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Advanced stress detection with optimized feature selection and hybrid neural networks

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ABSTRACT

Stress impacts both mental and physical health, potentially leading to serious conditions like cardiovascular diseases and mental disorders. Early detection of stress is crucial for reducing these risks. This study aims to improve stress detection by analyzing physiological signals, specifically electroencephalography (EEG) and electrocardiogram (ECG). EEG is affordable, while ECG provides detailed insights into cardiovascular health. Feature selection is a major challenge in analyzing these signals. To address this, the research introduces a novel method that combines the Archimedes optimization algorithm (AoA) with the analytical hierarchical process (AHP) to enhance accuracy in both single and multimodal systems. The proposed multimodal system employs a parallel-structured convolutional neural network (CNN) with a deep architecture to extract spatial features and uses a long short-term memory (LSTM) network to capture temporal dynamics. Experimental results show significant improvements: ECG stress detection accuracy rises from 88.6% to 91.79%, EEG accuracy increases from 95% to 96.6%, and multimodal stress detection accuracy reaches 98.6%. These results highlight the effectiveness of the AoA-AHP-based feature selection technique in boosting stress detection accuracy, contributing to improved mental health management and overall well-being.

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1. INTRODUCTION

In modern workplaces, high expectations, tight deadlines, and financial concerns often lead to stress, contributing to mental health issues like depression and anxiety. These problems result in accidents, reduced productivity, poor decision-making, and disrupted sleep. Researchers are exploring stress detection methods using audio, video, and physiological sensors. However, audio methods face challenges with mimicry, while video methods struggle with facial tracking in low light [1]–[5].

Electroencephalography (EEG) and electrocardiogram (ECG) signals are essential for stress detection, with EEG offering real-time, cost-effective analysis that improves mental health outcomes [6]–[8]. Stress impacts both the brain and cardiovascular system, potentially causing arrhythmias and heart issues. Recent studies leverage ECG data with machine learning to improve stress detection accuracy and cardiovascular health [9]–[12]. Research evaluates models like support vector machine (SVM), linear discriminant analysis (LDA), and logistic regression (LR) for stress detection using EEG and ECG, emphasizing the need for affordable, noise-free multimodal solutions [13]. Another study enhances accuracy with adaptive fusion technology for feature extraction and decision-making [14].

Key challenges include computational complexity and noisy data. This paper introduces the Archimedes optimization algorithm-analytical hierarchical process (AoA-AHP) feature selection method and a hybrid parallel deep convolutional neural network-long short-term memory (PDCNN-LSTM) model to boost accuracy and address signal complexity, offering reliable stress detection solutions. Section 1 reviews mental stress detection, section 2 outlines the methods, and section 3 presents the experimental findings, comparing them with current approaches.

2. MATERIAL AND METHOD

The multimodal stress detection system enhances accuracy by tackling challenges such as noise, complexity, and data integration. Advanced preprocessing methods, including noise removal and artifact rejection, improve signal clarity. Robust feature selection combined with deep learning models enables the detection of intricate patterns for more reliable stress detection.

2.1. Dataset

The proposed multimodal stress detection system integrates EEG signals from the online DEAP dataset and ECG signals from the online WESAD dataset. This research conducts experiments across three distinct configurations: ECG stress detection, EEG stress detection, and multimodal stress detection. EEG and ECG data samples are considered under normal and stress conditions, as listed in Table 1.

Table 1. EEG and ECG stress detection sample

Class	EEG samples (DEAP dataset)	ECG samples (WESAD dataset)
Normal	104	283
Stress	140	165
Total	244	448

Multimodal stress detection utilizes paired EEG and ECG data to examine stress effects on brain and heart activity. The dataset comprises 244 samples, with 104 from normal conditions and 140 from stress conditions, facilitating analysis of both systems. This approach provides a comprehensive evaluation of stress indicators, enhancing detection accuracy and reliability.

