Detection of Stress Levels Using Biomedical Signals and Artificial Intelligence

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Abstract: Stress is a state that occurs when an individual's physical and mental resources are taxed in response to demands, becoming especially evident under heavy mental exertion. Mental workload is a significant psychophysiological metric that directly influences task performance and can also lead to mental diseases such as depression. Thus, the objective evaluation of stress levels using physiological data is crucial for enhancing work productivity and assuring safety. This work employed an integrated approach utilizing electrocardiography (ECG) and photoplethysmography (PPG) signals for stress detection. The data were sourced from the publically accessible MAUS dataset and gathered from 22 healthy participants utilizing wearable sensors during N-back activities. The signals were segmented into epochs, and a total of 50 features were extracted at both temporal and spectral levels. The features were examined utilizing diverse machine learning algorithms. The models' performance is assessed using accuracy, specificity, F-score, and AUC criteria, with the Bagged Trees method achieving the greatest accuracy of 98.6%. The results indicate that employing several biosignals and sophisticated signal processing techniques provides excellent precision in stress detection. The device provides a pragmatic option for real-time monitoring of individuals' stress levels in their daily lives, thanks to its portable design.

Keywords: *Component; Photolethysmography(PPG), Electrocardiography(ECG), Stress Detection, Machine Learning, Biomedical Signal Processing, Artificial Intelligence.*

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I. INTRODUCTION

Stress is a psychological condition characterized by the comprehensive array of coping mechanisms in reaction to a perceived threat. It has garnered extensive scientific attention owing to its influence on an individual's health and performance. While acute stress is linked to numerous physiological and psychological diseases, it may also yield advantageous outcomes in certain instances. Consequently, it is essential to empirically examine it using approved stressors capable of eliciting various forms of stress. To diminish reliance on subjective questionnaires for stress evaluation, physiological signals offer more objective and individualized input. Electrocardiography (ECG) data, utilized to evaluate alterations in heart rate and rhythm, have proven to be markedly successful in assessing the impacts of stress. Photoplethysmography (PPG) signals are an excellent means of assessing stress responses through vasodilation, blood volume, and peripheral circulation.

In contemporary society, stress is a prevalent issue jeopardizing both the physical and emotional well-being of individuals. Stress is recognized as a precursor to severe diseases, including hypertension, cardiovascular disease, depression, and anxiety over time. Consequently, the prompt and precise identification of stress is crucial for preventive healthcare services. Despite the plethora of strategies presented in the literature for stress detection utilizing diverse biophysical signals, many of these approaches concentrate on singular signal sources, resulting in classification accuracy rates typically confined to 70–85%. Utilization of individual signals: Electrodermal activity (GSR or EDA), Electroencephalography (EEG), Heart rate variability (HRV), Photoplethysmography (PPG), Electrocardiograms (ECG), and respiration signals. This singular application is especially susceptible to signal aberrations in mobile contexts or real-world circumstances, rendering precise stress categorization challenging [18]. Conversely, the integration of various biosignal sources (e.g., PPG and ECG) facilitates more reliable and precise stress detection [17],[18]. Moreover, a notable deficiency in the literature is the lack of evaluation of these signals by modern signal processing and feature extraction techniques, resulting in suboptimal data quality [19].

Current methodologies for stress detection in the literature predominantly rely on singular biosignal sources, hence constraining their classification accuracy. Moreover, several studies assess signals in their unprocessed state, neglecting to fully utilize the advantages provided by sophisticated feature extraction and signal processing methodologies. This work will rectify these deficiencies by integrating ECG and PPG signals, administering experimental stress-inducing activities to participants, and conducting feature extraction in both time and frequency domains by segmenting the acquired signals into temporal epochs. The collected features will be input into various machine learning algorithms, and their performance will be assessed according to accuracy, specificity, F-measure, and AUC metrics. A unique methodology will be proposed to address the existing limitations in the literature, facilitating the accurate categorization of stress through the integration of many biosignals and advanced signal processing techniques.

II. MATERIAL AND METHOD

The technical sections of this study were encapsulated in Figure 1. Thus, ECG and PPG signals were obtained from the individuals. The acquired raw were filtered to eliminate noise and artifacts and segmented into designated time intervals (epochs). For each epoch, twenty-five features were extracted from both the time and frequency domains, resulting in a total of fifty features. Subsequently, various machine learning algorithms were trained utilizing these extracted features, and stress classification was conducted employing these models.

