

Implementation and Analysis of an Optimized Feature Selection Algorithm for Stress Detection

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Abstract—Feature selection is crucial for optimizing machine learning in high-dimensional data domains like biomedical signal processing. This paper introduces a novel methodology that enhances feature selection for stress detection by using an electroencephalography (EEG) signal, integrating the Archimedes optimization algorithm (AOA) with the Analytical Hierarchical Process (AHP). AOA optimizes biosignal feature selection by balancing exploration and exploitation phases to refine significant features crucial for stress detection. Meanwhile, AHP systematically evaluates biosignal criteria to prioritize features for stress detection. The proposed methodology employs AOA-AHP integration to identify relevant biosignal features efficiently. Experimental results demonstrate significant improvements in classification performance, achieving optimal accuracy. Additionally, the methodology ensures computational efficiency by reducing trainable parameters and training time. The robust performance of the AOA-AHP framework across various feature set sizes underscores its suitability for real-world applications in healthcare diagnostic and monitoring systems.

Index Terms—Archimedes optimization algorithm, Analytical Hierarchical Process, Biomedical signal processing, Electroencephalography, Feature selection, Stress detection.

I. INTRODUCTION

In modern workplaces, work stress often arises from demanding management expectations, tight deadlines, and financial pressures, leading to mental health issues such as depression and anxiety [1-3]. The research survey highlights the critical need for a systematic approach to understand how various biosignals respond to stress stimuli. EEG is an effective tool for real-time stress detection, offering precise analysis. Its cost-effectiveness makes it accessible for widespread adoption, potentially improving health outcomes and preventing stress-related mental disorders [4-8].

The study[9-11] highlights feature selection's importance in bioinformatics, examining its techniques and applications, particularly in detecting seizures from EEG data using diverse machine learning algorithms. The research articles[12-14] introduce the Archimedes Optimization Algorithm, a novel metaheuristic inspired by Archimedes' Principle, which shows superior performance in solving complex optimization problems compared to established algorithms. Engineers, social scientists, and individuals use AHP for evaluation and selection in decision-making. They consult expert or user experience to determine decision-making criteria when applying AHP [15-18]. [15-18].

By integrating the AOA and AHP, this research paper proposes an innovative method for enhancing feature selection in stress detection from EEG signals. By matching the exploration and exploitation phases, AOA optimizes the selection procedure and refines the subset of features essential for stress detection. In contrast, AHP enables the systematic assessment and ranking of criteria, supporting well-informed decision-making throughout the feature selection process.

This paper outlines its structure: Section I provides background and context based on a literature survey on mental stress detection and the AOA-AHP Process. Section II explains the Archimedes optimization algorithm and the Analytical Hierarchical Process. Section III introduces the proposed methodology to enhance feature selection in EEG-based stress detection using AOA-AHP. Section IV explores the experimental results and discussion.

II. OPTIMIZATION ALGORITHM

The AOA-AHP approach is more effective than algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) for EEG feature selection in stress detection due to its adaptive balance of exploration and exploitation alongside structured prioritization. While GA relies on crossover and mutation, and PSO depends on swarm-based particle movement—which can sometimes lead to premature convergence or excessive computation—AOA-AHP dynamically adjusts feature subset densities and volumes, maintaining an optimal search scope. AHP further enhances this by systematically ranking features based on weighted criteria such as covariance and entropy, a capability lacking in standard GA, PSO, and ACO. This combined adaptability and precise prioritization allow AOA-AHP to achieve a more refined and efficient selection of significant EEG features, optimizing the process for accurate stress detection.

A. Archimedes Optimization Algorithm

The Archimedes optimization algorithm optimizes EEG feature selection for stress detection by initializing various variables and random constants. It then creates a population of EEG feature subsets with random volumes, positions, and densities. Balancing exploration and exploitation phases using a transfer operator, it adjusts feature subset densities and volumes. During exploration, interactions between feature subsets occur, while in exploitation, they do not. Object positions are updated accordingly to optimize feature selection. The process computes fitness for each subgroup and selects the one with the best fitness, indicating optimal stress detection. This iterative approach refines significant EEG features, enabling efficient optimization for stress detection.