2.2. Proposed methodology

The proposed multimodal stress detection methodology involves five key stages: enhancing EEG/ECG signals via wavelet packet transform, extracting multiple features, performing feature-level fusion, selecting relevant features with the AoA-AHP algorithm, and utilizing PDCNN-LSTM for final detection, as shown in Figure 1. Each stage addresses challenges like noise, complexity, and high-dimensional data. The wavelet packet transform improves signal clarity by removing noise and retaining essential information, while the AoA-AHP algorithm optimizes feature selection to enhance model efficiency and accuracy.

2.2.1. Enhancing EEG/ECG signals via wavelet packet transform

Raw EEG and ECG signals go through preprocessing to remove noise and artifacts using techniques like filtering, artifact rejection. After preprocessing, the signals are enhanced by the wavelet packet decomposition method as it divides them into frequency bands and reconstructs them to improve clarity and reduce noise, as illustrated in Figure 2.

This method includes decomposing the EEG/ECG signal using wavelet packet transform (WPT) and then applying Donoho's soft thresholds to eliminate noise and artifacts efficiently.

$$w_{i,j} = \begin{cases} x_{i,j} + \frac{2}{\pi}\tan^{-1}(\beta \frac{x_{i,j}}{Th} + sgn(w_{i,j})\,\alpha\,)Th & |w_{i,j}| \geq \lambda \\ \frac{2}{\pi}\tan^{-1}(\alpha)\, w_{i,j} & |\,w_{i,j}\,| < \lambda \end{cases} \tag{1}$$

In this context, $w_{i,j}$ is the threshold wavelet coefficient. $x_{i,j}$ is the original wavelet coefficient. β and α are parameters that control the shape and behavior of the threshold. Th is the threshold value. λ is a value that differentiates between two thresholding behaviors. $sgn(w_{i,j})$ is returns -1, 0, or 1 based on the sign of $w_{i,j}$.

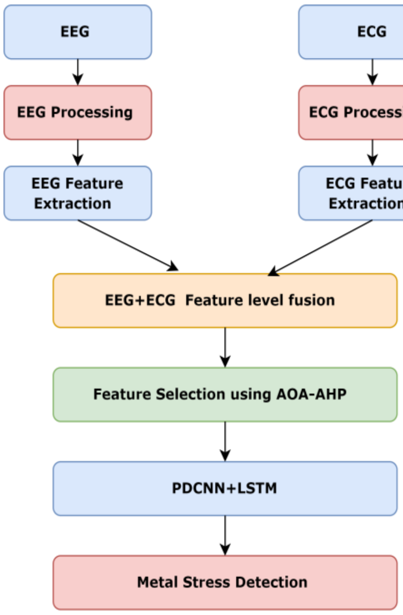

Figure 1. Proposed methodology

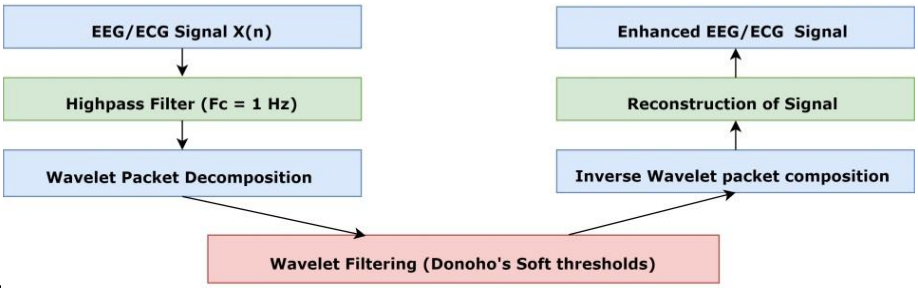

Figure 2. Enhancing EEG signals via WPT

2.2.2. Extracting multiple EEG/ECG features

This research integrates 513 EEG features and 72 ECG features to effectively analyze stress levels. EEG features encompass statistical measures, temporal patterns, and frequency-domain attributes, capturing critical brain signal characteristics linked to stress. ECG features reflect changes in heart activity, offering valuable insights into stress-induced cardiovascular responses. Together, these features provide a comprehensive analysis, enhancing the accuracy and reliability of the proposed detection system.

a. Multiple EEG features

This stress detection study extracts multiple EEG features from both the temporal and frequency domains, including variance, mean, local gradient patterns (LGP), local neighbor difference patterns (LNDP), local binary patterns (LBP), Hjorth parameters, intensity-weighted mean frequency and bandwidth (IWBF and IWBW), and wavelet packet decomposition. These approaches enhance EEG signal representation by incorporating various time-domain and frequency-domain components, as detailed in Table 2. 513 EEG features capture brain signals' spectral, temporal, and spatial properties, essential for identifying stress-related patterns.

