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Optimized EEG-Based Stress Detection: A Novel Approach

Sangita Ajit Patil[1]* and Ajay N. Paithane[2]

[1]Department of Electronics and Telecommunication, Faculty at Pimpri Chinchwad College of Engineering (PCCOE) and Research Scholar at JSPMs Rajarshi Shahu College of Engineering, Savitribai Phule Pune University (SPPU), Pune, India.
[2]Department of Electronics and Telecommunication, Faculty at Dr. D.Y.Patil Institute of Engineering management and Research (DYPIEMR), Savitribai Phule Pune University (SPPU), Pune, India
*Corresponding Author E-mail:phdsangita@gmail.com

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Mental stress from tight deadlines and financial worries often causes both mental and physical health issues, affecting productivity and decision-making. This study aims to improve stress detection by analyzing EEG signals, which provide a cost-effective, non-invasive method for tracking brain activity. Recent stress detection systems face challenges such as computational complexity, noisy data, and high dimensionality. This study introduces optimal feature selection in an EEG-based stress detection system using the Archimedes Optimization Algorithm (AOA) and Analytical Hierarchical Process (AHP). AOA balances exploration and exploitation, while AHP prioritizes EEG criteria. The system processes EEG data from the DEAP dataset, which includes recordings from 32 participants who watch 40 music clips. It operates in four main stages: enhancing EEG signals with Wavelet Packet Transform (WPT), extracting features, selecting relevant features with the AOA-AHP algorithm, and detecting stress using deep convolutional neural networks and long short-term memory networks (DCNN-LSTM). After evaluating various features with 244 EEG samples, the system optimizes to 350 key features, achieving 95.25% accuracy, 0.97 recall, 0.98 precision, and 0.98 F1 score. This setup enhances accuracy, reduces training time, and minimizes parameters, making it highly reliable for real-time mental stress detection.

Keywords: Archimedes optimization algorithm(AOA); Analytical Hierarchical Process(AHP); Deep Convolution Neural Network(DCNN); Electroencephalography(EEG); Long Short Term Memory(LSTM); Wavelet Packet Transform(WPT).

Mental stress disrupts daily life and can lead to health issues such as hypertension, anxiety, and depression[1]. Stress can be acute or chronic and arise from mental, physical, or emotional stressors[2]. Traditional assessments, including self-report questionnaires, tend to be subjective and prone to bias, whereas physiological measurements such as EEG provide a more objective evaluation [3]. Wearable sensors monitor mental stress in various daily situations, including stressful work environments, academic pressures, and challenging driving conditions[4]. Researchers analyze various biosignal patterns to investigate stress[5]. EEG signals capture magnitude, frequency, power, and phase, providing rich, multi-dimensional information and high temporal resolution to detect rapidly changing cognitive data[6].EEG is a user-friendly, low-cost method for studying brain function. Researchers use non-invasive scalp electrodes to record brain activity in five frequency bands—delta, theta, alpha, beta, and gamma—each associated with distinct mental states[7].

In EEG-based mental stress evaluation, key processes include feature extraction, selection, and classification. Features fall into time-domain, frequency-domain, and statistical categories and are fed into machine learning classifiers to assess stress levels. Traditional methods rely heavily on accurate feature selection for effective classification[8]. Recently, deep learning architectures have gained traction in mental stress evaluation[9]. The whale optimization approach enhances the accuracy of stress detection models and recommends refining feature selection techniques to improve stress detection systems through further research[10].

To tackle challenges such as computational complexity, noisy data, and high dimensionality, the system gracefully integrates Wavelet Packet Transform (WPT) and AOA with the hybrid DCNN-LSTM approach. This innovative combination provides a more robust and accurate solution for stress detection. Section I provides background and context through a literature review on mental stress detection. Section II details the proposed novel stress detection model, which integrates AoA-AHP optimized feature selection and deep learning algorithms. Section III discusses experimental results and the future scope of the stress detection system.

