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Analysis of auditory attention based on different semantic levels using a Multi-objective Coati optimization algorithm

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***Abstract*—Auditory attention is a cognitive mechanism which permits us to consciously pay attention to certain sounds while neglecting others. It is captured by various sources such as electroencephalogram (EEG), heart rate, photoplethysmogram (PPG), and galvanic skin response (GSR) signals. Out of them, the EEG signal is employed for evaluating auditory attention due to it is a non-invasive and complex signal that has several applications in biomedical domains. In this study we used Physiology of Auditory attention (PhyAAt). It consists of a dataset of 25 healthy volunteers performing three distinct tasks (resting, writing, and listening) under various noise levels, including native speakers and non-native speakers. To our knowledge, there is no attempt at different semantic level classification using optimization-based channel selection, especially for this dataset. So, in this work we examine auditory attention at various semantic levels. To increase the efficiency of classification while minimizing computational complexity, we utilize the multi objective Coati Optimization Algorithm (MOCOA) for channel selection and voting classifiers. From the findings, it suggests that semantic-level classification performed better, whether channel selection was used or not.**

***Keywords*—** *Auditory attention, COA, EEG, PhyAAt, Voting Classifiers.*

I. INTRODUCTION

Auditory attention is a type of focused attention, a cognitive process in which a person's attention can be assessed through listening/listening activities. Specifically, it relates to the process that occurs when a person deliberately focuses on an interesting stimulus, ignoring other stimuli. The ability of individuals to consciously filter out certain noises and sounds and focus on specific ones is called selective hearing, and it is essential to recognize that it is not a disease like autism or dementia [1]. Electroencephalogram (EEG) can be used to examine brain activity, while photoplethysmogram (PPG) and galvanic skin response (GSR) signals can be used to determine heart rate and sympathetic response, respectively. Amongst them, the EEG signal is used to assess auditory attention that has many applications in biomedical domains [2]. The Physiology of Auditory attention supplemented this to Speech Dataset (PhyAAt) [3]. It consists of a dataset of 25 healthy volunteers performing three distinct tasks (resting, writing, and listening) under various noise levels, including native speakers and non- native speaker. To our knowledge, there has been no attempt at distinct semantic level classification. So, in this study, we analyze auditory attention at various semantic levels. Fig. 1, 2, and 3 represent the raw, non-semantic, and semantic EEG signals, respectively.

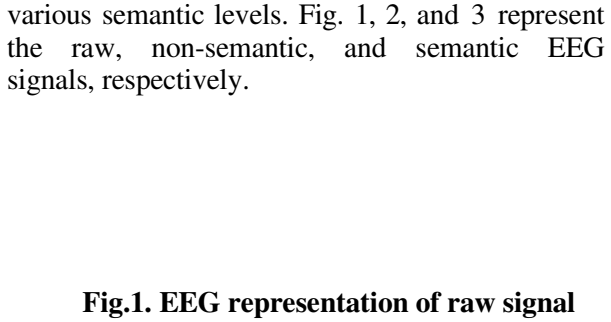


Fig.1. EEG representation of raw signal

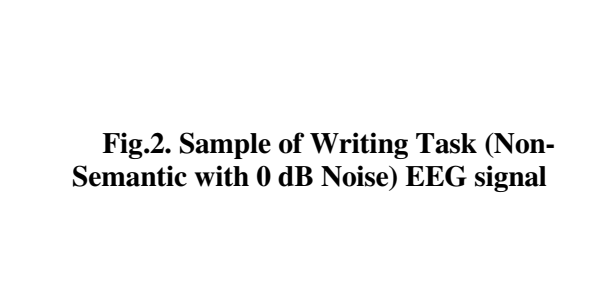


Fig.2. Sample of Writing Task (Non-Semantic with 0 dB Noise) EEG signal

Fig.3. Sample of Writing Task (Semantic with 0 dB Noise) EEG signal

Another important point to note is that since a natural EEG signal can consist of multiple channels, effective channel selection is crucial to achieve the best performance. There is no attempt to perform channel selection for semantic-level attention task classification, especially for this dataset. Therefore, we use our proposed multi-object COA channel selection algorithm for channel selection. Our proposed channel selection algorithm is inspired from the COA [4] optimization algorithm. Additionally, we used a voting classifier [5] for classification, which includes Random Forest, XGBoost (XGB), and Adaboost (ADA). This study is organized into five sections. Related work details presented in Section II. Proposed methodology details presented in section III. Experimental results are presented in Section IV. Conclusion is presented in Section V.

