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Enhancing Electrocorticography Brain Computer Interfaces with Genetics

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ABSTRACT

BrainComputer Interfaces (BCI) technology exploits the brain's intuitive computing power. So far, the development of BCIs was considered to be science fiction. Scientists have been trying to decode brain signals since the introduction of Electroencephalography (EEG). EEG equipment is extensively utilized for recording the brain signals in BCI systems due to its attributes such as non-invasive, the potential for user mobility,high time resolution,and comparatively low cost. Of late, ElectroCorticoGraphy (ECoG)has garnered much interest as a recording technique for utilization in BCIs. ECoG will involve recording electrical signals from the human brain's surface, often in patients who are being monitored prior to surgery. In comparison to the EEG, the ECoG has a higher spatial resolution. In this paper, the ECoG signals are pre-processed, and the features are extracted by utilizing Wavelet Packet Trees (WPT) and Common Spatial Patterns (CSP). Feature selection is carried out by the Genetic Algorithm (GA). ECoG signal classification is done using Random Forest, Logistic Regression, and Support Vector Machine (SVM) classifier.

Keywords: Brain Computer Interface (BCI), Electrocorticography (ECoG), Support Vector Machine (SVM), Genetic Algorithm (GA).

1. INTRODUCTION

The initial release of the Brain-Computer Interface (BCI) research was made in the 1970s.The research dealt with an alternate transmission conduitthat was independent of the peripheral nerve and the muscle output pathways of the brain. The proposal for earlier BCIsinvolved the measurement as well as the decoding of brainwave signals to maneuverthe prosthetic limb and execute therequiredmovement. Hence,the 'BCI' term can be formally defined as a direct communication pathway between an external device and the human brain. Over the last ten years, much attention has been focused on human BCIs. The human BCI systems' objectiveis to interpret human cognition patterns through brain activities. The systems utilize recorded brain activity for computer communication to control external gadgets or environments in such a way that it is harmonious with human intentions.

BCIs are of two chief types:the active and reactive BCI and the passive BCI. The active BCI will control a device by deriving patterns from brain activity under direct and conscious control by the user, independent of any external events. On the other hand, the reactive BCI will

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control an application by extracting outputs from brain activities in reaction to external stimulation that is indirectly modulated by the user. As the second type, the passive BCI will explore the user's perception, awareness, and cognition without any voluntary control objective to enrich theHuman-Computer Interaction (HCI) with implicit information [1].

A brain Electroencephalography's(EEG's) electrical activity can demonstrate substantial complex behaviour along with strong non-linear as well as dynamic properties. In the brain cells, the communication will occur via electrical impulsesmeasured through electrode placement on the subject's scalp. These signals are highly non-Gaussian, non-stationary and also are non-linear in nature. The EEG technique isnon-invasive and is utilized for the diagnosis of brain-related diseases as well as symptoms. This technique will aid in the diagnosis of numerous neurological diseases like depression, cerebrovascular lesions,tumours, epilepsy, and trauma-related problems. Distinct brain activities have distinct EEG traces. With the utilization of signal processing approaches,it is possible to easily differentiate an abnormal person's brain activity from a normal person[2].

The technique of ElectroCorticoGraphy(ECoG) will measure the cerebral cortex's electrical activity via electrodes that are directly placed on the brain's surface. In comparison to the EEG, the ECoG has abilities like higher amplitudes, higher temporal and spatial resolution, andlower susceptibilityto artifacts like eye movement and blinks. Nevertheless, the ECoG is an invasive methodas it needs a craniotomy for the implantation of an electrode grid, which will entail significant health hazards. Due to this, animals were initially used for studies on the ECoG.

In human beings, the ECoG is utilized for analyzing alpha and beta waves or gamma waves that are generated during voluntary motor action. Regarding the ECoG utilization in BCIs systems, a BCI will classify motor actions depending on the identification of Event-Related Potentials (ERP) by ECoG usage. The preliminaryECoG-based BCI developed for moving the one-dimensional cursor and it was observed to be more easily controlled than the EEG-based BCIs. After a few years, developing a more advanced ECoG-based BCI for controlling a two-dimensional cursor. Based on these studies, it is concluded that ECoG-based BCIs are viable for people having severe motor disabilities to employit to control andcommunication [3].