The proposed novel stress detection model

The proposed stress detection system improves accuracy by addressing noise and complexity issues through advanced preprocessing, innovative feature selection techniques, and a deep learning approach. This model sets a new benchmark with superior accuracy in identifying stress from EEG signals, surpassing existing models. It uses Wavelet Packet Transform (WPT) to minimize noise, integrates the Archimedes Optimization Algorithm (AOA) with the Analytical Hierarchical Process (AHP) for precise feature selection, and employs Deep Convolutional Neural Networks (DCNN) with Long Short-Term Memory (LSTM) for in-depth analysis. This cutting-edge approach enhances data quality, improves computational efficiency by reducing training time and parameters, and ensures reliable stress monitoring. The model tests the DEAP database, which includes EEG recordings from 32 healthy participants (50% female, ages 19-37) who watch 40 one-minute music video clips. Data records at 512 Hz with 32 AgCl electrodes (10-20 system) and is downsampled to 128 Hz before preprocessing and segmenting in Matlab.

The system, illustrated in Figure 1, includes four stages: WPT enhancement, feature extraction, AOA-AHP selection, and DCNN-LSTM detection. Its performance is assessed based on accuracy, precision, recall, F1-score, training time, and parameter count.

Enhancing EEG signals via Wavelet Packet Transform

Figure 2 presents the process flow of the suggested WPT-based EEG signal enhancement method and explains the breakdown and reconstruction of the signal.

This method uses Wavelet Packet Transform (WPT) and Donoho's soft thresholding to remove noise from EEG signals by adjusting wavelet coefficients based on a set threshold as follows.

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

Where:

$W_{i,j}$ is the thresholded 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 the sign function, which returns -1, 0, or 1 depending on the sign of $W_{i,j}$

Extracting multiple EEG features

This stress detection study extracts various EEG features to identify stress. It includes time-domain measures like Mean, Standard Deviation (S.D.), Variance, Median, Skewness, and Zero-Crossing Rate (ZCR) and temporal features such as Shannon Entropy, Nonlinear Energy, and Line Length. In the frequency domain, the study assesses features like Energy, Instantaneous Wavelet Mean Frequency (IWMF), and Instantaneous Wavelet Band Frequency (IWBF). It also incorporates spectral features such as Kurtosis and Hjorth Parameters (Activity, Mobility, Complexity) to capture stress-related changes. The study applies encoding techniques like Local Binary Patterns (LBP), Local Non-Directional Patterns (LNDP), and Local Gradient Patterns (LGP) to transform time series data into stress-indicative patterns. The Wavelet Packet Transform (WPT) provides detailed information across various frequency bands to enhance stress detection[11].

Relevant features selection using the AOA-AHP algorithm

The study uses the Archimedes Optimization Algorithm (AOA) and the Analytical Hierarchical Process (AHP) for feature selection[12]. AOA effectively optimizes feature subsets by balancing exploration and exploitation, while AHP enhances feature relevance by assigning relevant weights [13]. This approach is more precise and interpretable than Principal Component Analysis (PCA), which may need to capture non-linear relationships more effectively. Integrating AHP, AOA overcomes challenges with random weight assignments and refines the feature selection process[14].

AOA Algorithm

Step 1: Initialization phase

Initialization of the random object population that represents the possible combination of the feature set is given by Equation 1

If i = 1, 2,...N, then

$$O_i = lb_i + [rand.\ (ub_i - lb_i)] \quad ...(1)$$

$$den=rand,\ vol=rand \quad ...(2)$$

$$acc_i = lb_i + [rand.\ (ub_i - lb_i)] \quad ...(3)$$

Here, O_i is the i^{th} object in the population of N objects. Ub_i and lb_i are the exploration space's lower and upper bounds, and a rand is a random number between [0,1]. Equations 2 and 3 arbitrarily initialize the volume, densities, and acceleration.