II. RELATED WORKS

Typically filter-based, wrapper-based, and hybrid-based channel selection algorithms are used for many EEG applications such as emotion recognition, motor imagery detection, etc[6, 7]. Due to their ability to effectively explore complex, high-dimensional search spaces and identify globally optimum subsets of important channels the optimization-based channel selection techniques are currently attracting greater interest than traditional filter and wrapper techniques in EEG signal processing.

Study [8], employed a greedy selection technique to select suitable EEG channels for auditory attention decoding (AAD). By continuously selecting channels that improve stimulus reconstruction accuracy, they found that just four channels could outperform the entire 64-channel configuration.Study

[9] presented a Geometry-Constrained Convolutional Regularization Selection method for selecting an appropriate subset of channels based on their spatial layout to improve speech intelligibility in multi-speaker circumstances. Apart from AAD based works some EEG based channel selection works discussed below.

In [10], focused on EEG-based cognitive state identification for customized instruction by optimizing channel selection and feature selection. It applies Random Forest-based Sequential Forward Selection (RF-SFS) to find the most important features and a Genetic Algorithm (GA) to select the most appropriate channels in order to improve the accuracy of classification while minimizing computational complexity. In [11], the Binary Gray Wolf Optimizer (BGWO) optimization algorithm was used for the binary channel selection task and the classification was performed using SVM with radial basis function (RBF) kernel and it achieved 94.13% accuracy for motor image datasets.

An improved genetic algorithm (GA) [12] was used for adaptive EEG channel selection. It reduces noise and unwanted signals without specifying the number of channels. Discrete wavelet transform (DWT) and common spatial shape (CSP) are used for feature extraction. SVM is used for motor imaging EEG signals classification. Study [13], use NSGA-II optimization algorithm for channel selection, which reduces EEG channel from 22 to 3. It uses 1D-CNN for feature extraction and classification in seizure prediction application.

All of these current works, with only limited work, focus solely on decoding auditory attention, and there is no work attempting channel selection specifically for optimization-based channel selection for this PhyAAt dataset. Therefore, in this study, we used our proposed channel selection method to select appropriate channels and a voting classifier to improve the classification performance.

III. PROPOSED METHODOLOGY

In this study, we employed a frequency domain feature extraction and multi-objective COA channel selection algorithm in conjunction with voting classifiers to estimate and detect task classification in the PhyAAt dataset. Our proposed approaches have three important phases of work: 1. Preprocessing, 2. Frequency domain feature extraction, 3. Multi objective Coati channel selection algorithm and, 4. Voting

classifier. Fig. 4. indicates the general block diagram of proposed work.

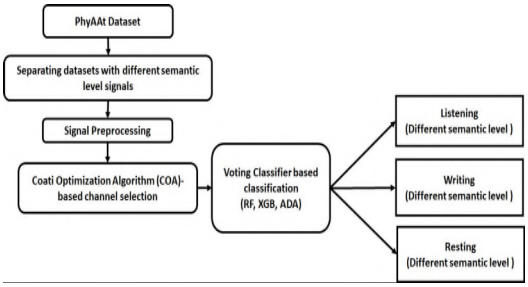


Fig 4. General block diagram of proposed work

A. Preprocessing

In the pre-processing phase, we first remove unnecessary data and duplicates from the original EEG dataset. After that, we perform label segmentation to extract label-wise signal from the signal (-1 = unwanted data, 0 = listening, 1 = writing, 2 = resting). Only listening, writing, and test data will be considered for the upcoming process. These three tasks have different noise levels and semantic-level signals, in this work we focus on semantic level classification, so we extract semantic level signals separately (0= Semantic, 1=non-Semantic).

B. Frequency domain Feature extraction

We perform Power Spectral Density (PSD) [14] to convert the time domain signal into a frequency domain signal. The Power Spectral Density provides insight into how signal power is distributed across various frequency components. After that, we extract statistical features [15] including mean, variance, standard deviation, RMS, skewness, and kurtosis, as shown in Table 1. Additionally, we also include alpha, beta, and gamma band power analysis with these statistical features to achieve better performance.