Feature Extraction is defined as the process of detecting particular information froma signal like ECoG for identifying the pattern. Features are a signal's characteristics that have the ability to differentiate variousactions.The feature extraction's key taskinvolves the derivation of the salient features that are able to map the ECoG data into subsequentactions. The ECoG signal analysis can be done using different feature extraction methods. Once the noise-free signals are obtained from the signal enhancement phase, there will be an extraction of the important features from the brain signals. Discrete wavelet transforms (DWT), Fast Fourier Transforms (FFT), Adaptive Auto Regressive parameters (AAR), PCA, ICA,multivariate AAR, Bilinear AAR, and Genetic Algorithms (GA) are some of the proposed methods. The most frequently used feature Extraction methods are the FFT, DWT, ICA, and PCA [4].

The process of feature selection implies the eliminationof redundantas well as irrelevant features leading toa small set of discriminative features which are adequateandnecessary for good classification. Itis one of the mainaspectswhich has an impact on a classification algorithm's success. Moreover, this process will minimize the data's dimensionality, i.e.,quicker classifier construction, and usually yields a more compact and easily interpretable classification rule. In addition to that, this process helps avoidthe curse of dimensionality - a low ratio of the sample size to the number of features. A critical role is served by the process of feature selection in a classification algorithm's good performance. Filter and wrapper approaches are the two key groups of the feature selection approaches. The filter methodwill evaluate the features or the subsets of features based onpredefined parameters, independentof the learning algorithm. For evaluation of the feature subset, the filters will utilize a search algorithm to produce subsets for their posterior evaluation. On the other hand, the wrapper approach will require a learning algorithm and will utilize its performance to assess the subsets of features chosen by a search algorithm [5].

While a better method can be chosen using different extraction methods, the extracted features will serve as the input for further classification. It is performed by a suitable classifier for the identification of the action. A classifier is defined as a system that will partition certain data into different classes and offer the relationship between the features and the action that belongsto that part of the ECoG signal. While there are numerous classification methods such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Convolutional Neural Networks (CNN), and Linear Discriminant Classifier-NN classifiers and PNN Classifier are employed for classification that can be comprehended and also can be picked from the different classifiers [6].

A framework for the classification of ECoG signals is presented in this work. The feature selection is done through the use of the Genetic Algorithm (GA) for enhancing classification. The remainder of the paper is organized: Section 2 discusses the related available studies in literature, Section 3 presents the various methodsemployed, and Section 4 detailed the experimental outcomes. Section 5 presents the work's conclusion.

2. RELATED WORK

Shahtalebi et al. [7] had proposed a novel EEG processing and feature extraction modelthat was based on Siamese NNsfor the convenient merge as well as scale-up of multi-class problems. The concept of Siamese networks involved the training of a double-input NN on the basis of a contrastive loss-function to verify whether two input EEG trials belonged to a similar class. The Siamese architecture was basedCNN,will offer a binary output on the similarity of two inputs, and afterward, it will be integrated with the techniques of One vs. Rest (OVR) and One vs. One (OVO) to be scaled up for multi-class problems. This architecture's efficiency is assessed on a 4-class Motor Imagery (MI) dataset from BCI Competition IV 2a. It is evident

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from the experimental results that, in comparison with its counterparts, the proposed architecture's performance is quite promising.

Rashid et al. [8] presented an ECoG-based MI signalclassified via long short-term memory (LSTM) utilization. The BCI competition III datasets I was used to obtaining the ECoG-based motor imagery data. The proposed LSTM approach could accomplish an outstanding classification accuracy of 99.64% when compared with other highly advancedapproacheswhich used the same dataset.

While the feature selection method is quite viablefor resolving this problem, the MI based BCI still does not have an effective method of selection to determine the best feature set,which would offer a substantial classification performance. Idowu et al. [9] had investigated the efficiency of metaheuristicslikeGA, Cuckoo Search Algorithm (CSA),Ant Colony Optimisation (ACO), and Modified PSO (M-PSO) on EEG andECoG data. The SVM classifier's performance demonstrated that the M-PSO was decidedlyefficient with the least selected feature and could converge at an acceptable speed in low iterations.

For feature selection, Li et al. [10] had given the proposal for a modified PSO method with Multi-stage Linearly-Decreasing inertia Weight (MLDW). With the MLDW algorithm, the inertia weight reduction process can be easily refined. In the end, the SVM classifier is used for the classification of the emotion types. Two offline experiments were done using the different extracted features from the EEG data in the DEAP datasetcollected by 32 subjects. It was proved from the experimental outcomes that the average accuracy of four-class recognition had reached 76.67%.