Step 2: Assess and select the object with the most suitable fitness value using AHP

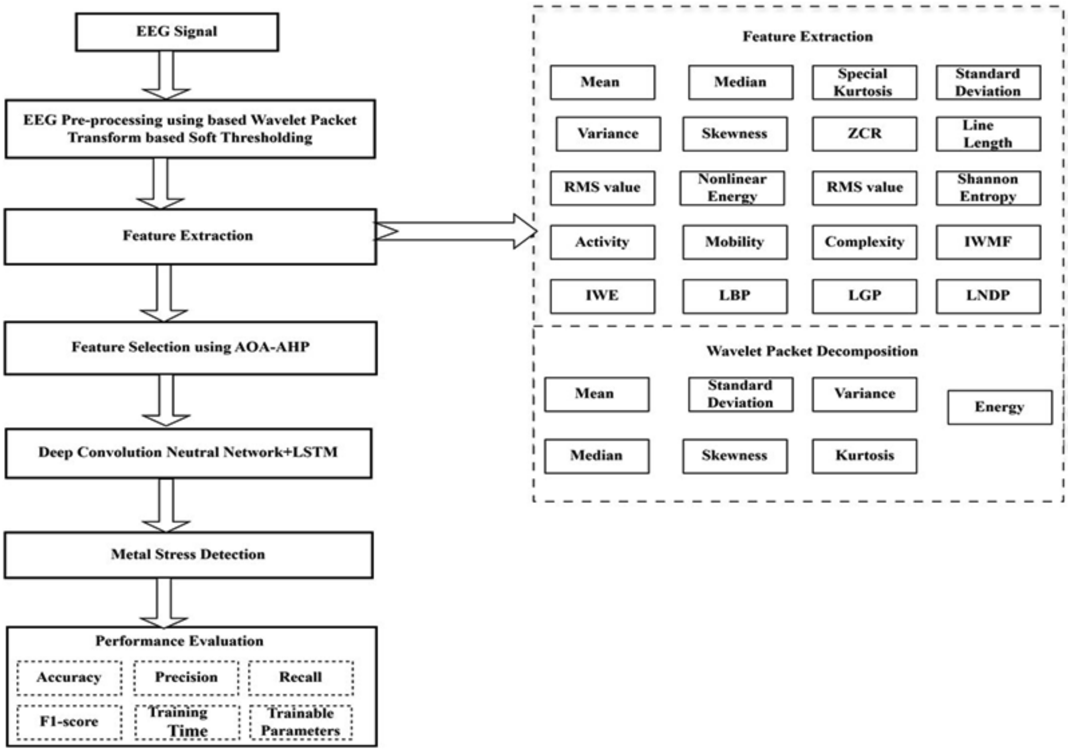

Fig. 1. Four primary stages of the proposed novel stress detection model

Compute the fitness for all objects and select the object with the best fitness value using equation 4.

$$Fitness = W_x*CV+W_y*EN+W_z*RII \quad ...(4)$$

Here, CV indicates the covariance of features, EN represents the entropy of features, and RII represents the ratio of inter-class to intra-class variability of the features. The weights W_x, W_y, and W_z decide the weight of each decision variable for feature selection, such as $W_x+W_y+W_z=1$. Choose the weights W_x, W_y, and W_z based on the AHP algorithm and use them as decision criteria. Based on the best fitness value, select an object with den_{best}, vol_{best}, and acc_{best}

Step 3: Update of Density and Volume in Iterative Process

For each iteration, update the density and volume of the i^{th} objects according to equations 5 and 6, respectively.

$$Den_i^{t+1}= den_i^t + [rand. (den_{best} – den_i^t)] \quad ...(5)$$

$$Vol_i^{t+1} = vol_i^t + [rand. (vol_{best} – vol_i^t)] \quad ...(6)$$

In these equations, den_{best}, and vol_{best} represent the density and volume of the best object, respectively.

