Biomedical & Pharmacology Journal, March 2025. Vol. **18**(Spl.), p. 245-255

Special Issue – AI-Driven and Multimodal Innovations in Biomedical Imaging and Sensing

AI-Driven Multimodal Stress Detection: A Comparative Study

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https://dx.doi.org/10.13005/bpj/3085

(Received: 12 December 2024; accepted: 22 January 2025)

Stress affects mental and physical health, contributing to cardiovascular diseases and cognitive disorders, and early detection plays a crucial role in mitigating these risks. This study enhances stress detection by analyzing electroencephalography (EEG) signals from the DEAP (A Database using Physiological Signals) data set and electrocardiogram (ECG) signals from the WESAD (Wearable Stress and Affect Detection) data set, with EEG offering a cost-effective solution and ECG providing detailed cardiovascular insights. It compares individual sensor analysis with multi-sensor fusion, demonstrating that fusion improves accuracy, as the ECG model achieves 91.79% accuracy, the EEG model reaches 96.6%, the feature-level fusion model achieves 98.6%, and the score-level fusion model achieves 97.8%. Using the Archimedes Optimization Algorithm (AoA) and Analytical Hierarchical Process (AHP) for feature selection and a hybrid Deep Convolutional Neural Network-Long Short-Term Memory (DCNN-LSTM) model for processing, the study highlights the effectiveness of a multi modal approach for real-time, accurate stress monitoring in clinical and industrial settings. It also integrates additional modalities and refines methods to enhance the system further, positioning AI-driven multimodal systems as powerful tools for early intervention and improved mental health management.

Keywords: Archimedes optimization algorithm (AOA), Deep Convolution Neural Network DCNN), Electrocardiogram (ECG), Electroencephalography (EEG), Long Short Term Memory (LSTM).

Stress significantly impacts health, leading to issues such as anxiety, accelerated heartbeat rate, and hypertension[1]. Financial pressures and demanding workloads worsen stress, creating emotional imbalances in adults and children. While various detection methods, including audio, video, and physiological sensors exist, physiological methods offer the most reliable results[2]. EEG signals effectively detect early-stage stress and improve clinical interventions, although artifact management and pattern interpretation challenges persist[3]. Acute stress also affects heart rate variability and ECG, highlighting stress management's importance in preventing arrhythmia [4]. Combining EEG and ECG for stress detection holds promise, as stress impacts the brain and cardiovascular system[5]. Multi modal bio-signal analysis enhances stress detection by clarifying bio-signal behavior under stress[6]. The research underscores the need for cost-effective, user-friendly systems that optimize machine-learning models and biological features[7]. Sensor fusion techniques, especially feature-level and score-level fusion, improve the accuracy and consistency of detection[8]. Hybrid models that combine Deep Convolutional Networks (DCNN) with Recurrent Neural Networks (RNN) offer enhanced accuracy [9]. This paper explores multi modal stress detection using EEG and ECG to improve classification accuracy over single-modality methods.

The paper is organized into four sections: Section 1 reviews the literature on mental stress detection, Section 2 presents the proposed methods for automated stress detection strategies, Section 3 analyses and evaluates the experimental results, and Section 4 concludes the study.

MATERIALS AND METHODS

Automated stress detection strategies

The research compares two automated stress detection strategies: the single-sensor strategy analyzes data from one source, and the multi-sensor fusion strategy combines data from multiple sensors to improve accuracy.

Dataset

This study detects stress by combining EEG data from the DEAP and ECG data from the WESAD datasets. It collects EEG signals from 32 participants (50% female, aged 19–37) using 32 active AgCl electrodes at 512 Hz during a 2-minute baseline and 40 video trials with self-assessments. Researchers record ECG data from 15 participants (average age 28) using a RespiBAN chest device. They preprocess and filter the data (0.5–40 Hz), remove artifacts, and segment it into epochs. With 244 paired samples (104 normal and 140 stress), the study examines how stress impacts brain and heart activity.

EEG\ECG Preprocessing

Preprocessing methods like filtering and artifact rejection eliminate noise and artifacts from raw EEG and ECG signals[27]. After preprocessing, the wavelet packet method splits the data into spectral components and reconstructs it to reduce interference and enhance clarity [28].