Hajizamani et al. [11] had proposed a novel hybrid feature selection method utilizinga filter bank Common Spatial Pattern (CSP)and a grey wolf optimization algorithm for an optimal feature subset's search and generation with performance evaluation by the SVM classifier. Furthermore, to increase the proposed feature selection algorithm's search performance, aproposal was also given for a new parallel combined Grey Wolf and Differential Evolution Optimisationalgorithm. Experiments demonstrated that the proposed approachescould enhance the MI-BCI performance when compared with other highly advanced approaches, even with a smaller training data.

3. METHODOLOGY

In this work, the features are extracted using Wavelet Packet Transform (WPT) and CSP. The WPT utilizesthe DWT to decompose a signal by transferring it through a series of high-pass and low-pass filter banks to analyze the ECoG signals in different scales and time resolutions. In WPT, both the detail d[n] as well as approximate a[n] coefficients are applied with the decomposition to obtainthe nodes at all the decomposed levels [12]. Spatial filtering is a crucial part of the detection of neuromodulatory changes over the motor cortex. CSP is the most successful and frequently employed method for the discrimination of such changes. CSP has been chiefly utilized in EEG anomalies detection, object recognition, andfacial recognition. Moreover, it has had successful applications in BCI. The CSP algorithm is a type of multidimensional statistics that is frequently applied to EEG and ECoG signals feature extraction and analysis in two-class multi-channel methods. CSP will identify optimal spatial filters which maximize the ratio of average variances between two different classes. In terms of computations, the CSP's resolution is done by the simultaneous diagonalization of the two classes' covariance matrices [13].

In this section, the Genetic Algorithm for feature selection is explained. TheRandom forest, Logistic Regression, SVM are used for the classification.

3.1 BCI Competition III (Data Set I)

Unlike the other datasets, this dataset employs ECoG activity rather than EEG activity. Acquisition of the ECoG signal is done from an array of 8×8 platinum electrode grid which has been placed on the right motor cortex. At the time of the BCI experimentation,the subject was asked to imagine the movement of either the left smallfinger or the tongue. For all individual trails, the recording of the brain signalwas done for a 3-second duration at a 1000 Hz sampling rate [14]. For reflecting the ECoGsignal's non-stationarity, the two recording sessions were doneone week apart. While the first recording session had 278 trials that were to be utilized as training data, the second recording session had 100 trials to be utilized for evaluation.

3.2 Genetic Algorithm basedFeature Selection

GA is one of the best optimization problems. This heuristic search method is useful for feature reduction, in particular for high dimensional data. Initially, the GA will pickrandom chromosomes. Then, at each step, the GA will try to pick the best individuals. Afterward, to create a new successive generation, these chromosomes will undergo the processes of mutation and crossover. There will be a continuation of this process until the formation of an optimal feature subset [26]. The following are the GA's five critical issues: the GA's termination criteria, encoding of chromosomes, mechanisms for selection, evaluation of fitness values, and the genetic operators.

A. GA Search Space: GA will workas a chromosome on the binary search space (0 or 1). At first, there will be a generation of an initial population that is often random and is assessed with a fitness function. In binary chromosomes, '1'is used to indicate a selected feature,while '0'is used to indicate a featurenot selected. Figure 1illustrates the features that are indexed utilizing 1's, ranked chromosomes are chosen for the next generation.

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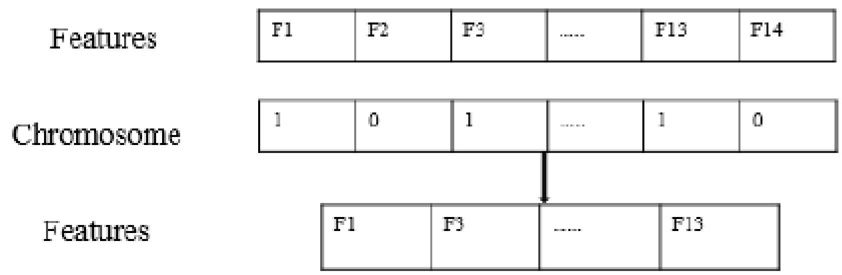

Figure. 1. Search space of GA.

B. Initial Population: After encoding, there will be the initial population's definition. In this work, the initial population will be a matrix of chromosome length and population size,made up of only irregular binary (that is, 0 or 1) digits. The population size will denote the initial population's number of individuals (chromosomes). Each chromosome is depicted in Figure. 2. To ensure that every population chromosome will extend up to the search space, the population size must be equivalent to at least the chromosome length's value.