TABLE I. STATISTICAL FEATURES

Statistical features	Formula
Mean	$Mean_{freq} = \frac{1}{M}\sum_{m=1}^{M} F_m$
Variance	$Var_{freq} = \frac{1}{M}\sum_{M=1}^{M}(F_m - Mean_{freq})^2$
Standard deviation	$std_{freq} = \sqrt{\frac{1}{M}\sum_{m=1}^{M}(F_m - Mean_{freq})^2}$
Root mean Square	$rms_{freq} = \sqrt{\frac{1}{M}\sum_{m=1}^{M} F_m^2}$
Skewness	$Skew_{freq} = \frac{\frac{1}{M}\sum_{m=1}^{M}(F_m - Mean_{freq})^3}{(\sqrt{\frac{1}{M}\sum_{m=1}^{M}(F_m - Mean_{freq})^2})^3}$
Kurtosis	$Kur_{freq} = \frac{\frac{1}{M}\sum_{m=1}^{M}(F_m - Mean_{freq})^4}{(\sqrt{\frac{1}{M}\sum_{m=1}^{M}(F_m - Mean_{freq})^2})^4}$

Where Fm = each data point, and M = total number of samples.

C. Proposed Multi objective Coati optimization channel selection algorithm

Channel selection is an important pretreatment procedure in EEG data analysis that enhances classification performance by selecting the most appropriate channels while minimizing computational complexity. In this work, we used the proposed multi-objective Coati optimization channel selection algorithm to select the optimal channel. It is inspired by the Coati optimization algorithm. Coatis (candidate solutions) are updated in the COA [4] by simulating two natural behaviors. These behaviors include: Coatis' approach to hunting iguanas, Coati's escaping approach from predators. Pseudo code of the proposed channel selection given in Algorithm 1.

Algorithm 1: Multi-objective Coati Optimization channel selection Algorithm

Input: Frequency domain Features (F), Number of search agents (S), number of iteration (I) Output: Selected channels

1. For i = 1 to N

Initialization of population for all search agents

$$Xi,j = lbj + r.\,(ubj - lbj) \quad (1)$$

$i = 1,2, \ldots S$ and $j = 1,2, \ldots S$

End

Where lb (lower bound) , ub (upper bound) and r is a rand value.

2. While (up to max iteration I) For i = 1 to S

Calculate the fitness function for all search agents

If current fitness is better, update best with previous

$pbest$; otherwise, keep pbest End

Compute $pbest$ to global best ($gbest$) value from the fitness function

Phase 1: Hunting and attacking strategy on the iguana

(Exploration phase)

For i = 1 to S/2

Update the position by

$$X_{P1} = Xi,j + r.\,(Iguanaj - I.\,Xi,j) \quad (2)$$

Update the boundary conditions End

Where $XP1$ phase 1 updated position and $Iguanaj$ is a $gbest$ position For i = 1 + S/2 to S

Calculate the random position for iguana

$$IguanaG = lbj + r.\,(ubj - lbj)$$

Update the position by

$$X_{i,j}^{P1} = \begin{cases} X_{ij} + r.\left(I_{guana_j}^{u} - \mathrm{I}.X_{ij}\right), & FIguana^{g} > F_i \\ X_{ij} + r.\,(X_{ij} - Iguana_j^{G}, & else \end{cases} \quad (3)$$

End

Update the boundary by using equation

Where $FIguanag$ is objective function of $Iguanag$.

Phase 2: The Process Of Escaping From Predators

(Exploitation Phase)

For i = 1 to S

Compute local bounds for variable by

$$lb_j^{local} = \frac{lb_j}{M} \quad (4)$$

$$ub_j^{local} = \frac{ub_j}{M} \quad (5)$$

Update the position by

$$X_{P2} = X_{i,j} + (1-2r) \times (lb_j^{local} + r \times (ub_j^{local} - lb_j^{local})) \quad (6)$$

Update the boundary conditions End for

While

End

3. From the $gbest$ where each bit denotes whether a channel is selected (>0.5) or not selected (0).

First, perform population initialization by assigning a random value to all search agents with the range of 0 to 1. After that computing fitness function for all search agents and determine p_{best} and g_{best} with the help of Algorithm 2. After that, it executes the exploration phase. In this exploration phase, half of the search agents' positions are updated using Equation 2, and the remaining search agents' positions are updated using Equation 3; Update boundary conditions. Once the exploration stage is completed, it will move to the study stage. Calculating local boundaries for the variable using Equations 4 and 5, followed by updating the positions using Equation 6. The process will continue until it reaches maximum iteration. The selected channel indices were computed from g_{best}.