Extracting multiple EEG /ECG features

This study combines 513 EEG and 72 ECG features to assess stress levels efficiently. Critical brain signal properties associated with stress are captured by EEG features, which include statistical metrics, temporal patterns, and frequency-domain parameters. ECG characteristics reflect heart activity changes, which provide essential information on cardiovascular reactions to stress. These characteristics offer a thorough study that improves the suggested detection system's accuracy.

Multiple EEG features

Several EEG features, such as variance, mean, local gradient pattern (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, are extracted from the temporal and frequency domains in this stress detection study. As indicated in Table 1, these methods improve the representation of EEG signals by adding different time-domain and frequency-domain components.

This research extracts 513 EEG features that comprehensively capture the spectral, temporal, and spatial characteristics of brain signals. These features are vital for identifying patterns associated with stress.

Multiple ECG features

The ECG features essential for stress detection and monitoring include morphological features, which reveal structural changes in the heart. Hjorth's parameters capture dynamic behavior, while wavelet transform features and statistical parameters provide detailed insights into the signal. Researchers use impulsive metrics to detect sudden variations in heart activity. These features collectively reflect changes in heart function, enhancing the effectiveness of stress monitoring through ECG.

Analyzing 513 EEG features and 72 ECG features improves stress detection accuracy. EEG features like mean, variance, and wavelet packet transform (WPT) capture diverse brain signal properties, while ECG features such as morphological metrics and Hjorth's parameters reflect changes in heart activity.

Relevant features selection using the optimized Algorithm

Feature selection plays a crucial role in analyzing high-dimensional EEG and ECG data. Principal Component Analysis (PCA) reduces dimensionality but may discard valuable features, while Genetic Algorithms (G.A.) and Recursive Feature Elimination (RFE) effectively identify features but demand significant computational resources. The Archimedes Optimization Algorithm (AoA) addresses these challenges by balancing exploration and exploitation through a robust fitness function, optimizing convergence, and avoiding local minima. AoA generates and refines feature subsets to optimize feature selection for stress detection. Integrating AoA with the Analytical Hierarchy Process (AHP) further enhances this process by structuring decision-making hierarchically, assessing criteria like Covariance, Entropy, and the Ratio of Inter to Intra-class Variability. AHP conducts pairwise comparisons to prioritize the most indicative stress features and includes a consistency check to ensure reliable outcomes. This combined approach provides a robust, optimized feature selection for effective stress detection.

Classification techniques

Effective stress detection relies on advanced classification techniques that can accurately interpret complex patterns within physiological data, such as ECG and EEG signals. Two of the most prominent methods used for this purpose are Deep Convolutional Neural Networks (DCNNs) and Long Short-Term Memory (LSTM) networks.

Deep Convolutional Neural Networks (DCNNs)

Enhance stress detection by automatically learning and extracting spatial and temporal features from EEG and ECG signals. Each layer in a DCNN applies filters to generate feature maps highlighting stress-related patterns. The ReLU (Rectified Linear Unit) activation function applies a non-linear transformation, enabling the model to capture complex patterns in the data. Pooling layers reduce the spatial dimensions of feature maps, simplifying the model and improving computational efficiency. DCNNs adapt directly from the data, eliminating the need for predetermined features. Stacking deeper CNN layers improves feature correlation and representation. The convolution process uses $w \times w$ filters on the spectrogram to extract features.

From a 1D vector selected by AOA-AHP, the operation at each position (5ØeÜ, 5ØfÜ) is detailed in Equations 1.

$$C(x, y) = \text{Feat} * K \quad ...(1)$$

Where Feat represents the feature input, and K represents the convolutional kernel. The convolution process for a single dimension appears as follows:

$$C(x) = \sum_{n=1}^{N} \text{Feat}(x - n).K(n) \quad ...(2)$$

The Conv filter's weights start as random values and are optimized using the Adam algorithm. The B)N. layer normalizes the Conv layer's output, reducing internal covariance variation and lessening layer dependency. Negative values in the Conv layer output decrease feature non- linearity, so ReLU replaces negative values with zero, as shown in Equation 3.