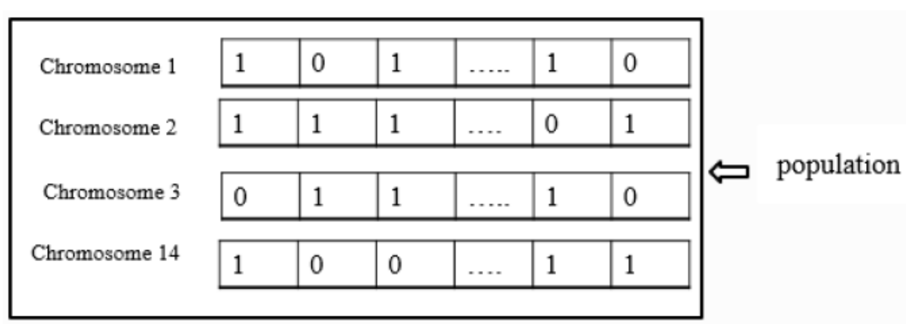

Figure. 2. The initial population of GA.

C. Fitness Function: A KNN-based classifier error rate is used to check the fitness of every chromosome of the current populationin the proposed algorithm. The k-nearest neighbours algorithm will work based on the shortest distance between a training set and a test set. The Euclidean distance is measured between test data x_{test} and the training sets xi. Hence, Eq. 1 will provide the shortest distance (closest point) found from a training set to a test set.

$$D(x_{text}, x_i) = \sqrt{\sum_{m=1}^{M} (x_{text}, x_i)^2} \quad (1)$$

For evaluation of the results, the population is applied with the fitness function.It is on the basis of this fitness function that the ranking of the population's fitness is done. The lower-rank individuals are more likely to proceed to the next generation. Iterationsare performed to decrease the error rate and pick the individual who has a lower rank value. The below Eq. 2 will give each individual's fitness as follows [15]:

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$$fit = \frac{\alpha}{N_f} + \exp\left(\frac{-1}{N_f}\right) \quad (2)$$

wherein,

α– the classification error which is based on the k-nearest neighbours Algorithm;

N_f – the number of selected features.

D. Phenomena for the Creation of New Child

After fitness evaluation, the new population's generationis from three different children. The new population will be generated through the use of crossover and mutation.

Elite Children: These children are the individuals having the best fitness values. They will get automatically pushed into the next generation. The proposed method will choose the top two best chromosomes and will automatically push these chromosomes into the next generation.

Crossover Children: The crossover operator in GA will generate a new child (chromosome) for the next generations by combining two chromosomes. Crossover requires two individuals (chromosomes), and these individuals are taken from the tournament selection. In the utilized arithmetic type crossover function, 0.8 is the probability of crossover children, and the XOR operation is done on two-parent chromosomes (since they are binary strings) for producing a child for the next generation, as depicted in Figure. 3. The below Eq. 3 will provide the XOR operation as:

Crossover Kid = P1$\oplus$ P2, (3)

wherein,

P1 – the chromosome which is utilized as the crossover operation's first parent;

$\oplus$ – the XOR operation,which is operated on binary values;

P2 – the chromosome which is utilized as the crossover operation's second parent.

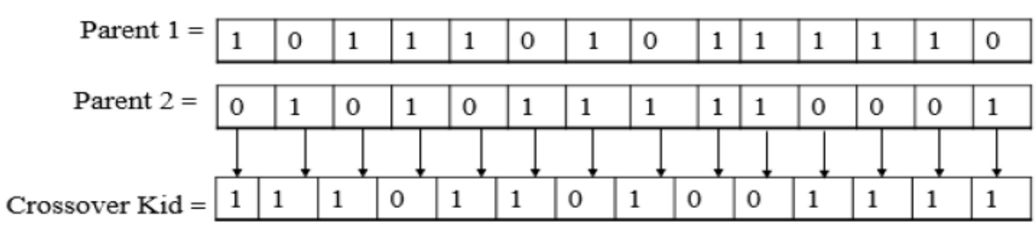

Figure.3. Arithmetic crossover.