Step 4: Compute Transfer and Density Factors Initially, items collide, leading objects to attempt to reach an equilibrium condition. AOA accomplishes this equilibrium condition by utilizing the transfer operator TF, which converts the search process from exploration to exploitation, as described in equation 7.

$$TF = EXP(\frac{t-tmax}{tmax}) \quad ...(7)$$

In this context, "t" represents the current iteration, and "max" denotes the maximum iterations. The T.F. (Transfer Function) steadily increases, indicating exploration progress. Along with T.F., the density factor aids the AOA in transitioning from global to local search, gradually minimizing over time using equation 8. Effectively

Table 1. Comparative Analysis of Machine Learning Algorithms

Accuracy	Accuracy	Recall	Precision	F1 score
LSVM	46.6	42.9	34.3	38.12
RSVM	52.2	30.3	45.5	36.37
PSVM	54.8	17.9	33.3	23.28
KNN	39.7	66	39.7	56.83
C.T.	54.8	72	54.8	70.80
E.S	49.3	69	49.3	66.04

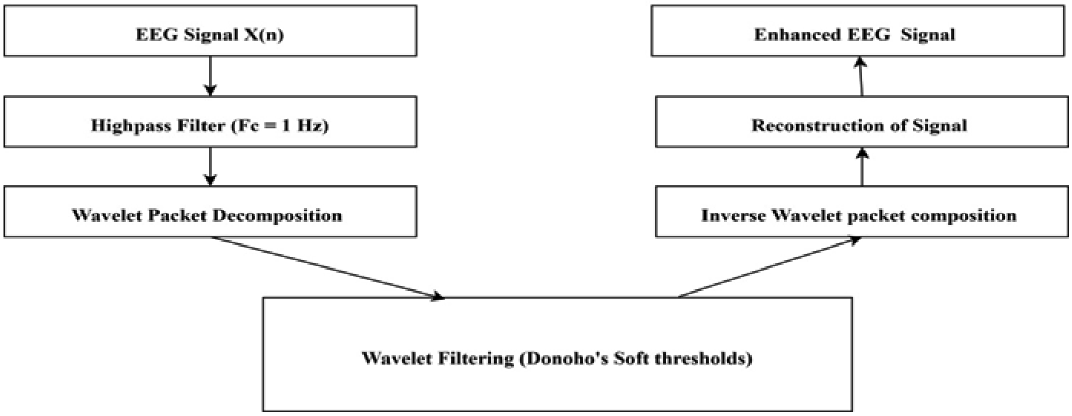

Fig. 2. Enhancing EEG signals via WPT

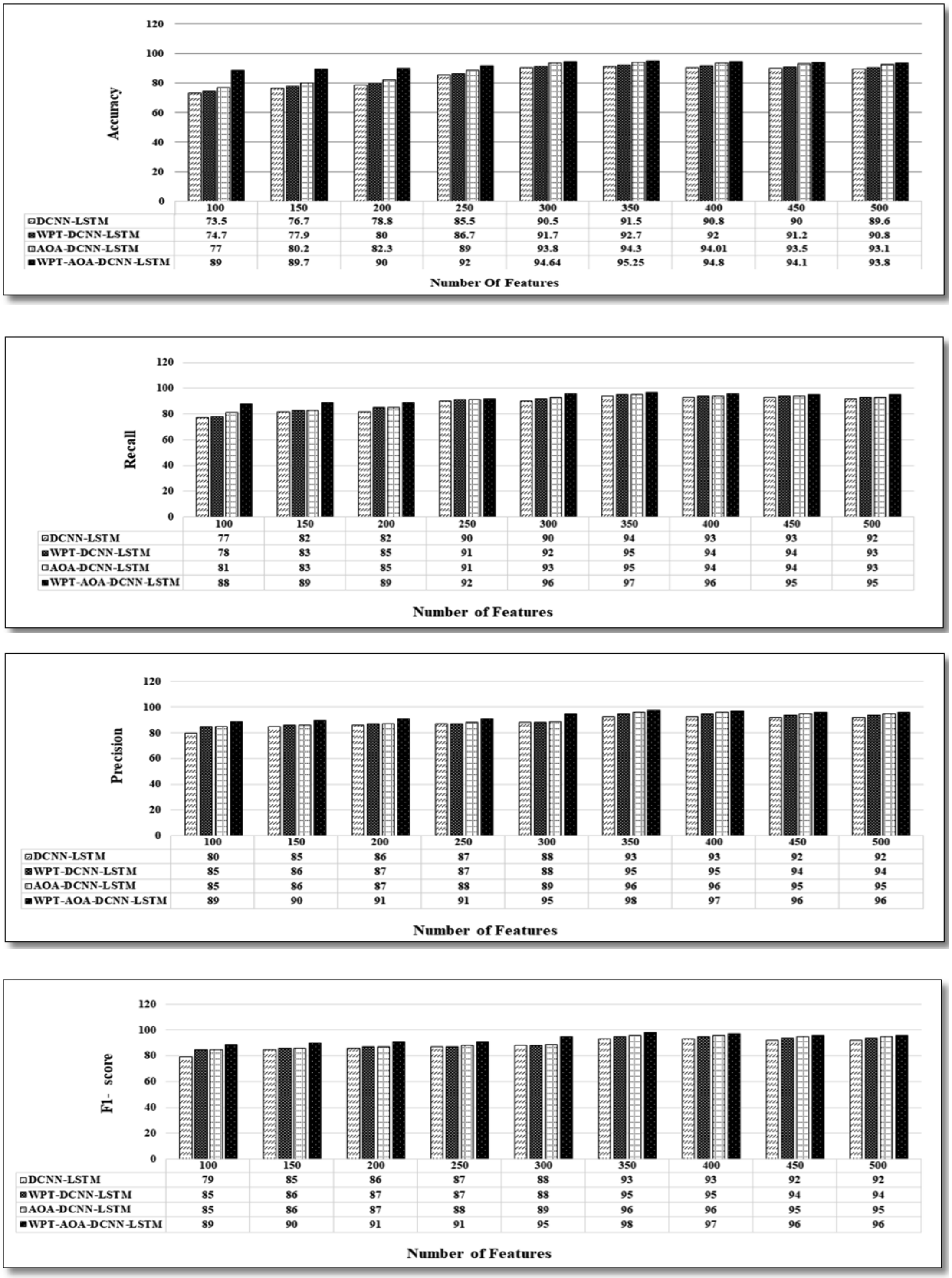

Fig. 3. Comparative Analysis of Performance Evaluation Measures

Table 2. Performance evaluation of proposed stress detection system against state-of-the-art

