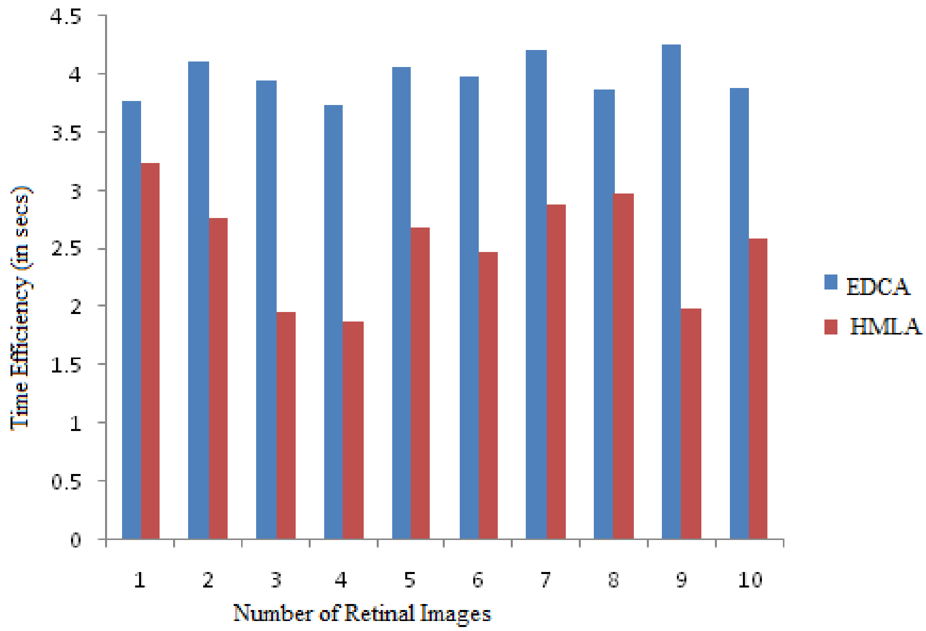

Figure 4. Performance of time efficiency values for different retinal images.

Sensitivity calculation results for normal retinal images with feasible environment for detection of EEGs in reliable data classification and feature extraction shown in fallowing Table 2.

Retinal Images	EDCA	HMLA
1	1.2	0.9
2	1.28	1.2
3	1.4	1.35
4	1.5	1.45
5	1.6	1.4
6	1.68	1.5
7	1.75	1.6

Table 2. Sensitivity results for different retinal images

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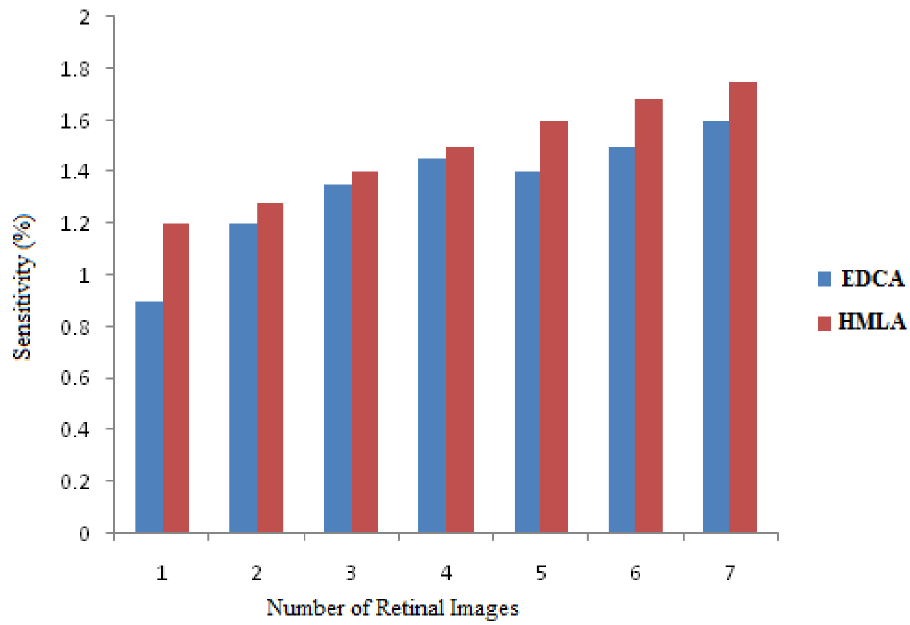

Figure 5. Sensitivity results with respect to different retinal images at different pixel values.

Specificity of the normal retinal images results show in fallowing Table 3.

Table 3. Specificity results of the uploaded common retinal images.

Retinal Images	EDCA	HMLA
10	0.9	0.8
20	1.1	0.9
30	1.25	1
40	1.3	1.2
50	1.5	1.3
60	1.6	1.4
70	1.9	1.6

Comparison results of the retinal with differential presentation in specificity values in recent contribution of present work shown in Figure 5.