$$\text{ReLU}(x,y)=\max\ (C(x,y),0) \quad ...(3)$$

The MaxPool layer selects significant features and minimizes size by choosing the highest value in a 2x2 pixel frame. Equation 4 calculates the maximum possible value from the ReLU layer output as follows.

$$MP.(x, y) = \max_{\substack{x=1:\,row-wm,\\ y=1:\,col-wm}} \{\text{ReLU}(x + wm - 1, y + wm - 1)\} \quad ...(4)$$

These processes illustrate how DCNNs extract, refine, and condense relevant stress-related features from EEG and ECG data, creating a more effective stress detection model.

B) Long Short-Term Memory (LSTM)

LSTM enhances recurrent neural networks (RNNs) by addressing vanishing and exploding gradient issues, common challenges in learning long-term dependencies in sequential data. It operates with the following equations at any time step t:

$$ft = \sigma (Wf \cdot [ht\text{-}1 ,xt]+bf) \quad ...(5)$$
$$it = \sigma (Wi \cdot [ht\text{-}1 ,xt]+bi) \quad ...(6)$$
$$ot = \sigma (Wo \cdot [ht\text{-}1 ,xt]+bo) \quad ...(7)$$
$$Ct\sim = \tanh (c \cdot [ht\text{-}1, xt] +bc) \quad ...(8)$$
$$Ct = ft \cdot Ct\text{-}1+ it \cdot Ct\sim \quad ...(9)$$
$$ht = ot \cdot \tanh(Ct) \quad ...(10)$$

The forget gate f_t determines what information to discard from the cell state, while the input gate decides which values to update. The output gate controls the cell's current output, and the candidate cell $C_t^{\sim}$ serves as a potential update. The updated cell state C_t combines the old.

State with the candidate state based on the gates' decisions, resulting in the hidden state output $!_t$ at time t. LSTM updates and outputs information from sequential data to detect stress using given equations. It captures complex patterns and retains essential information over long sequences. Combined with DCNNs, it improves reliability and accuracy by leveraging spatial and temporal features.

Multiple Sensor Fusion Strategy

Stress responses vary by individual, with some reacting differently to the same situation. A single sensor may detect stress in some but not others. Using multiple sensors improves detection, providing richer data for machine learning algorithms to create a more robust model[10].

The multiple-sensor fusion strategy includes two types: feature-level fusion, which combines data before feeding it into the model, and score-level fusion, applied after the model determines the outcome[11]. This study uses feature-level fusion through concatenation and score-level fusion with a weighted technique.

Feature-level fusion

Fusion technologies such as concatenation, PCA, LDA, and Min-Max fusion enhance model performance by integrating diverse data sources. Concatenation merges all feature sets into a single vector, preserving the complete information from different sources and often leading to better accuracy. Unlike PCA and LDA, which reduce or transform data and may lose essential details, or Min-Max fusion, which only normalizes scales, concatenation keeps all original features intact, providing a richer and more comprehensive input for models. As shown in Figure 2, the methodology of the Feature-level fusion approach combines features extracted from EEG and ECG signals to form a unified feature set.

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 improve model accuracy and robustness in stress detection by retaining all relevant features and enabling the learning of intricate patterns and interactions between EEG and ECG signals, as illustrated in Figure 3

As shown in Figure 3, Concatenation fusion merges raw feature vectors directly, preserving all data without transformation. The concerted fusion data passes to the classifier model for stress detection.

Score-level fusion

In score-level fusion, researchers independently train separate models on EEG and ECG data. Each model generates a stress detection score, which they merge using methods such as weighted fusion, averaging fusion, majority voting, or adaptive fusion. This study focuses on weighted fusion, applying weights to EEG and ECG scores, as illustrated in Figure 4.

Efficient fusion technology is critical in enhancing multimodal stress detection systems by integrating data from multiple physiological sources, such as EEG and ECG signals. This study implements feature-level fusion using a concatenation technique and score-level fusion through a weighted score-level technique.