Author	No. of subjects	Preprocessing	Frequency	Deep learning model	Accuracy
Penchina B[15]	8	High pass, low pass, band pass	Whole range (0.5-30)Hz	CNN	60.21%
Jebelli H[16]	10	60 Hz low pass, 0.5 Hz high pass	Whole range 0.5-30 Hz	Deep CNN	64.20%
Khan T[17]	10	Bandpass, mean filter,	Whole range 0.5-30 Hz	CNN	77.90%
Kaminska D[18]	28	0.2 Hz High-pass, 45 Hz low-pass	Whole range 0.5-30 Hz	CNN	87.50%
Zeng H[19]	10	ICA, band pass, normalized using z-score	Whole range 0.5-30 Hz	EEG-Conv	82.95%
Martinez-R20	32	3 Hz high pass, 45 Hz low pass	Whole range 0.5-30 Hz	3-D AlexNet CNN	86.12%
Fu R[21]	22	Bandpass	Whole range 0.5-40 Hz	Symmetric DCAN	87.62%
A. M. Mane[22]	23	Bandpass	Whole range 0.5-40 Hz	2-DCNN	93.00%
Sundaresan A[23]	8	High pass, low pass, band pass	Whole range 0.5-30 Hz	Two-layer LSTM	93.27%
Kuanar S[24]	25	Bandpass	Alpha-beta & Theta	Hybrid CNN+ LSTM	84.48%
Das Chakladar[25]	48	4-32 Hz Bandpass	Alpha & theta	GWO+ BLSTM-LSTM	82.57%
Proposed Stress detection System	32	A Bandpass Filter from 4 Hz to 45 Hz	Alpha-beta	WPT-AOA-DCNN-LSTM	95.25%

managing these variables ensures a balance between exploration and exploitation in AOA.