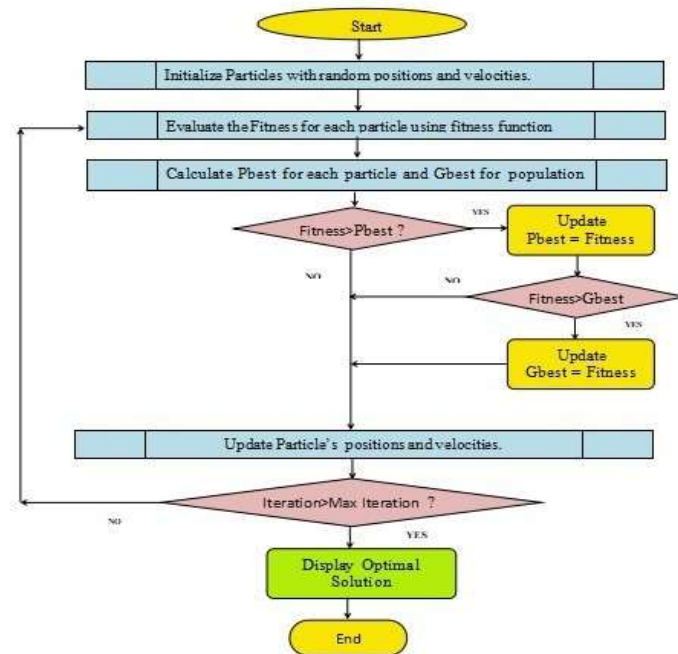


Figure 1 Workflow of Archimedes Optimization Algorithm

Mathematical model of AOA

The AOA Model begins by initializing parameters and object properties (position, volume, and density) before evaluating fitness based on AHP-determined weights, guiding objects toward optimal solutions. This AHP-based mathematical model optimizes a population using the Accelerated Optimization Algorithm (AoA) by assigning weights to critical attributes such as covariance, entropy, and variability.

Step 1: Initialization phase-

The process begins by configuring the parameters for the AoA, defining the population size ($N = 100$), the maximum number of iterations ($\text{itermax} = 1000$), and upper and lower bounds ($UB = 72$ and $LB = 1$). It also sets random constants ($c1, c2, c3, c4$). The algorithm then initializes objects with random volumes, positions, and densities.

Step 2: Initialization of object population with random volumes, positions, and densities-

Initialize the positions of all objects using.

$$\text{If } i = 1, 2, \dots, N, \text{ then } O_i = lbi + \text{Rand} \times (ubi - lbi). \quad (1)$$

Set each object's initial density (Den) and volume (Vol).

$$\text{Den} = \text{Rand}, \text{Vol} = \text{Rand} \quad (2)$$

Lastly, set the i th object's acceleration (Acci) using.

$$\text{Acci} = lbi + \text{rand} \times (ubi - lbi) \quad (3)$$

Step 3: Evaluate and Pick the object with the most favorable fitness value using AHP.

In this step, evaluate the weights of attributes of fitness function using AHP where CV indicates the covariance,

EN represents entropy, and RII represents the ratio of inter-class to intra-class variability.

$$\text{Fitness} = W1 * CV + W2 * EN + W3 * RII \quad (4)$$

The weights $W1, W2$, and $W3$ determine the importance of each criterion variable in feature selection.

$$W1 + W2 + W3 = 1 \quad (5)$$

Analytical Hierarchical Process determines the weights $W1, W2$, and $W3$. The model uses AHP to assign weights for multi-criteria optimization, refining object selection in each iteration. Combining AHP with AoA enhances decision-making, demonstrating the strength of AHP in complex, iterative optimization tasks.