RESULTS

The performance analysis of the suggested stress detection systems is shown in this section. It assesses individual sensor strategies using EEG and ECG data as well as numerous sensor fusion techniques, such as feature-level and score-level fusion. The investigation shows how hybrid DCNN-LSTM models, enhanced feature selection, and advanced preprocessing methods improve stress detection accuracy.

Experimentation on Individual Sensor Strategy

The analysis evaluates stress identification using separate EEG and ECG sensors. It highlights preprocessing methods, enhances feature selection, and applies hybrid DCNN-LSTM models to examine their impact on detection accuracy.

EEG Stress Detection Modal Implementation

This research detects stress using EEG by preprocessing signals and extracting related features. The system enhances accuracy using Wavelet Packet Transform, selects features with the AoA-AHP algorithm, and employs a hybrid DCNN-LSTM approach. Figure 5 presents the results, showing accurate stress detection based on features extracted from denoised EEG signals. The performance metrics confirm that increasing the number of relevant EEG features to 350 improves accuracy, recall, precision, and F1-score. The system achieves peak performance at 350 features, with 95.25% accuracy, 97 recall, 98 precision, and 98 F1-scores. Performance slightly declines beyond 350 features due to the inclusion of non-relevant features, confirming that selecting approximately 350 key features optimizes EEG-based stress detection.

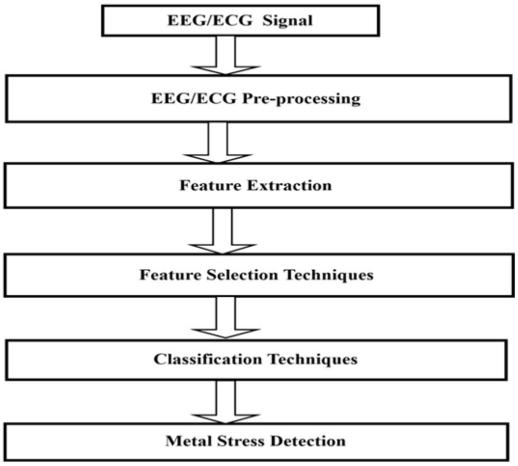

Fig. 1. Proposed Methodology for Individual Sensor Strategy

ECG Stress Detection Modal Implementation

The proposed ECG stress detection model enhances ECG signals using a Wavelet Packet.

Transform before extracting morphological, statistical, time-domain, and frequency-domain features. It then selects prominent features with the AOA-AHP optimization algorithm. It applies a hybrid of DCNN and LSTM deep learning techniques to improve feature distinctiveness and capture long-term temporal dependencies in the ECG signal.

Table 1. Extracted multiple EEG features

Feature Group	Feature Group Category	Features
1	Statistical Measure	Mean, SD, Variation, Median, Skewness
2	Temporal Feature	Activity, Mobility, Mobility
3	Non-linear &Energy Measure	Entropy, Non-linear Energy, Line Length
4	Pattern based feature extraction	LBP, LNDP, LGP
5	Energy and Frequency Measure	Energy, IWMF, IWBF
6	Wavelet Transform	WPT

Table 2. Extracted multiple ECG features

Feature Group	Feature Group Category	Features
1	Morphological Features	QRS duration, S.T. Segment, and 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	Peak Value, Crest, Impulse, and Clearance Factor
5	Hjorth's Parameters	Activity, Mobility, and Complexity

The proposed ECG stress detection model, shown in Figure 6, steadily improves performance metrics as the number of relevant features increases. With 50 features, it achieves peak performance, delivering 91.79% accuracy, 92 recall , 95 precision, and a 93 F1 score. Even as metrics slightly decline beyond this point, the model consistently detects stress effectively using distinct ECG features.