$$d^{t+1} = exp\left(\frac{tmax - t}{tmax}\right) - \left(\frac{t}{tmax}\right) \quad ...(8)$$

Step 5: Exploration stage

If the value of T.F. is less than or equal to 0.5, it indicates a collision between objects. In this scenario, AOA selects a random material (rm) and updates the object's acceleration for the next iteration (t + 1) using equation 9.

$$acc_i^{t+1} = \frac{den_{rm} + vol_{rm} \times acc_{rm}}{den_i^{t+1} \times vol_i^{t+1}} \quad ...(9)$$

Where den_{rm}, vol_{rm}, and acc_{rm} are the density, volume, and acceleration of random material

Step 6: Exploitation stage

If the value of T.F. is more significant than 0.5, it indicates no collision between objects. In this case, the object's acceleration is updated for the next iteration (t + 1) using equation 10.

$$acc_i^{t+1} = \frac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} \quad ...(10)$$

Where den_{best}, vol_{best}, and acc_{best} are the density, volume, and acceleration of the best object

Step 7: Normalization Stage

Equation 11 standardizes the value of "acc" with the lower bound (l) and upper bound (u) for normalization set at 0.1 and 0.9, respectively.

$$acc_{i-norm}^{t+1} = u \times \frac{acc_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + l \quad ...(11)$$

When object O_i is far from the global optimum, its high acceleration indicates exploration, while closer objects enter exploitation. This transition, marked by decreasing acceleration, helps find the global optimum while avoiding poor local solutions and maintaining a balance between exploration and exploitation.

Step 8: Position upgradation stage

The algorithm updates the positions of

objects according to exploration as following Equation 12.

$$O_i^{t+1} = O_i^t + C_1 \times rand \times acc_{i-norm}^{t+1} \times d \times (O_{rand} - O_i^t) \quad ...(12)$$

Where C1 =2 (constant), in this experiment, the algorithm updates the positions of objects according to exploitation as follows in Equation 13.

$$O_i^{t+1} = O_{best}^t + F \times C_2 \times rand \times acc_{x-norm}^{t+1} \times d \times (T \times O_{best} - O_i^t) \quad ...(13)$$

In this experiment, with C2 at 6, T increases over time and initially reduces the ideal site by a low percentage, creating large step sizes. As T increases, the rate rises, narrowing the gap between the best and current positions and balancing exploration and exploitation.

Step 9: Compute fitness for each object and then return an object with the best fitness value

As X_{best}, den_{best} , vol_{best} and acc_{best}

This method identifies and selects the optimal EEG features to boost stress detection accuracy.

Stress detection through DCNN-LSTM

Existing deep neural networks face limitations such as managing high computational complexity and addressing high dimensionality, which often decrease accuracy and reliability in stress detection. To effectively overcome these challenges, this study develops a hybrid Deep Convolutional Neural Network (DCNN) and Long Short-Term Memory Network (LSTM) model. The DCNN processes the 1D feature vector through convolutional layers, using Batch Normalization and ReLU activation functions to stabilize and accelerate training. Pooling layers then reduce dimensionality and highlight the most significant features. The LSTM captures temporal dependencies by managing long-term relationships with memory cells, gates, and activation functions like Sigmoid and Tanh. Combining DCNN and LSTM into PDCNN-LSTM allows for a comprehensive analysis of both spatial and temporal dynamics, providing a more accurate and robust solution for stress detection compared to existing architectures.