Table 2. Extracted multiple EEG features

Feature group No.	Feature group category	Features
1	Statistical measure	Mean, SD, variation, median, skewness
2	Temporal feature	Activity, mobility, mobility
3	Non-linear and energy measure	Entropy, nonlinear energy, line length
4	Pattern based feature extraction	LBP, LNDP, LGP
5	Energy and frequency measure	Energy, IWMF, IWBF
6	Wavelet transform	WPT

Note. IWMF: instantaneous wavelet mean frequency, IWBF: instantaneous wavelet band frequency

b. Multiple ECG features

As listed in Table 3, ECG features are crucial for detecting stress and reflecting heart activity changes. Morphological features indicate structural changes. Wavelet transform features and statistical parameters provide signal insights. Impulsive metrics highlight sudden changes. Hjorth's parameters capture dynamic behaviors, enhancing stress detection and monitoring through ECG.

EEG features complement ECG by capturing neural activity patterns linked to stress. These features provide insights into brain dynamics across temporal and frequency domains, enabling the detection of stress-induced neural changes. Using EEG and ECG data, the system identifies both neural and cardiovascular patterns, providing a reliable and inclusive approach to stress detection.

Table 3. Extracted multiple ECG features

Feature group No.	Feature group category	Features
1	Morphological features	QRS duration, ST. segment elevation, T wave amplitude
2	Wavelet transform features	Mean, Kurtosis, SD, variance of 3rd level WPT
3	Statistical features	Mean, Kurtosis, shape factor, and skewness
4	Impulsive metrics features	Crest factor, peak value, impulse factor, clearance factor
5	Hjorth's parameters	Activity, mobility, and complexity

2.2.3. EEG and ECG feature level fusion

Fusion technologies like concatenation, PCA, LDA, and Min-Max fusion enhance model performance by integrating diverse data sources. These methods ensure a comprehensive representation of patterns in the data. As shown in Figure 3, concatenation fusion directly merges raw feature vectors, preserving all information without transformation.

This approach simplifies implementation and prevents the loss of critical information. The proposed system uses concatenation fusion to combine EEG and ECG feature vectors into a unified vector, preserving the original data. This method aims to enhance model accuracy and robustness in stress detection by retaining all relevant features and allowing for the learning of intricate patterns and interactions among the EEG and ECG signals.

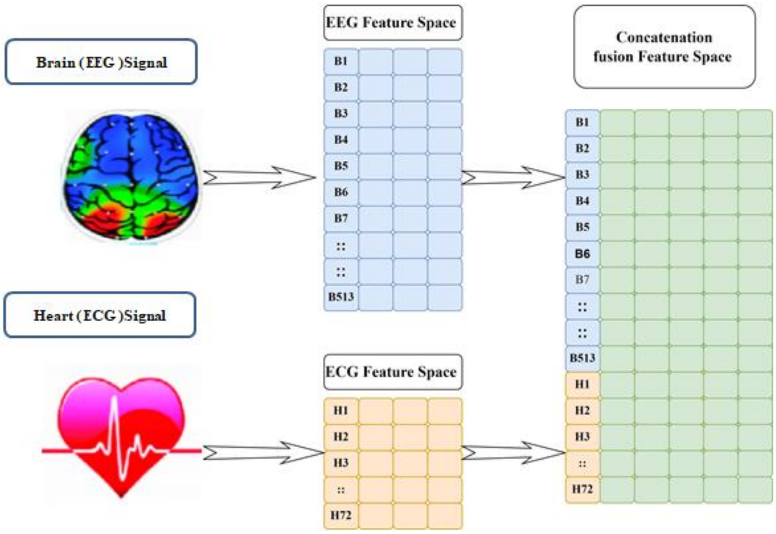

Figure 3. Concatenation feature level fusion

2.2.4. Identification of relevant features using AoA-AHP algorithm

Feature selection is essential for analyzing high-dimensional EEG and ECG data. While PCA reduces dimensionality, it often loses important features. Genetic algorithms (GA) and recursive feature elimination (RFE) identify features effectively but are computationally expensive. The AoA efficiently selects key features by balancing exploration and exploitation through a strong fitness function, ensuring optimal convergence and avoiding local minima. To enhance feature selection, AoA integrates the AHP, using weighted metrics to prevent disruptions in the fitness landscape caused by random weight assignments.