Algorithm 2: Multi objective fitness function

Input:Frequnecy domain features (F), selected channels Output : Fit_{Pbest}

For all Search agents:

Take train and test set features separately.

$$Fitn = inf$$

If the selected channel count >7

Select the same selected channels for both the train and test set features. Compute test accuracy by suing voting classifier

$$Fitn = 1 - accuracy$$

End

If $FitPbest > Fitn$

$FitPbest = Fitn$

The pseudocode of the multi-objective fitness function is given in Algorithm 2. Before perfroming fitness function estimating all search agents postion was conveted to binary where postions values greater than 0.5 are set to 1 and the rest are set to 0. In the fitness function evaluation, we have two objectives: one is to have the selected channel count be greater than 7 (half of the total channels), and the second objective is reduced accuracy. If the selected channels fail to meet objective one, it does not implement objective 2 and provide accuracy as Inf; otherwise, it implements objective 2. If the selected channels met the objective 1 algorithm, the respective features of the selected channels were extracted separately from the train and set features. After that, calculate the test accuracy using the voting classifier. The voting classifier includes three machine learning algorithms such as Random Forest, XGBoost, and AdaBoost. The fitness function was estimated from the calculated accuracy. If the current fitness function is better than $FitPbest$ means, the Fit_{Pbest} is updated as Fit_n; otherwise Fit_{Pbest} remains unchanged. Where $_{pbest}$ is a current best position and $pbest$ is a global bets position.

IV. Results and Discussion

In this section, we analysed the performance of the voting classifier in terms of accuracy, F1 score, ROC curve, and confusion matrix for semantic and non-semantic levels. We utilized multi objective coati optimization algorithm for

channel selection. For classification we used voting classifier which includes three machine learning algorithms such as Random Forest, XGBoost, and AdaBoost. Table II shows the Performance of the classifiers for semantic and non-semantic Speaker frequency domain analysis for all 25 subjects (with and without channel selection). Table III shows the Performance of the classifiers for Semantic speaker frequency domain analysis for all 25 subjects (with and without channel selection)Fig. 5 and 6 show the confusion matrix and ROC curve with channel selection performance in non-semantic level analysis. On other hand Fig. 7 and 8 show the confusion matrix and ROC curve without channel selection performance in semantic level analysis. Fig. 9 and 10 show the confusion matrix and ROC curve with channel selection for semantic level analysis. On other hand Fig. 11 and 12 show the confusion matrix and ROC curve without channel selection performance for semantic level analysis.

From the findings, we achieved an average accuracy of 76.86% and 79.17% without channel selection and with channel selection for semantic level analysis, respectively. On the other hand, for non-semantic level analysis, we achieve an average accuracy of 77.10% and 79.23% with and without channel selection, respectively. These results indicate that channel selection improves classification accuracy in both cases, and has a more significant impact at the semantic level.

For semantic-level classification, the proposed channel selection methods achieved a 2.76% accuracy increase compared to methods without channel selection. Meanwhile, for semantic-level classification, our proposed methods achieved a 3% improved accuracy, respectively. This improvement indicates that selecting the most appropriate EEG channels helps reduce noise and redundancy, leading to better modeling performance.

Table II. Performance of the classifiers for Non-semantic speaker frequency domain analysis for all 25 subjects (with and without channel selection)

Sub /Metrics		**Non-Semantic**	
		Without Channel selection	With Channel selection
S1	Accuracy	85.94	89.06
	F1 Score	85.86	89.2
S2	Accuracy	84.38	87.5
	F1 Score	84.44	87.45
S3	Accuracy	70.31	71.88
	F1 Score	69.88	71.67
S4	Accuracy	67.19	67.19
	F1 Score	65.96	66.2
S5	Accuracy	76.19	79.37
	F1 Score	75.94	79.23
S6	Accuracy	89.06	90.62
	F1 Score	89.06	90.61
S7	Accuracy	70.31	78.12
	F1 Score	70.27	78.01
S8	Accuracy	78.12	79.69
	F1 Score	77.93	79.45
S9	Accuracy	84.38	87.5
	F1 Score	84.26	87.5
S10	Accuracy	75	76.56
	F1 Score	74.14	75.84
S11	Accuracy	82.81	79.69
	F1 Score	82.97	79.68
S12	Accuracy	65.62	70.31
	F1 Score	65.65	70.28