B. Analytical Hierarchical Process

AHP uses three basic concepts to guide its activities: consistency assurance, priority evaluation, and hierarchical organization. It begins by hierarchizing the choice problem, placing the primary goals or objectives at the top level. It then moves to intermediate levels, where criteria and sub-criteria are defined. Finally, it reaches the lowest level, presenting decision options as the last stage. This process enhances understanding by following a structured nine-step approach outlined as follows:

Implementation workflow of AHP Model –

This AHP-based workflow implements a mathematical model to prioritize criteria for identifying compelling EEG features for stress detection. It begins by defining goals, building a hierarchical structure, and assigning weights to essential criteria like covariance, entropy, and variability through pairwise comparisons.

- Set the desired goal - AHP assists in identifying the most practical features for detecting stress through EEG signals.
- Construct a hierarchical structure -

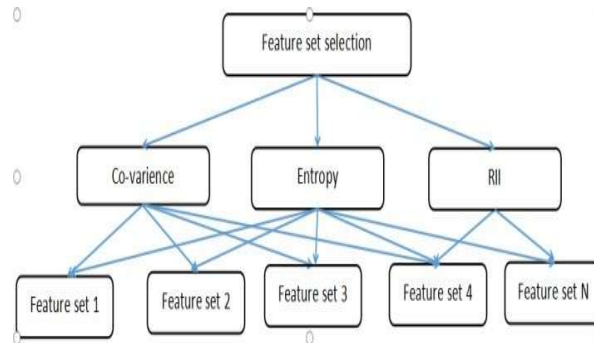


Figure 2 Hierarchical framework

As illustrated in Figure 2, the Hierarchical framework begins by defining the goal as feature selection for stress detection. Criteria, including covariance, entropy, and RII, are established, followed by a list of search objects. Level 1 involves goal selection, where objective G signifies feature selection for stress detection, expressed as

$$G = \text{feature selection}$$

Level 2, C denotes the criteria for feature selection, including Covariance, Entropy, and Ratio of inter-class to intra-class variability—these criteria guide feature selection for stress detection.

$$C = \{\text{Covariance, Entropy, Ratio of inter-class to intra-class variability}\}$$

Level 3, the alternatives are represented by A consisting of N search objects labeled from a1 to aN where N equals 100.

$$A = \{a1, a2, \dots, aN\}$$

- *Develop a matrix for pairwise comparisons* - In the AHP methodology, decision-makers use pairwise comparison matrices to determine exact ratio scale priorities. These matrices produce evaluations of relative importance at every level of the hierarchy.
- Decision makers evaluate each element through relative pairwise comparisons, as shown in Table 1.

TABLE I. SCALE OF PAIR-WISE COMPARISON [19]

Relative intensity	Explanation
1	Two variables are equally important.
3	Slightly favors one variable over another.
5	Strongly favor one variable over another
7	Strongly favor one variable over another
9	The evidence strongly supports one option over another.
2, 4, 6, 8	Between two neighboring judgments

In this study, AHP employs pairwise comparisons, as depicted in Table 2, to construct matrix P to assess the relative importance of criteria regarding the goal. Decision makers' expertise informs judgments, supported by the comparison scale.

TABLE II. CREATE A PAIRWISE COMPARISON MATRIX

	Criteria 1	Criteria 2	Criteria 3			Co- variance	Entropy	RII
Criteria 1	1	A12	A13		Covariance	1	0.333	0.2
Criteria 2	1/A12	1	A23		Entropy	3	1	0.333
Criteria 3	1/A13	1/A23	1		RII	5	3	1

Synthesizing the pairwise comparison -Determination of Criteria Weights: Utilizing the geometric mean method to derive normalized priority weights for each criterion.

$$A1 = \text{Geometric Mean} = (A_{n1} \times A_{n2} \times \dots \times A_{nn})^{1/n} \quad (6)$$

$$\text{Total Geometric Mean} = \sum GM \quad (7)$$

$$A2 = \text{Criteria Weight} = \text{Geometric Mean} / \text{Total Geometric Mean} \quad (8)$$