a. Archimedes optimization algorithm

The Archimedes optimization algorithm (AoA) enhances EEG and ECG feature selection for stress detection by initializing variables and random constants, as illustrated in Figure 4. It generates a population of feature subsets with random volumes, positions, and densities. This algorithm balances exploration and exploitation using a transfer operator to adjust feature densities and volumes. During exploration, feature subsets interact, while in exploitation, they do not. The algorithm continuously updates positions to refine key EEG features through iterative fitness computations, ultimately selecting the subset with the best fitness for optimal stress detection.

b. Analytical hierarchy process

The analytical hierarchy process (AHP) aids in selecting the most relevant features for stress detection through EEG and ECG signals by structuring the decision-making process hierarchically, as illustrated in Figure 5. The AHP evaluates criteria such as covariance, entropy, and the ratio of inter-class to intra-class variability through pairwise comparisons, generating priority weights that rank each feature's importance. A consistency check ensures that the comparisons remain reliable and logical, helping to determine the most significant features for stress detection.

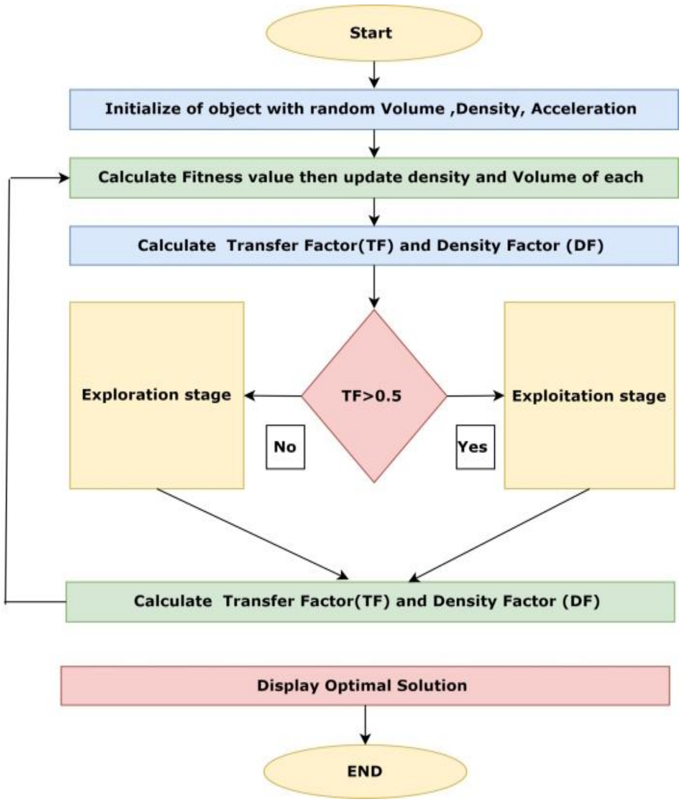

Figure 4. Archimedes optimization algorithm

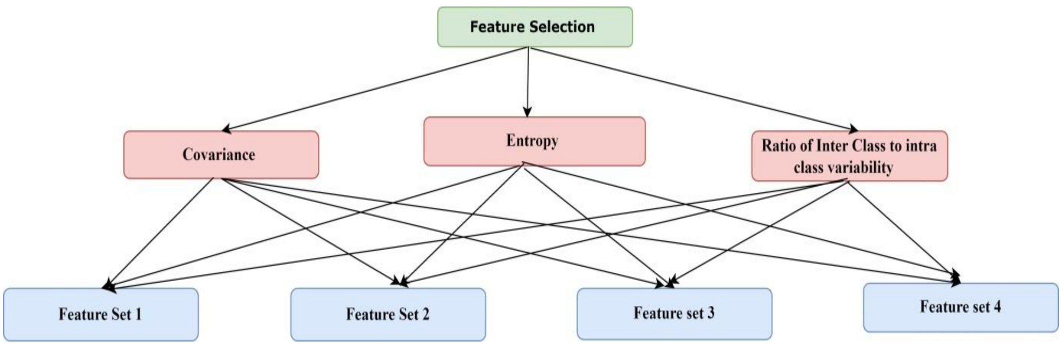

Figure 5. Hierarchically flowchart of analytical hierarchy process

2.2.5. Stress detection through PDCNN-LSTM

The AoA-AHP approach generates a 1D feature vector, passing through PDCNN convolutional layers. Batch normalization and rectified linear unit (ReLU) activation enhance nonlinearity. Pooling layers reduce spatial dimensions while retaining critical information. Subsequently, the LSTM network captures temporal dependencies using memory cells and