Experimental Results and Discussions

This research uses EEG to detect stress and mitigate its impact on mental health. It enhances EEG signal quality with preprocessing techniques and extracts stress-related features from alpha and beta waves. The study applies various machine learning algorithms to these features, including Linear Support Vector Machine (LSVM), Radial Basis Function Support Vector Machine (RSVM), Polynomial Support Vector Machine (PSVM), K-Nearest Neighbors (KNN), Classification Trees (C.T.), and Ensemble Systems (E.S.). To evaluate the effectiveness of these algorithms, it analyzes 244 EEG samples—104 from normal conditions and 140 from stress conditions. In the EEG-based stress detection model, accuracy measures the proportion of correctly classified stress and non-stress instances out of the total predictions. The model also calculates additional metrics such as precision, recall, and F1-score, as shown in Table 1.

Optimization techniques enhance stress detection accuracy in machine learning by improving efficiency, preventing overfitting, and optimizing feature selection. This study combines AoA-AHP feature selection with a hybrid DCNN-LSTM approach and evaluates model performance using accuracy, precision, recall, and F1-score across four configurations:

• DCNN-LSTM: Uses raw, noisy EEG features.
• WPT-DCNN-LSTM: Denoise EEG with WPT before extraction.
• AOA-DCNN-LSTM: Selects features with AOA from raw EEG.
• WPT-AOA-DCNN-LSTM: Denoise EEG with WPT selects features with AOA and integrates them into the model.

The stress detection system evaluates and measures performance parameters like accuracy, recall, precision, and F1-score. Figure 3 shows that performance metrics improve with up to 350 features, after which non-salient features slightly reduce performance. The analysis highlights that DCNN-LSTM achieves 91.5% accuracy with 1.2M parameters and 18 minutes of training; WPT-DCNN-LSTM reaches 92.7% accuracy with the same parameters in 16 minutes; AOA-DCNN-LSTM achieves 94.3% accuracy with 800K parameters in 14 minutes; and WPT-AOA-DCNN-LSTM leads with 95.25% accuracy, 800K parameters, and 10 minutes of training. The proposed system significantly reduces training time and the number of trainable parameters.

The proposed stress detection system surpasses state-of-the-art methods and achieves an outstanding accuracy of 95.25%. It outperforms other models, including Sundaresan A's two-layer LSTM, which achieves 93.27% accuracy, and A. M. Mane's 2-DCNN, which reaches 93.00%. The system applies a bandpass filter from 4 Hz to 45 Hz and integrates Wavelet Packet Transform (WPT) with the Archimedes Optimization Algorithm (AOA) for feature selection. It combines deep convolutional neural networks (DCNN) with long short-term memory (LSTM) networks. This approach effectively tackles challenges like computational complexity, noisy data, and high dimensionality, delivering superior performance compared to methods that use simpler preprocessing and model structures.

CONCLUSION

This study introduces a novel EEG-based stress detection system that combines the Archimedes Optimization Algorithm (AOA) and the Analytical Hierarchical Process (AHP) with deep convolutional neural networks and long short-term memory networks (DCNN-LSTM). The system achieves 95.25% accuracy, 0.97 recall, 0.98 precision, and 0.98 F1 score by effectively selecting features and reducing noise. The DEAP dataset, which includes EEG recordings from 32 participants exposed to 40 music video clips, demonstrates the system's effectiveness and reliability. By integrating Wavelet Packet Transform (WPT) and AOA with the hybrid DCNN-LSTM approach, the system addresses challenges like computational complexity and noisy data, delivering a highly accurate and efficient solution for real-time stress management through EEG signals. This method surpasses existing approaches and significantly improves real-time stress management. Future research enhances stress detection by integrating diverse datasets, refining preprocessing techniques to minimize noise, expanding feature extraction methods, exploring more accessible hardware solutions, and incorporating real-world stress scenarios to boost the model's accuracy and applicability across various populations and environments.

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Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials.

Authors' Contribution

Sangita Patil: Conceptualized the study, developed the methodology, collected and analyzed data, and written and edited the manuscript; Ajay Paithane: Visualization, supervision the project, managing administration, and reviewing and editing of the manuscript.

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