As per calculation A2 = 0.1047, 0.2582, 0.6369

- *Calculate Eigenvalue (λ max)*- To obtain the Eigenvalue (λ max), multiply the judgment matrix by the priority vector or eigenvector to produce a new vector. The calculation proceeds: the normalized matrix of weighted sum values (A3) equals 0.3182, 0.7848, and 1.935. The ratio of the normalized matrix of weighted sum values to the criteria weights (A4) results in 3.0385, 3.0385, and 3.0385. Here, λ max represents the maximum Eigenvalue of the pairwise comparison matrix, with λ max = max(A4) = 3.0385.
- *Perform consistency* - One of the main benefits of AHP is that it includes a last operation called consistency verification to guarantee consistency in judgments. This procedure calculates the consistency ratio to assess the level of consistency between paired comparisons. It derives the consistency ratio (CR) by taking the ratio of the consistency index (CI) to the random index (RI) for matrices of the same order. Calculating the consistency ratio involves the following three steps:

Consistency index: The calculation of the consistency index (CI) assesses the consistency of the judgments.

$$\text{Index of consistency} = CI = (\lambda \text{ max} - n) / (n - 1) \quad (9)$$

$$CI = 0.0192$$

Random index (RI)-Choosing the accurate RI value for a matrix size of three, referring to Table 3, results in RI = 0.58.

TABLE III RANDOM INDEX OF AHP [20]

Size of Matrix(n)	1	2	3	4	5	6	7
Random index (RI)	0	0	0.58	0.90	1.1	1.2	1.3

Calculate consistency ratio (CR)-

Ratio of Consistency (CR) = CI / RI

(10)

Consistency ratio (CR) = 0.0192/0.58 = 0.033

Consistence & Valid Check:

If CR is ≤ 0.1 , the assigned weights are consistent and valid.

(11)

As CR = 3.33 %, which is $< 10\%$

The AHP-based model validates the criteria weights $W1 = 0.1047$, $W2 = 0.2582$, and $W3 = 0.6369$, as the consistency ratio (CR) remains below 0.1. By implementing a structured process, the model effectively prioritizes criteria for selecting optimal EEG features for stress detection. With validated criteria weights (CR < 0.1), the model ensures consistent and reliable decision-making, demonstrating AHP's effectiveness in systematic feature selection.