gates with Sigmoid and Tanh activations. By combining spatial feature extraction with sequential processing, the PDCNN-LSTM effectively analyses spatially dependent data. This model optimizes layer sizes, dropout rates, and learning rates during training, making it suitable for detecting complex patterns like stress.

3. EXPERIMENTAL RESULTS AND DISCUSSION

Experimental results show that various algorithms detect stress from EEG and ECG data effectively. Traditional methods like decision trees (CT) and k-nearest neighbors (KNN) struggle with complex patterns, while SVM, especially the radial basis function (RBF) variant, handles non-linearity better. Ensemble methods improve accuracy but lag behind deep learning models.

Figure 6 highlights PDCNN-LSTM as a top performer, achieving 97.3% accuracy and 100% precision by combining spatial and temporal features for effective stress detection. The research tests the PDCNN-LSTM algorithm for stress detection using EEG-only, ECG-only, and multimodal (EEG+ECG) configurations. It highlights this algorithm's performance, and Table 4 compares its accuracy with leading methods and confirms its effectiveness for stress recognition in each setup.

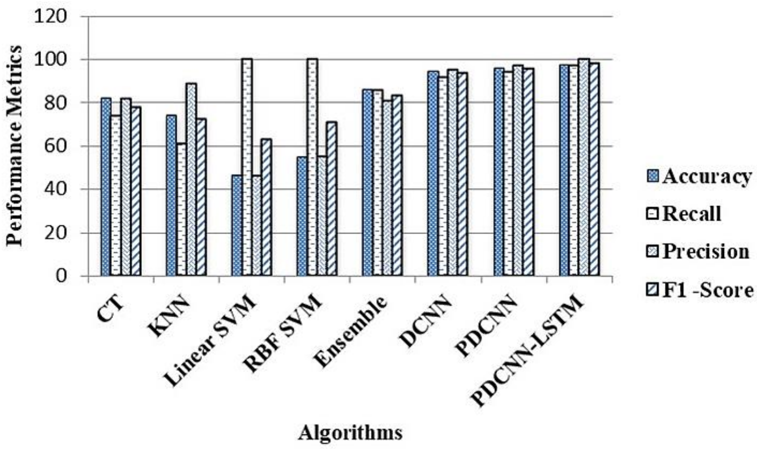

Figure 6. Comparative analysis of algorithms

Table 4. Performance evaluation of the proposed stress detection systems against state-of-the-art

Author	Bio signal used	Deep learning model	Accuracy
[15]	EEG	CNN	60.21%
[16]	EEG	Deep CNN	64.20%
[17]	EEG	CNN	77.90%
[18]	EEG	EEG-Conv	82.95%
[19]	EEG	3-D AlexNet CNN	86.12%
[20]	EEG	Symmetric DCAN	87.62%
[21]	EEG	2-D CNN	93.00%
[22]	EEG	Two-layer LSTM	93.27%
[23]	EEG	ConNet+LSTM	84.48%
[24]	EEG	GWO+BLSTM	82.57%
[25]	ECG, EDA	FDA	87.5%
[26]	ECG, EDA, BVP	ANN	79%
[27]	EEG, ECG	PCA, SVM	79.54%
[28]	EEG, ECG, EMG	LDA	86.0%
[29]	EEG, ECG, EDA	PCA, SVM	86.0%
Proposed modal	ECG		88.6
	EEG	PDCNN+LSTM	95
	EEG+ECG		97.3