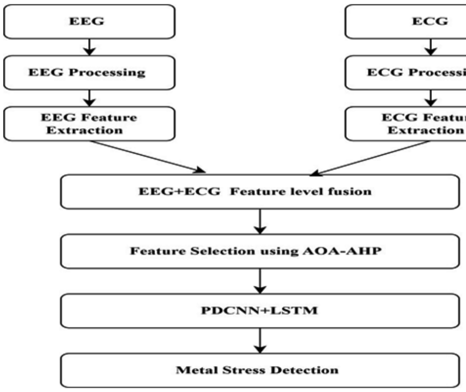

Fig. 2. Feature-level fusion

Experimentation on multiple sensor fusion strategy

This section explores AI-driven multimodal fusion strategies for stress detection by combining EEG and ECG data. It focuses on feature-level and score-level fusion techniques to improve accuracy and enhance stress detection performance using machine learning algorithms.

Feature-level fusion strategy study enhances stress detection by applying feature-level fusion of EEG and ECG data with machine learning algorithms. It combines features from both modalities to capture stress-related patterns. It evaluates traditional models like Decision Trees (C.T.), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Ensemble methods, as well as advanced deep learning models.

Figure 7 shows that the DCNN-LSTM algorithm achieves 97.3% accuracy in detecting

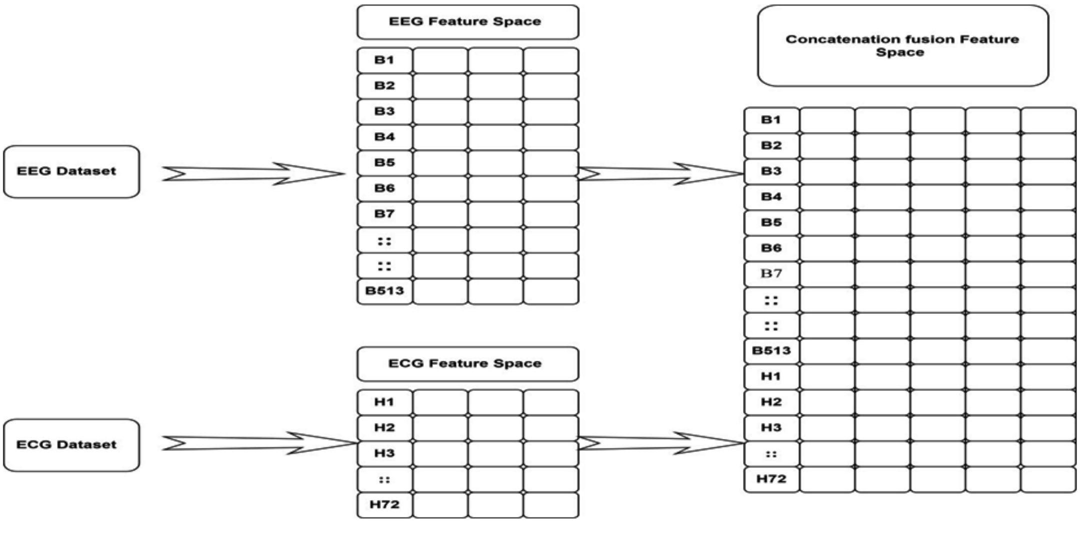

Fig. 3. Concatenation Feature level fusion

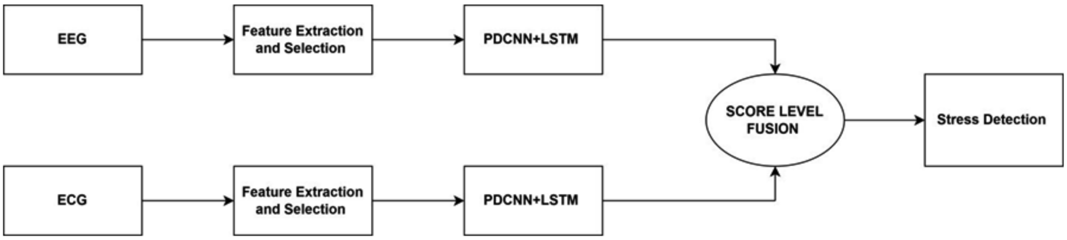

Fig. 4. Score-level fusion

stress from EEG and ECG signals, proving its effectiveness for real-time mental health monitoring. The model improves accuracy by denoising signals and applying the AoA-AHP technique to select critical features. Experiments reveal that AoA-AHP with 350 features achieves 98.6% accuracy, surpassing the 97.3% accuracy achieved with 586 features. This approach optimizes feature selection, reduces dimensionality, and enhances performance.