III. PROPOSED METHODOLOGY FOR ENHANCING FEATURE SELECTION IN EEG-BASED STRESS DETECTION USING AOA-AHP

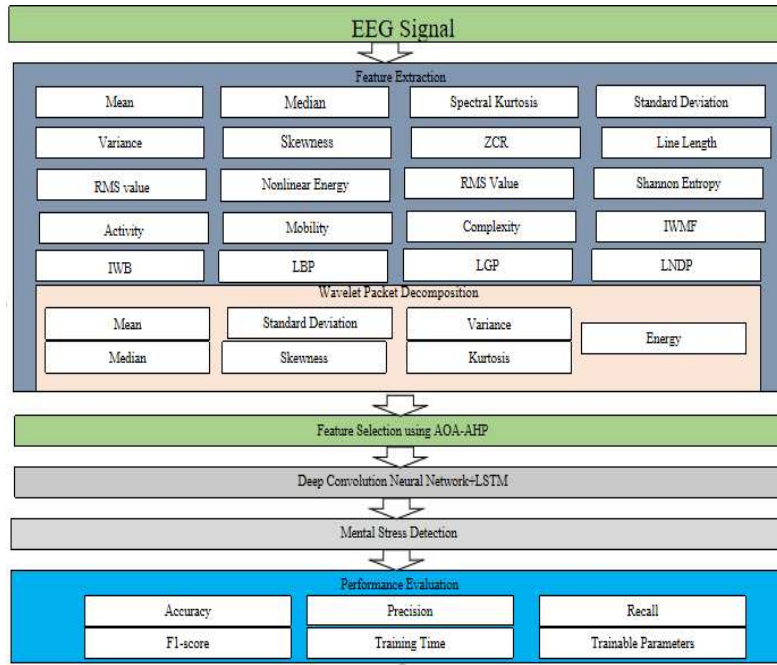


Figure 3. Proposed methodology

The proposed methodology extracts features from EEG signals across multiple domains, including time, frequency, and time-frequency, computing parameters like mean, variance, and kurtosis to achieve detailed representations. It then integrates AOA and AHP to improve feature selection. AOA controls the exploration and exploitation of feature subsets, while AHP systematically evaluates feature significance, assigning weights based on entropy, covariance, and disparity ratios. This integration ensures identifying the most relevant EEG features crucial for stress detection. Then, elements of deep learning are incorporated to enhance hierarchical feature extraction and temporal dependencies, thereby increasing the accuracy of stress detection. The architecture of these components comprises the Long Short-Term Memory (LSTM) and Deep Convolutional Neural Network (DCNN) layers, which incorporate Rectified Linear Unit (ReLU) and Batch Normalization. The methodology aims to enhance healthcare diagnostic systems by integrating AOA and AHP, providing insights into stress-related brain activity patterns, and improving EEG-based biomarker understanding. Additionally, it enhances diagnostic precision.

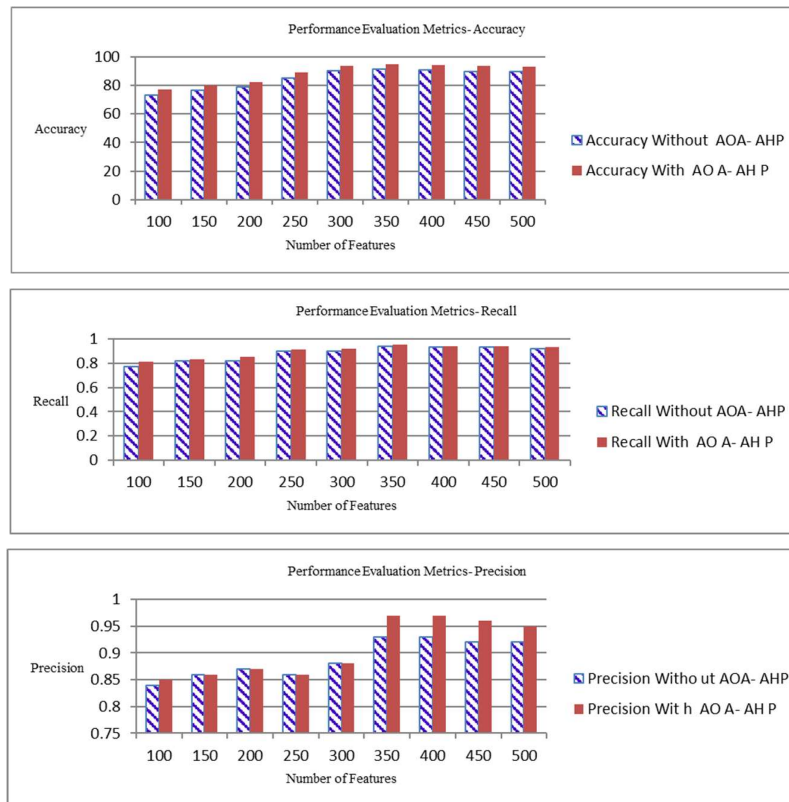
IV. EXPERIMENTAL RESULT AND DISCUSSION

The experimental evaluation underscores the effectiveness of the proposed methodology in stress detection using EEG signals. Integrating the AOA with AHP significantly enhances classification performance observed under two conditions: With & Without AOA-

TABLE IV. PERFORMANCE: AOA-AHP INTEGRATION VS WITHOUT

	Accuracy		Recall		Precision		F1 Score	
	Without AOA-AHP	With AOA-AHP	Without AOA-AHP	With AOA-AHP	Without AOA-AHP	With AOA-AHP	Without AOA-AHP	With AOA-AHP
100	73.5	77	0.77	0.81	0.84	0.85	0.8	0.83
150	76.74	80.24	0.82	0.83	0.86	0.86	0.84	0.85
200	78.83	82.33	0.82	0.85	0.87	0.87	0.85	0.86
250	85.5	89	0.9	0.91	0.86	0.86	0.88	0.88
300	90.5	94	0.9	0.92	0.88	0.88	0.89	0.9
350	91.5	95	0.94	0.95	0.93	0.97	0.93	0.96
400	90.8	94.3	0.93	0.94	0.93	0.97	0.93	0.95
450	90	93.5	0.93	0.94	0.92	0.96	0.92	0.95
500	89.6	93.1	0.92	0.93	0.92	0.95	0.92	0.94