Note. EDA: electrodermal activity, BVP: blood volume pulse, EMG: electromyography, GWO: grey wolf optimizer, FDA: functional data analysis, ANN: artificial neural network

3.1. Architecture design of the proposed multimodal stress detection

This study improves accuracy by integrating the optimized AoA-AHP feature selection technique with a novel multimodal stress detection architecture, as shown in Figure 7. The process begins by denoising EEG and ECG signals to enhance data quality. AoA-AHP then selects the most relevant features, boosting model performance. The experiments evaluate how AoA-AHP impacts accuracy across three configurations. In ECG stress detection, AoA-AHP selects 50 features and raises accuracy to 91.79%, compared to 88.6% with all 72 features using PDCNN+LSTM. In EEG stress detection, AoA-AHP with 350 features increases accuracy to 96.5%, up from 95% with all 513 features. For multimodal stress detection, AoA-AHP with 350 features boosts accuracy to 98.6%, surpassing the 97.3% achieved with all 586 features. Overall, AoA-AHP significantly enhances accuracy by optimizing feature selection, reducing dimensionality, and preserving essential information.

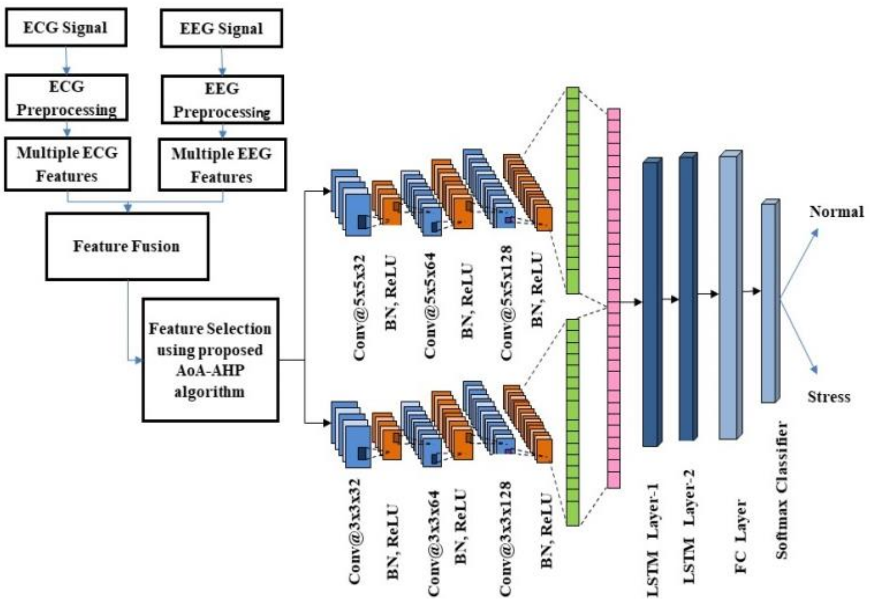

Figure 7. Architecture design of multimodal stress detection

4. CONCLUSION

This research improves stress detection by employing a hybrid architecture that combines a LSTM model with a PDCNN to analyze EEG and ECG signals. It enhances feature selection by integrating the AoA with the AHP. This proposed system effectively addresses noise and high dimensionality, achieving significant accuracy improvements: ECG stress detection rises from 88.6% to 91.79%, EEG detection improves from 95% to 96.6%, and the multimodal approach reaches 98.6% accuracy.

These advancements have substantial implications for clinical practice and industrial settings. Clinically, the system enables earlier and more precise identification of stress-related conditions, leading to timely intervention and better mental health management. In industrial contexts, it supports real-time stress monitoring and helps improve employee well-being and productivity by identifying stress early and implementing effective strategies. This research highlights the advantages of a multimodal approach and advanced feature selection, suggesting potential for further enhancement with additional modalities and refined methods.

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