S13	Accuracy	79.69	82.81
	F1 Score	79.66	82.91
S14	Accuracy	79.69	82.81
	F1 Score	80.09	82.72
S15	Accuracy	76.56	82.81
	F1 Score	73.23	82.44
S16	Accuracy	71.88	67.19
	F1 Score	71.7	67.33
S17	Accuracy	81.25	81.25
	F1 Score	80.87	80.91
S18	Accuracy	71.88	79.69
	F1 Score	70.77	79.32
S19	Accuracy	68.75	71.88
	F1 Score	69.12	72.28
S20	Accuracy	85.94	89.06
	F1 Score	85.91	89.03
S21	Accuracy	81.25	82.81
	F1 Score	80.82	82.58
S22	Accuracy	82.81	82.81
	F1 Score	83.14	82.95
S23	Accuracy	73.44	75
	F1 Score	74	75.44
S24	Accuracy	48.44	53.17
	F1 Score	50.11	53.92
S25	Accuracy	90.62	90.62
	F1 Score	90.72	90.49
	Average Accuracy	76.86	79.17

Table III. Performance of the classifiers for Semantic speaker frequency domain analysis for all 25 subjects (with and without channel selection)

Sub /Metrics		**Semantic**	
		Without Channel selection	With Channel selection
S1	Accuracy	90.48	92.06
	F1 Score	90.46	92.1
S2	Accuracy	76.19	80.95
	F1 Score	77.06	81.42
S3	Accuracy	75	78.12
	F1 Score	75.26	78.28
S4	Accuracy	56.25	67.19
	F1 Score	55.33	65.7
S5	Accuracy	89.06	90.62
	F1 Score	89.07	90.44
S6	Accuracy	92.19	89.06
	F1 Score	92.18	88.96
S7	Accuracy	78.12	82.81
	F1 Score	78.12	82.88
S8	Accuracy	82.81	85.94
	F1 Score	82.88	85.91
S9	Accuracy	84.38	82.9
	F1 Score	84.44	82.8
S10	Accuracy	70.31	73.44
	F1 Score	69.72	72.71
S11	Accuracy	82.81	71.88
	F1 Score	82.72	71.97
S12	Accuracy	76.56	78.12
	F1 Score	76.5	78.24
S13	Accuracy	78.12	82.81
	F1 Score	78.47	82.79
S14	Accuracy	81.25	85.94
	F1 Score	81.02	85.67
S15	Accuracy	84.38	85.94
	F1 Score	84.4	86.1
S16	Accuracy	60.94	64.06
	F1 Score	57.87	62.43
S17	Accuracy	70.31	71.88
	F1 Score	69.64	71.21
S18	Accuracy	71.88	73.44
	F1 Score	70.07	72.03
S19	Accuracy	67.19	70.31
	F1 Score	67.57	71.05
S20	Accuracy	79.69	82.81
	F1 Score	79.75	82.59
S21	Accuracy	76.56	76.56
	F1 Score	76.71	76.52
S22	Accuracy	81.25	82.81
	F1 Score	81.38	82.9
S23	Accuracy	75	79.69
	F1 Score	75.14	79.63
S24	Accuracy	60.94	62.5
	F1 Score	61.18	62.38
S25	Accuracy	85.94	89.06
	F1 Score	85.79	89.03
	Average Accuracy	77.10	79.23