The experimental results, presented in Table 3, compare the classification performance with and without AOA-AHP integration across different numbers of selected features. Optimal accuracy of with AOA-AHP optimization algorithm is achieved Selecting 350 features results in 95% accuracy, with precision, recall, and F1-score of 0.97, 0.95, and 0.95 respectively for stress detection.



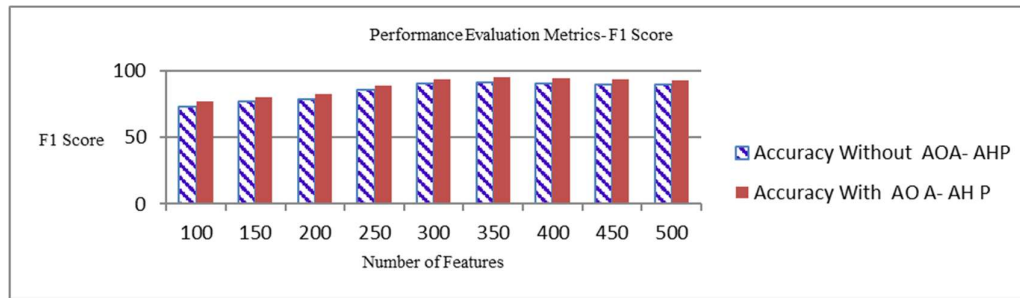


Figure 4. Performance Evaluation Metrics (Accuracy, Recall, Precision, F1-Score)

The AOA-AHP-based feature selection process identifies salient features with distinct properties to differentiate between ordinary and stress EEG patterns. Figure 4 displays the performance evaluation measures, showing that increasing the number of features improves the performance evaluation matrices up to 350. Beyond this threshold, a slight decline occurs due to including non-salient features. As shown in Table 5, the proposed methodology improves efficiency by reducing the number of trainable parameters and training time, ensuring computational efficiency.

TABLE 5. COMPUTATIONAL EFFICIENCY

Method	Total TrainableParameters	TrainingTime
Without AOA-AHP	1.2M	18Min
With AOA-AHP	800K	14 Min

This AOA-AHP integration offers a systematic framework for identifying relevant EEG features, significantly enhancing classification performance. The paper presents experimental results demonstrating the effectiveness of the proposed methodology and emphasizes its potential to advance diagnostic systems in healthcare. Additionally, the methodology underscores computational efficiency by reducing parameters and training time, making it suitable for real-world applications. Overall, integrating AOA and AHP presents a promising avenue for improving feature selection in EEG-based stress detection systems, with broader implications for enhancing healthcare diagnostics and monitoring.

V. CONCLUSION

Integrating the AOA with AHP demonstrates remarkable effectiveness in EEG signal stress detection. This integrated approach significantly boosts classification performance, achieving peak accuracy, precision, recall, and F1-score metrics. AOA-AHP accurately identifies crucial features, distinguishing between standard and stress-induced EEG patterns. Additionally, the method demonstrates computational efficiency by optimizing trainable parameters and training time, ensuring scalability for practical applications. Future research directions include extending the methodology to diverse biomedical signal processing tasks, exploring alternative optimization algorithms, and refining feature selection by incorporating domain-specific knowledge. Moreover, investigating the interpretability and physiological significance of selected features holds promise for informing clinical decision-making and personalized healthcare.

Conflicts of interest/Competing interests:

The authors have disclosed that we have no conflicts of interest

Authors' contributions:

In the experiment, Mrs. Sangita Patil showcased the impact of AOA-AHP integration on the performance of an EEG-based stress model. Dr. Ajay Paithane verified the experiment, thus enhancing its credibility.

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