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Mutation Children: In GA, the mutation operator will only modifyone or more gene values from its initial state such that a child is produced for the next generation. In mutation, the solution could change wholly from the previous solution. The different mutation forms include inversion mutation, uniform mutation, swap mutation, insert mutation, and so on. Suppose that there is the utilization of uniform mutation, in which there is a generation of a random number (RD) set for uniform distribution. Each gene bit's position will be attached with a random number in a chromosome. Afterward, the chromosomes will get checked from the left side to the right side. There will be a comparison of the mutation probability (mp) with each RD's value for every bit. If the RD at position 'i' is less than pm, then the gene (a bit) at position 'i' will get spun (0 to 1, 1 to 0). Otherwise, the gene will not be altered. This process is depicted in Figure. 4.

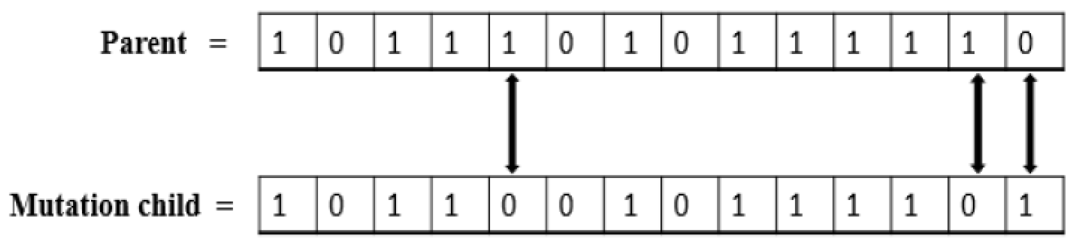

Figure.4. Mutation child.

E. Termination: The GA will come to a halt upon arriving at the optimal solution. The following are the termination conditions:

- For X iterations, no progress is shown by the GA;
- An absolute number of generations has been reached;
- A specific predefined value of the objective function has been reached.

In general, the GA will check the difference in the fitness values of generations. The GA will halt if the difference in average of hundred generations is equivalent to or less than 0.001or if maximum iterations reached [16].

3.3 Classifiers used Random Forest, Logistic Regression, SVM

3.3.1 Random Forest Algorithm:

Random Forest (RF) is an ensemble of the method-based learning algorithm. It will constitute a set of tree classifiers.Wherein every tree is made up of nodes as well as edges. The obtained ensemble will classify new data points via a consensus that has been obtained through each classifier's predictions.Figure 5. Below is the depiction of the Random forest classifier.

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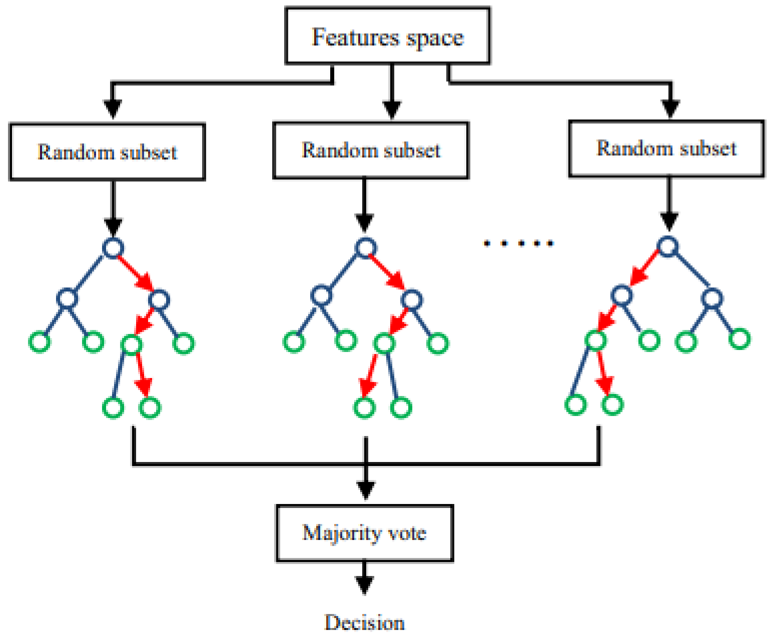

Figure 5. Random forest classifier.

This method is a combination of bagging (bootstrap aggregation) as well as a random split selection. Every tree is attained through a separate bootstrap sample from the dataset.Moreover, the data is classified by each tree. The final result is achieved via a majority vote amongst the trees [17].

3.3.2 Support Vector Machine (SVM)

As a supervised learning approach for data analysis and pattern recognition, the SVM is generally utilized for classification andregression analysis. Compared to other classifiers, the SVM can build a discriminant hyperplane to maximize the margins for class identification.Furthermore, the SVM can offer good performance with limited data, insensitivity to overtraining,and a good generalization property [18].