Fig 5. Confusion matrix for Non-Semantic (with channel selection) – S1

Fig 6. ROC curve for Non-Semantic (with channel selection) – S1

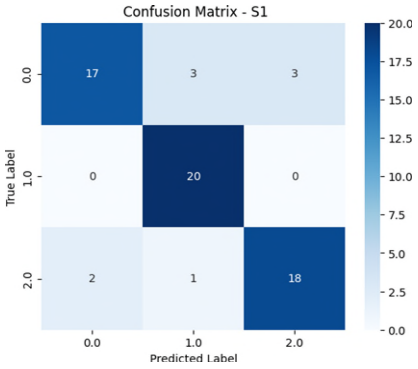


Fig 7. Confusion matrix for Non-Semantic (without channel selection) – S1

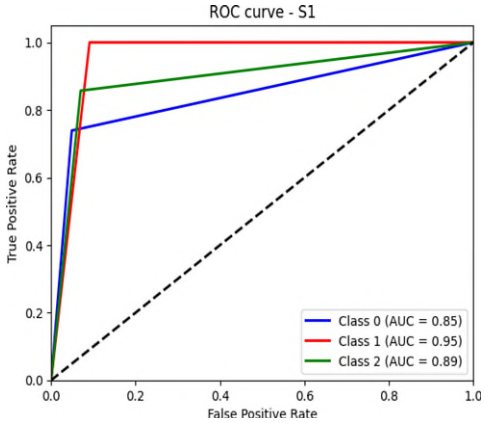


Fig 8. ROC curve for Non-Semantic (without channel selection) – S1

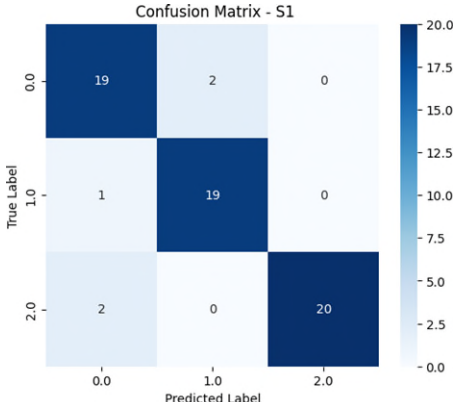


Fig 9. Confusion matrix and ROC curve for Semantic (with channel selection) – S1

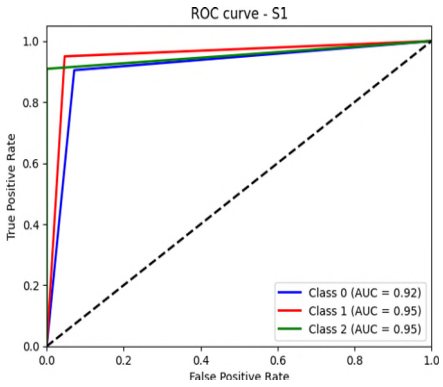


Fig 10. Confusion matrix and ROC curve for Semantic (with channel selection) – S1

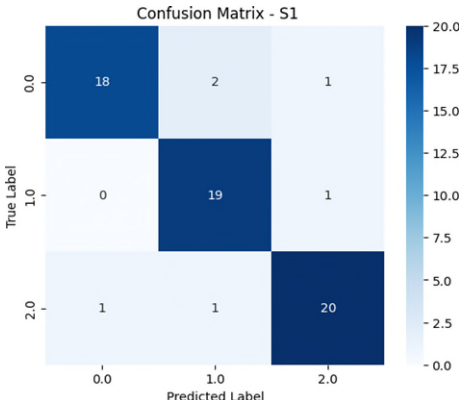


Fig 11. Confusion matrix for Semantic (without channel selection) – S1

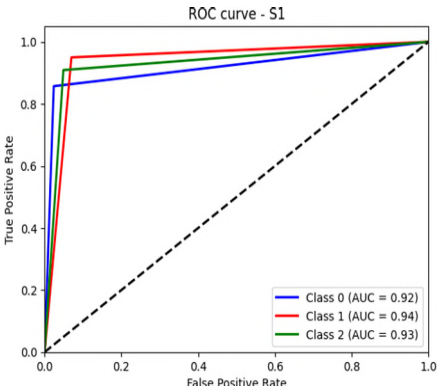


Fig 12. ROC curve for Semantic (without channel selection) – S1

During channel selection, the semantic level (79.23%) outperformed the non-semantic level (79.17%) by 0.07%. Even without channel selection, the semantic level (77.1%) exceeded the non-semantic level (76.86%) by 0.31 %. It indicates that EEG-based classification is more successful in detecting tasks under semantic contexts than in non-semantic conditions, independent of channel selection.

V. CONCLUSTION

This study used EEG signals to assess the reliability of task classification, including listening, writing, and resting, for different semantic levels of speakers, such as semantic and non-semantic. To boost the classification efficiency, we employed a voting classifier and a multi-objective Coati optimization method for channel selection. From the findings, with the help of the proposed channel selection, we have achieved an average accuracy of 79.17% and 79.23% for semantic and non-semantic level classification. In contrast, without channel selection, we achieved 76.86% and 77.10% accuracy for semantic and non-semantic level classification. These findings imply that channel selection improves classification accuracy, with a moderately greater influence at the non-semantic level. With channel selection, the semantic- level classification (performed somewhat better than the non- semantic level by 0.07% increased average accuracy. Even without channel selection, the semantic level still outperformed the non-semantic level by 0.31% increased average accuracy. This indicates that EEG-based classification was more successful under semantic-level classification, regardless of whether channel selection was used or not.

DECLARATIONS

1. Ethics approval and consent to participate - NA
2. Consent for publication -
3. Availability of data and materials - The data supporting the findings of this study are available in Physiology of Auditory Attention at https://phyaat.github.io/dataset
4. Competing interests - The authors declare that they have no competing interests.
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6. Authors' contributions –

SSJ: Conceptualization, Methodology, Data Curation, Writing – Original Draft, Software, Validation, Formal Analysis, Visualization.
TM: Supervision, Review & Editing.
7. Acknowledgements – NA.

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