Score-level fusion strategy

This strategy improves stress detection accuracy by combining EEG and ECG scores using Equation 12

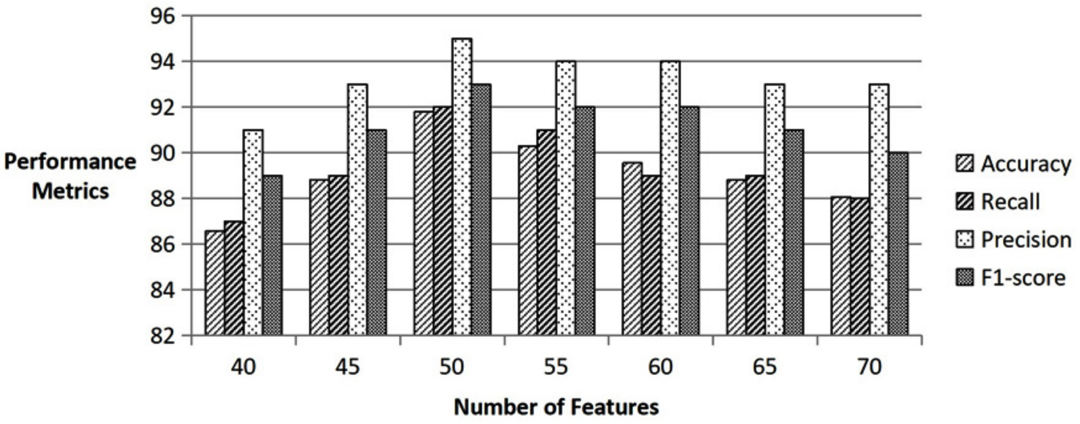

Fig. 5. Performance Metrics of EEG Stress Detection Modal

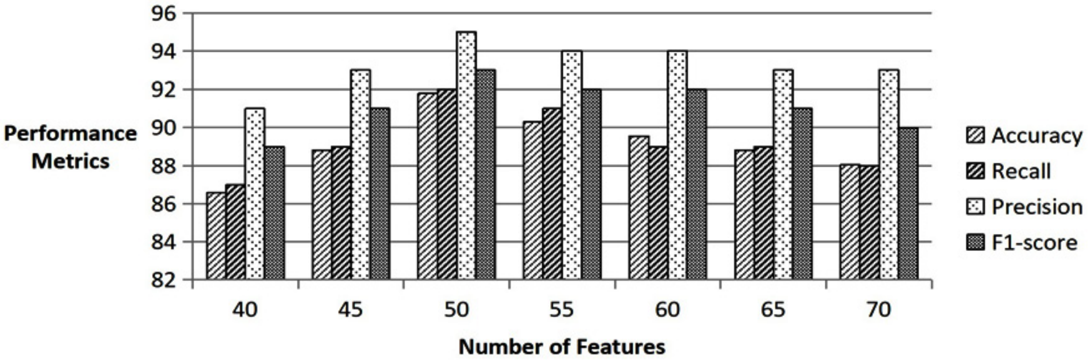

Fig. 6. Performance Metrics of ECG Stress Detection Modal

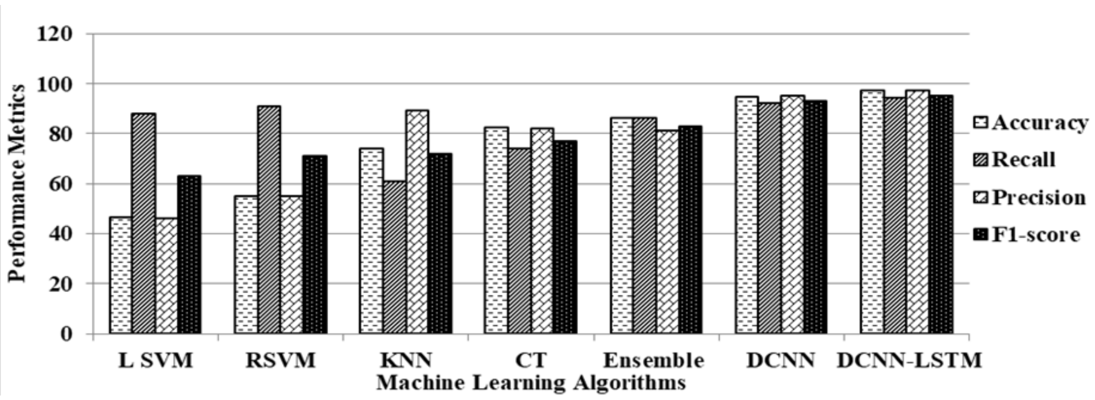

Fig. 7. Performance of Feature-level fusion Stress Detection Modal

$$\text{Final\_score} = (\alpha) \times \text{EEG\_score} + (1 -) \times \text{ECG\_score} \quad ...(11)$$

Where, (α) -Weight for the EEG score, (1-α) - Weight for the ECG score

The results demonstrate that á = 0.5 achieves the highest accuracy, as shown in Figure 8. Deviating from this value decreases performance, highlighting the importance of selecting the optimal weight factor for effective stress detection. With α = 0.5 yielding the best results, the system applies equal weights to EEG and ECG modalities across different algorithms, as presented in Figure 9.

DISCUSSION

This research investigates stress detection using advanced machine learning techniques and sensor fusion approaches to enhance accuracy and reliability. The study evaluates stress detection systems employing individual sensors (such as EEG and ECG) and multiple sensor fusion methods. The fusion strategies involve feature-level integration and score-level fusion, utilizing optimized algorithms such as DCNN-LSTM (Deep Convolutional Neural Network-Long Short-Term Memory) and AOA-AHP (Arithmetic Optimization Algorithm-Analytic Hierarchy Process). The comparison focuses on accuracy to assess the system's effectiveness in detecting stress.

The suggested stress detection systems, particularly those that incorporate feature-level and score-level fusion of EEG and ECG signals, surpass current leading methods regarding accuracy. The model achieves an impressive accuracy of 98.6% through feature-level fusion and 97.8% with score-level fusion, higher than the previous maximum accuracy of 93.27% reported by studies using a two-layer LSTM. This approach effectively