The majority of the BCI applications utilize the SVM as a linear classifier.Vapnik had devised the SVMbased on the statistical learning theory,which followed the structural risk minimizationprinciple. SVM will identify a hyperplane for the separate datasets. It will separate the datasets with a clear gap of sufficient width for the datasets' classification into their relevant categories. The hyperplane will maximize the margin,which is the distance between the hyperplane and the nearest points from each class referred to as support vectors. This approach's goal is to offer good generalization through maximization ofthe machine's performance whilst minimizing the learned model's complexity. The SVM was found to have a high computational complexity as well as more performance.

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3.3 Logistic Regression

Logistic regression may be viewed as a Bernoulli model's derivation. For a given predictor set x_n, the requirement is to determine the probability of a binary outcome y_n. Hence, a probability model will be defined as per Equation (4):

$$P(Y_n = 1 | X_n) = (w \,.\, X_n) \quad (4)$$

with the corresponding likelihood function as per below Equation (5) and Equation (6):

$$P(y | X_n, n = 1 \ldots N) = \prod_n \sigma(w.X_n)^{y_n} (1 - \sigma(w.X_n))^{(1-y_n)} \quad (5)$$

$$\prod_n \sigma(w.X_n)^{y_n} \sigma(-w.X_n))^{(1-y_n)} \quad (6)$$

Where the logistic function is in accordance with Equation (7):

$$\sigma(\theta) = \frac{1}{1 + \exp[-\theta]} \quad (7)$$

This Equationwill be a continuous increasing function which maps any real-valued θ into the interval (0, 1), and hence,it is well-suited to represent the probability of a Bernoulli trial outcome [19].

For the facilitation of repeated trials, a feasible variant for scientific and sociology experiments will employ a binomial instead of the Bernoulli formulation.

4 RESULTS AND DISCUSSION

Experiments were conducted with BCI Competition III's Data Set I; 278 instances from the data set were used. Features were extracted through WPT and CSP. Feature selection is applied for all techniques, and Random forest, Logistic Regression, SVMused for classification.

Table 1 Classification Accuracy

Techniques	Classification accuracy
WPT-Proposed GA-RF	92.45
WPT-Proposed GA-LR	92.81
WPT-Proposed GA-SVM	93.17
WPT-CSP-Proposed GA-RF	93.17
WPT-CSP-Proposed GA-LR	94.24
WPT-CSP-Proposed GA-SVM	94.6

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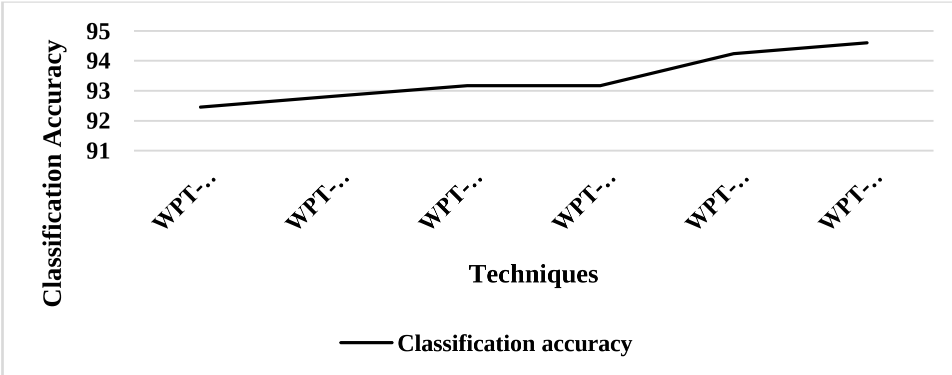

Figure 6 Classification Accuracy

From figure 6, it is observed that the proposed GA feature selection with SVM classifier achieves the best results. It is also obvious that the efficacy of the classifiers are improved with the application of feature selection.The WPT-CSP-Proposed GA-SVM has higher classification accuracy by 2.29% for WPT-Proposed GA-RF, by 1.91% for WPT-Proposed GA-LR, by 1.52% for WPT-Proposed GA-SVM, by 1.52% for WPT-CSP-Proposed GA-RF and by 0.38% for WPT-CSP-Proposed GA-LR respectively.