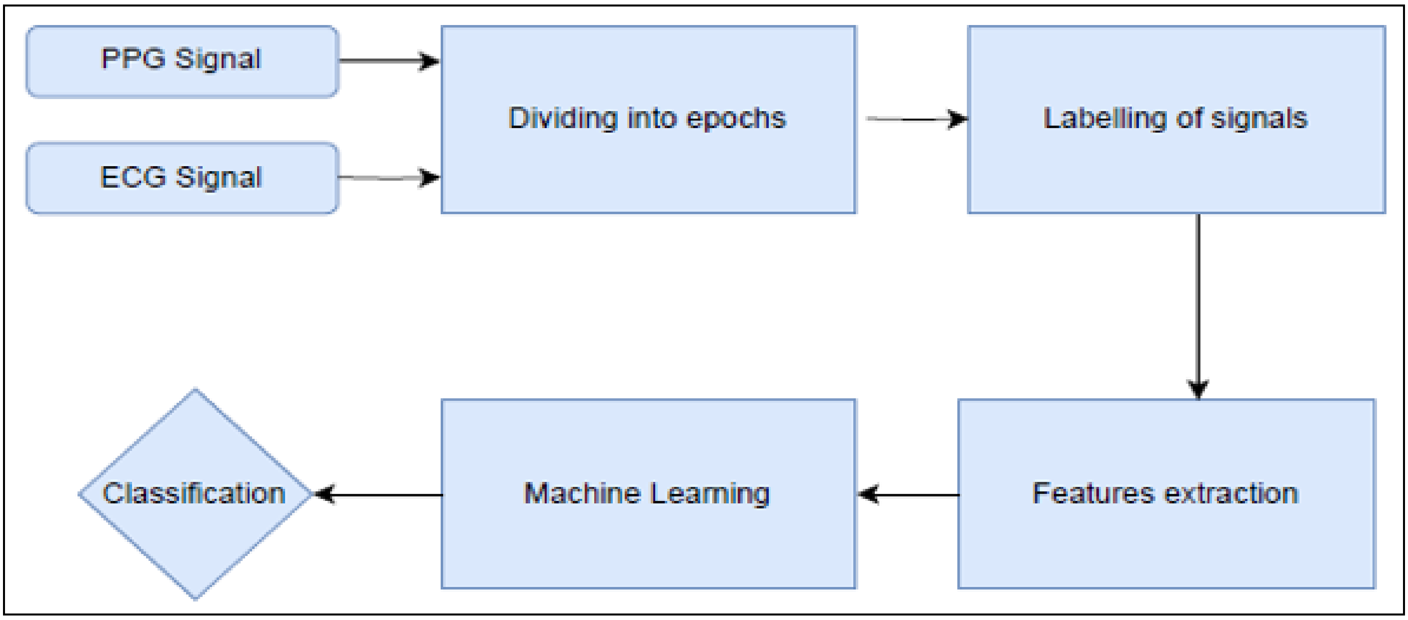

Fig 1 Flow Diagram

➢ *Data Collection*

The dataset included in the constructed model has been the publicly available MAUS (Mental Workload Assessment on N-back Task Using Wearable Sensor) dataset, which has comprised various physiological signals acquired via wearable devices [24]. The dataset has been methodically assembled for the evaluation of mental effort (MW) and has comprised ECG, fingertip PPG, wrist PPG, and GSR recordings. This has facilitated analysis of both individual biosignal sources and the combination of many signals.

The experimental technique has included the N-Back test presented to participants. In this activity, participants have monitored a sequence of rapidly displayed numbers and have been required to determine if the current number matched the nth preceding number. The activities have been arranged to progressively elevate cognitive burden (0→2→3→2→3→0). The 0-back test has indicated a low cognitive load, whereas the 2- and 3-back tasks have imposed high cognitive load conditions [23]. This configuration has guaranteed the systematic generation of varying degrees of cognitive demand.

The participant group has comprised 22 healthy volunteers (20 males, 2 females) with a mean age of 23±1.7 years. All subjects have provided informed consent prior to the experiment. At the outset of the trial, a 5-minute rest period has been observed, during which the Pittsburgh Sleep Quality Index (PSQI) questionnaire has been administered. Subsequent to each N-Back experiment, the NASA Task Load Index (NASA-TLX) scale has been utilized to document subjective assessments of cognitive workload. Consequently, subjective evaluations have been gathered in conjunction with physiological signs, enhancing the dataset [23], [25].