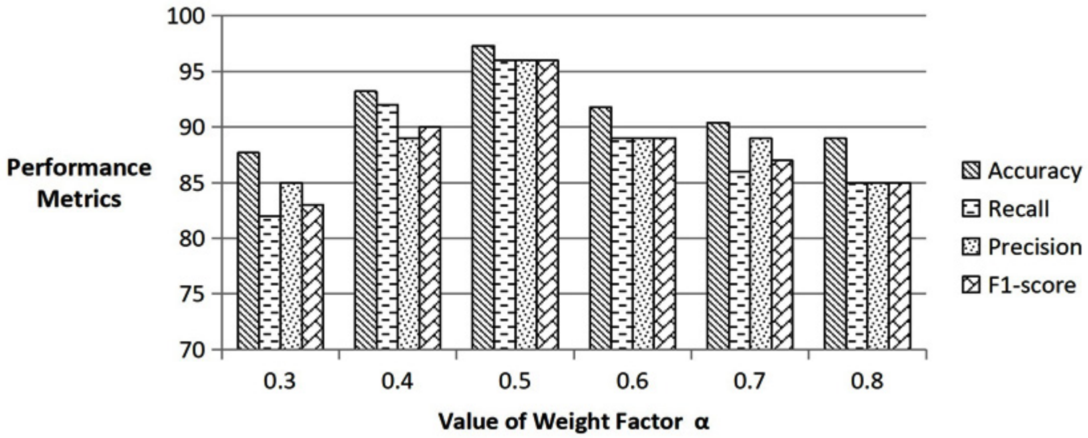

Fig. 8. Impact of Weight Factor α on Score-Level Fusion Performance

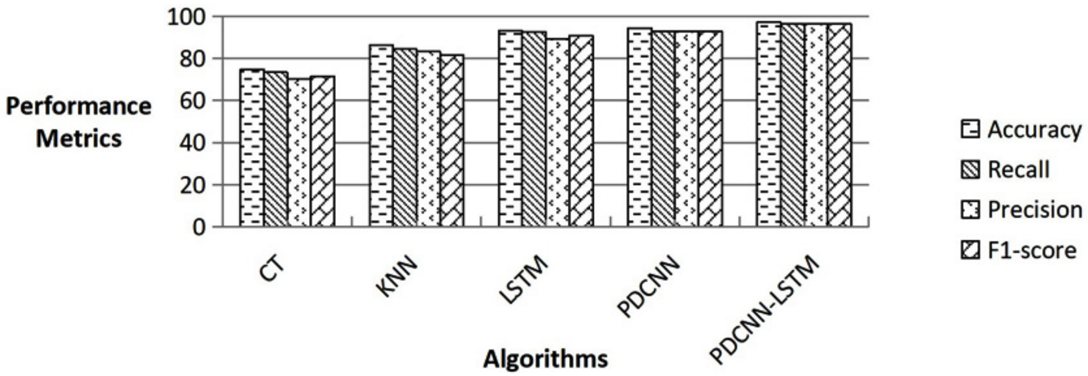

Fig. 9. Score-Level Fusion Performance at α = 0.5

Table 3. Performance Evaluation of Proposed Stress Detection Systems vs. State-of-the-Art

Reference	Biosignal used	Deep learning model	Accuracy
[12]	EEG	CNN	60.21%
[13]	EEG	Deep CNN	64.20%
[14]	EEG	CNN	77.90%
[15]	EEG	EEG-Conv	82.95%
[16]	EEG	3-D AlexNet CNN	86.12%
[17]	EEG	Symmetric DCAN	87.62%
[18]	EEG	2-D CNN	93.00%
[19]	EEG	Two-layer LSTM	93.27%
[20]	EEG	ConNet + LSTM	84.48%
[21]	EEG	GWO+ BLSTM	82.57%
[22]	ECG, EDA	FDA	87.5%
[23]	ECG,EDA, BVP	ANN	79%
[24]	EEG, ECG	PCA, SVM	79.54%
[25]	EEG, ECG, EMG	LDA	86.0%
[26]	EEG, ECG, EDA	PCA,SVM	86.0%
Proposed modal	ECG	PDCNN+LSTM	91.79
	EEG		96.5
	EEG+ECG (FeatureLevel fusion)		98.6
	EEG+ECG (ScoreLevel fusion)		97.8

identifies stress by utilizing cutting-edge deep-learning models and techniques that integrate data from multiple sensors.

CONCLUSION

The comparison of AI-powered multi modal stress detection demonstrates the crucial advantages of combining several sensors and sophisticated feature selection methods. The stress detection accuracy is increased by combining EEG and ECG signals with the Archimedes Optimization Algorithm (AoA) and Analytical Hierarchical Process (AHP) for feature selection and by employing a hybrid DCNN-LSTM model. The accuracy of feature-level fusion reaches 98.6%, score-level fusion reaches 97.8%, ECG stress detection increases from 88.6% to 91.79%, and EEG detection improves from 95% to 96.6%. These findings highlight the multi modal approach's efficacy in enhancing precise, real-time stress monitoring in clinical and industrial contexts. By incorporating more modalities and improving techniques, the study demonstrates the possibility of further improvements, solidifying AI-driven multi modal stress detection as a viable instrument for early intervention and better mental health.

ACKNOWLEDGMENTS

The authors extend their gratitude to the creators and contributors of the DEAP and WESAD datasets. We also appreciate the support from our colleagues in the E & TC Department of PCCOE and our research center, along with the unwavering support from our families and friends.

Funding Sources

The author(s) received no financial support for this article's research, authorship, and publication.

Conflict of Interest

The author(s) do not have any conflict of interest.

Data Availability Statement

This statement does not apply to this article.

Ethics Statement

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

Informed Consent Statement

This study does not involve human participants, so it does not require informed consent.

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 wrote and edited the manuscript; Ajay Paithane: Visualized and supervised the project, managed administration, and reviewed and editedthe manuscript.

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