Table 2 Recall

Recall	tongue	finger
WPT-Proposed GA-RF	0.903	0.9444
WPT-Proposed GA-LR	0.9098	0.9448
WPT-Proposed GA-SVM	0.9044	0.9577
WPT-CSP-Proposed GA-RF	0.9104	0.9514
WPT-CSP-Proposed GA-LR	0.9248	0.9586
WPT-CSP-Proposed GA-SVM	0.9318	0.9589

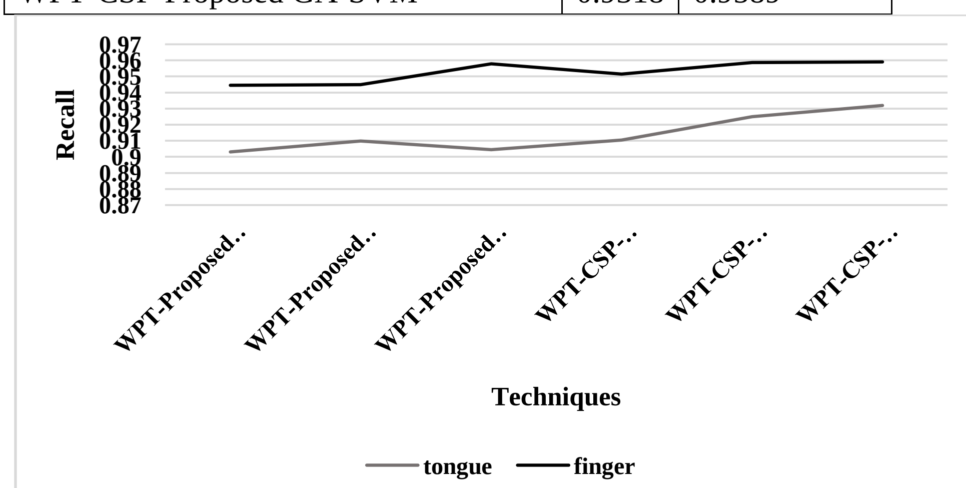

Figure 7 Recall

From figure 7, it is evident that the proposed GA feature selection improves the recall for all the classifier. The WPT-CSP-Proposed GA-SVM has a higher recall for tongue by 3.13% for WPT-Proposed GA-RF, by 2.38% for WPT-Proposed GA-LR, by 2.98% for WPT-Proposed GA-SVM, by 2.32% for WPT-CSP-Proposed GA-RF and by 0.75% for WPT-CSP-Proposed GA-LR respectively.

Table 3Precision

Precision	tongue	Finger
WPT-Proposed GA-RF	0.938	0.9128
WPT-Proposed GA-LR	0.938	0.9195
WPT-Proposed GA-SVM	0.9535	0.9128
WPT-CSP-Proposed GA-RF	0.9457	0.9195
WPT-CSP-Proposed GA-LR	0.9535	0.9329
WPT-CSP-Proposed GA-SVM	0.9318	0.9589

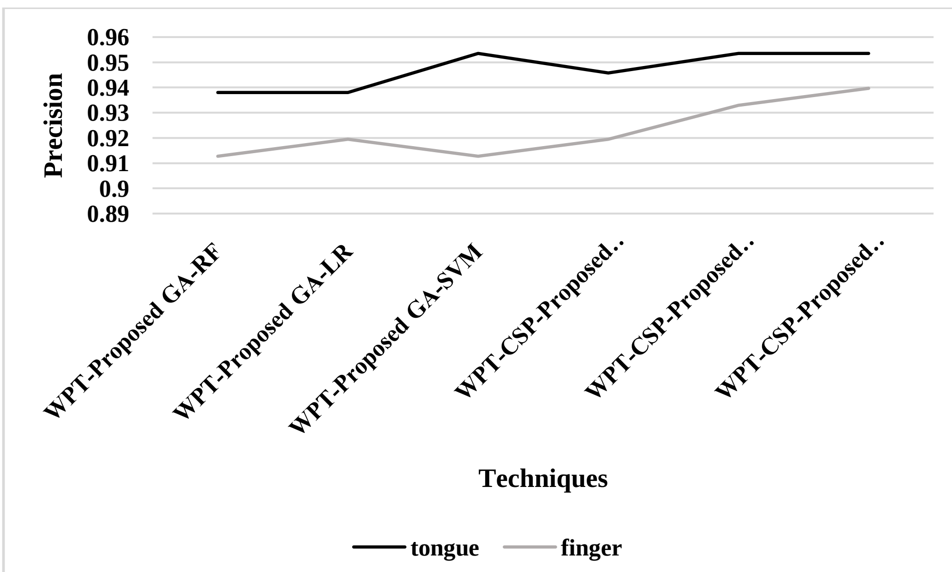

Figure 8 Precision

From figure 8, it is seen that the WPT-CSP-Proposed GA-SVM has higher precision for tongue by 1.63% for WPT-Proposed GA-RF, by 1.63% for WPT-Proposed GA-LR, no change for WPT-Proposed GA-SVM, by 0.82% for WPT-CSP-Proposed GA-RF and by 0.75% for WPT-CSP-Proposed GA-LR respectively.