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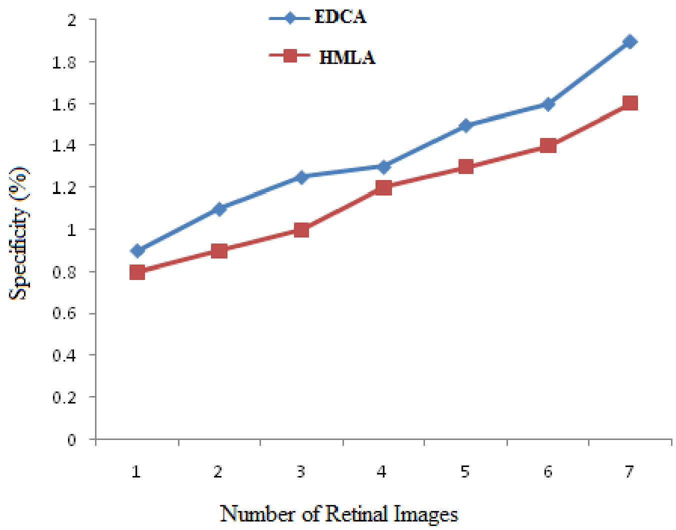

Figure 6. Specificity performance values with respect to different retinal images

Optimized classification accuracy values for different retinal images explored and show in table 4 and figure 7.

Retinal Images	EDCA	HMLA
10	0.89	0.712
20	0.91	0.51
30	0.96	0.764
40	0.97	0.604
50	0.94	0.47

Table 4. Optimized classification accuracy values.

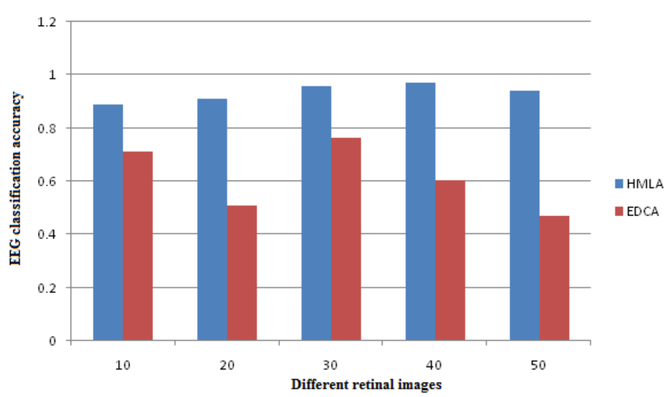

Figure 7. Classification accuracy performance evaluation with respect to different retinal images.

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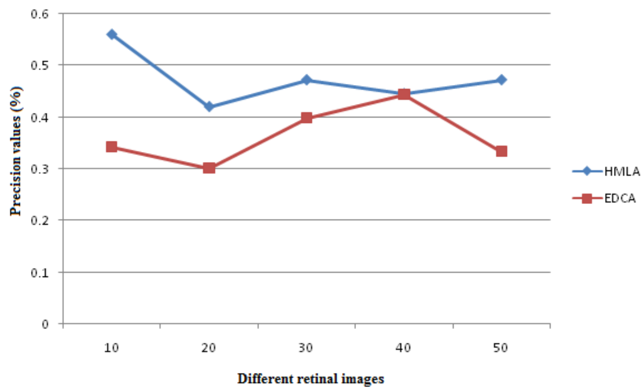

Figure 8. Performance evaluation of different retinal images

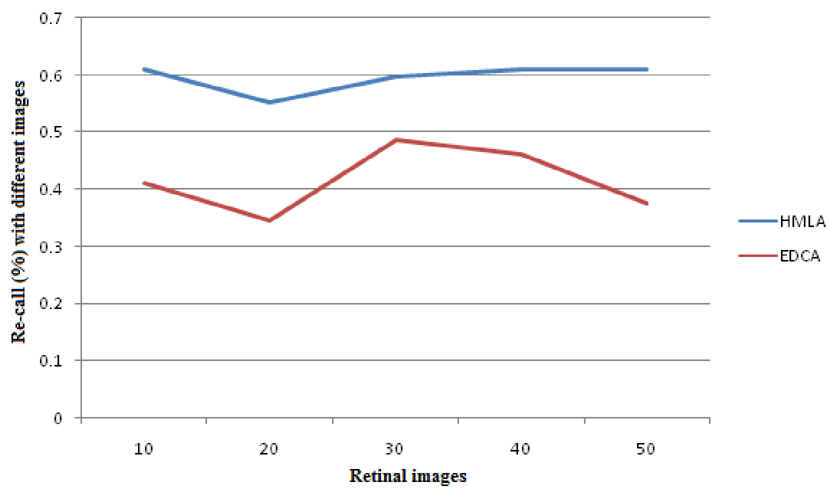

Figure 9. Performance of re-call values with different retinal images.

Based on above results from figure 5-9, proposed approach give better and efficient optimized features with respect to different retinal image evaluation at different pixels evaluations.

VI. SUMMERY

In this paper, we propose hierarchal machine learning based classification procedure to explore efficient EEG signal extraction from retinal images. This paper builds up a methodology utilizing GOA for include choice with SVM parameters improvement and the SVM classifier for programmed seizure location in EEG signals. The 100% order correctness's are gotten utilizing GOA-SVM for case 1, 99.577% for case 2, 99.332% for case 3 what's more, 98.268% for case 4. These outcomes outline the adequacy of utilizing GOA also, SVM classifier for seizure discovery in EEG signals. Experimental results shown that the proposed GOA-SVMs approach beat PSO-SVM and the regular SVMs arrangement calculation for RBF piece work. The proposed technique can be utilized as a quantitative measure to screen the EEG and might be a valuable apparatus for examining the EEG flag related with epilepsy

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