Table 4F-Measure

F-Measure	tongue	finger
WPT-Proposed GA-RF	0.9202	0.9283

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WPT-Proposed GA-LR	0.9237	0.932
WPT-Proposed GA-SVM	0.9283	0.9347
WPT-CSP-Proposed GA-RF	0.9277	0.9352
WPT-CSP-Proposed GA-LR	0.9389	0.9456
WPT-CSP-Proposed GA-SVM	0.9425	0.9492

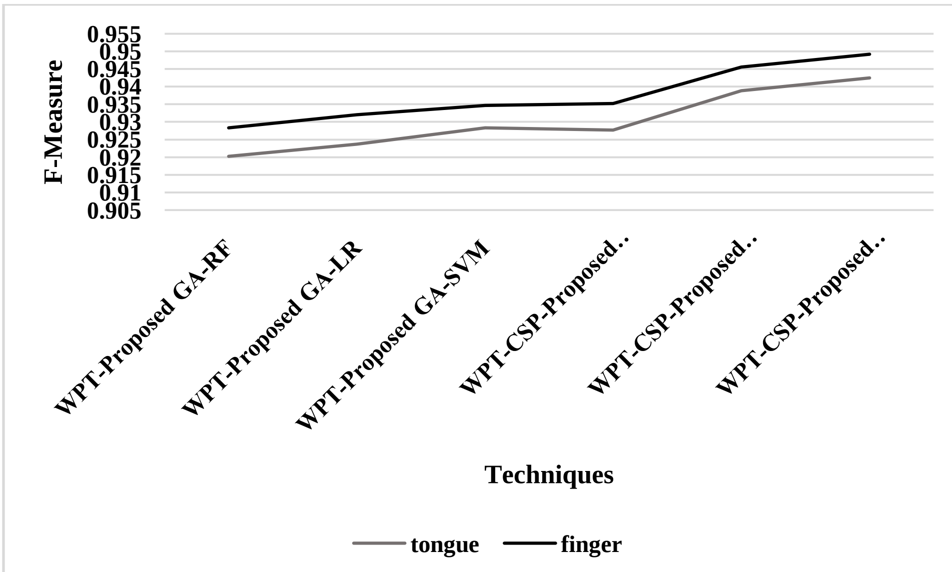

Figure 9 F-Measure

From figure 9, the efficacy of the proposed GA feature selection is seen. The WPT-CSP-Proposed GA-SVM has a higher F-Measure for tongue by 2.39% for WPT-Proposed GA-RF, by 2.01% for WPT-Proposed GA-LR, by 1.51% for WPT-Proposed GA-SVM, by 1.58% for WPT-CSP-Proposed GA-RF and by 0.38% for WPT-CSP-Proposed GA-LR respectively.

5 CONCLUSION

Nowadays, the utilization of brain-computer interfaces (BCIs)is bridging the ultimate frontier between humans and computers by facilitating computers to be intentionally controlled via the brain signal activity's monitoring. The method of Electroencephalogram (EEG) is popularly used to capture brain waves and also to analyze the neurological aspects. In comparison to EEG, brain signals recorded from the ElectroCorticoGram (ECoG) have numerous potential benefits for usage with BCI systems. This workhad proposed feature selection for the ECoG signals' classificationin BCI. Initially, there is the extraction of the features usingCSP, WPT, and WPT-CSP. The GA is utilized to pick the optimal features from the extracted features. The dataset I of BCI competition III is used to carry out the experimentations. The experimental results verify that, compared to other methods, the proposed feature selection will improve the performance with regards to accuracy, recall, and precision.

Furthermore, it is evident from the experimental outcomes that the WPT-CSP-Proposed GA-SVM has a higher classification accuracy by 2.29%, 1.91%, 1.52%, 1.52%, and 0.38% for the WPT-Proposed GA-RF, the WPT-Proposed GA-LR, the WPT-Proposed GA-SVM, the WPT-CSP-Proposed GA-RF, and the WPT-CSP-Proposed GA-LR, respectively.

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