The recordings have been executed with two distinct devices. The ProComp Infiniti system has delivered superior reference data with a sampling frequency of 256 Hz, capturing ECG, GSR, and fingertip PPG signals. ECG recordings have been acquired in a single channel by electrodes affixed to the body, while fingertip PPG has been recorded using a sensor attached with an elastic band. A PixArt wrist-mounted PPG watch has been utilized to replicate a wearable technology scenario. This green LED sensor has operated at a frequency of 100 Hz and has communicated data to a tablet computer

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using Bluetooth. Consequently, both reference recordings exhibiting excellent accuracy in laboratory settings and data acquired from portable devices suitable for everyday usage have been consolidated into a single database.

The MAUS dataset has comprised over 35 minutes of physiological measurements, encompassing raw signals, participant responses, N-Back task recordings, and subjective questionnaire outcomes. The dataset has been distinguished as one of the most extensive open-access datasets utilized in research on stress and mental workload classification.

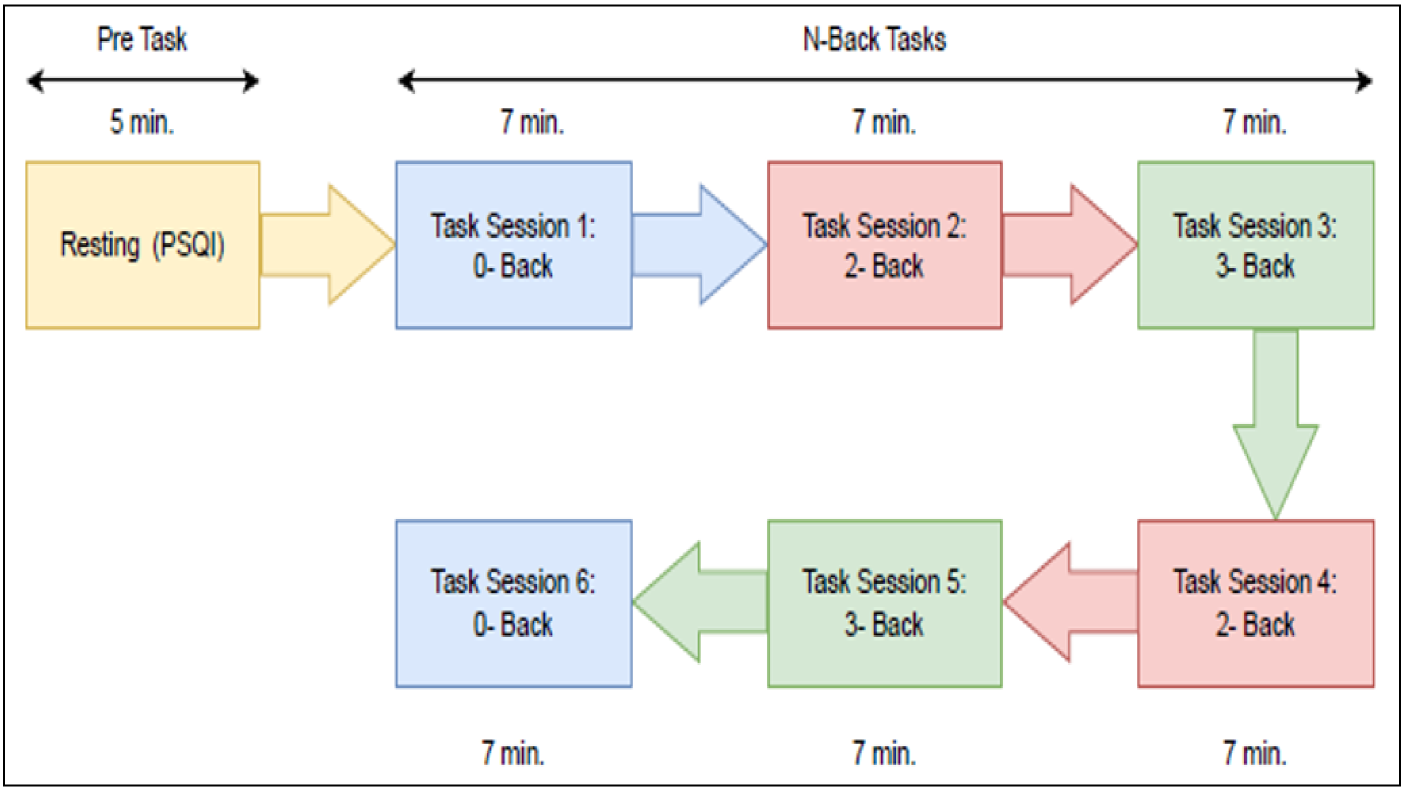

Fig 2 Dataset Tasks

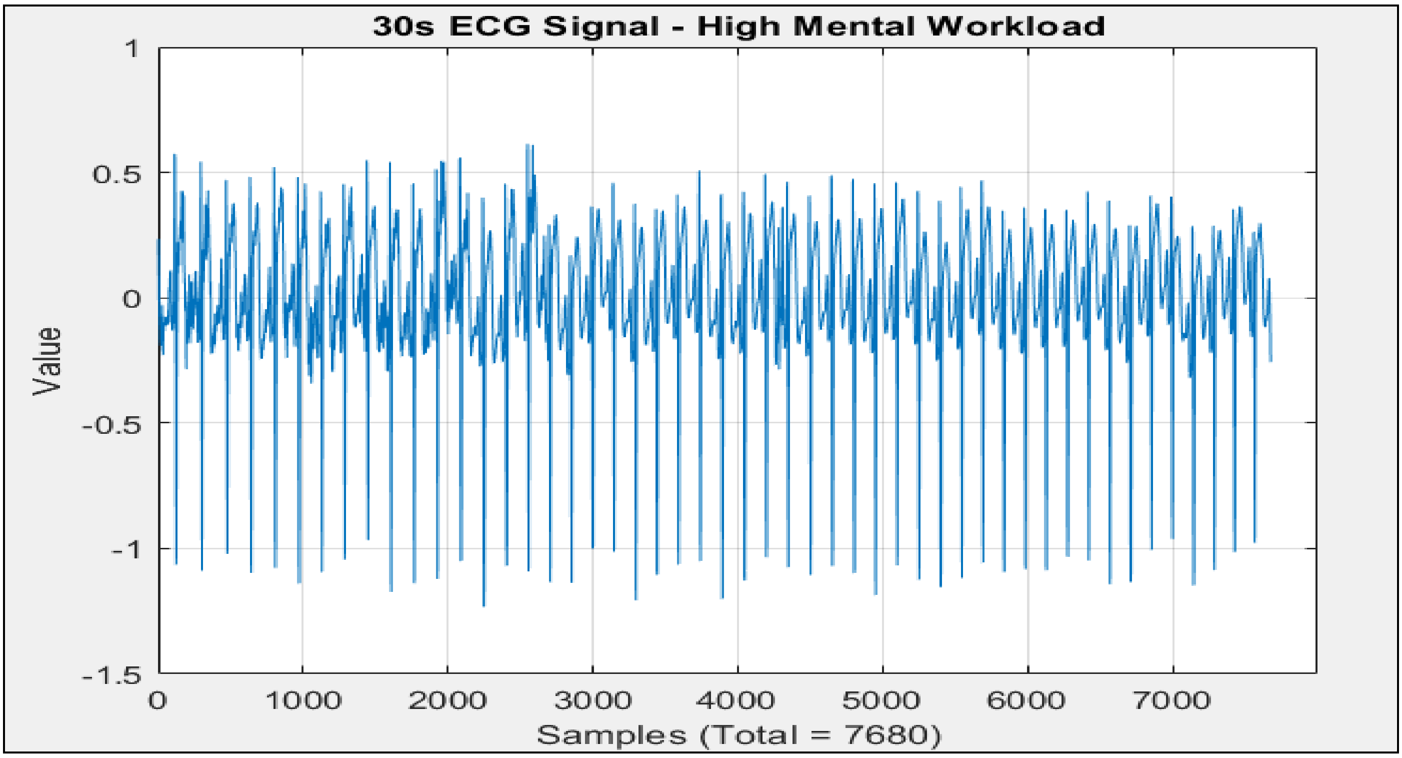

Fig 3 Plot of 30 Sec ECG High Mental Workload

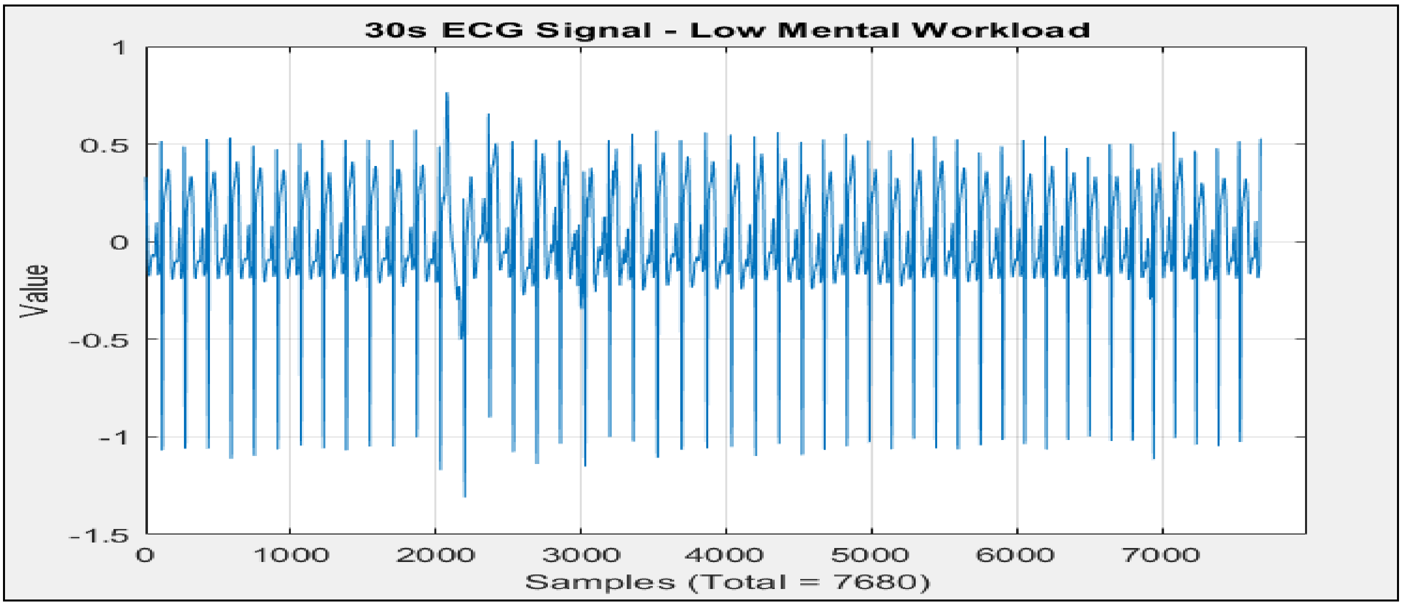

Fig 4 Plot of 30 Sec ECG Low Mental Workload

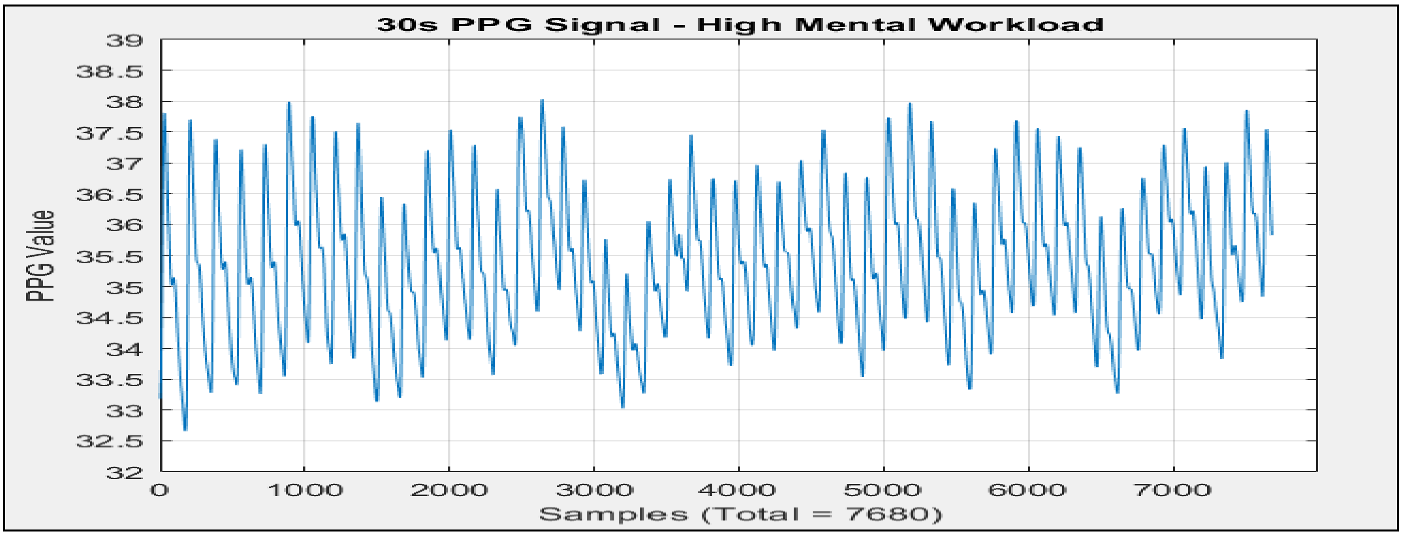

Fig 5 Plot of 30 Sec PPG High Mental Workload

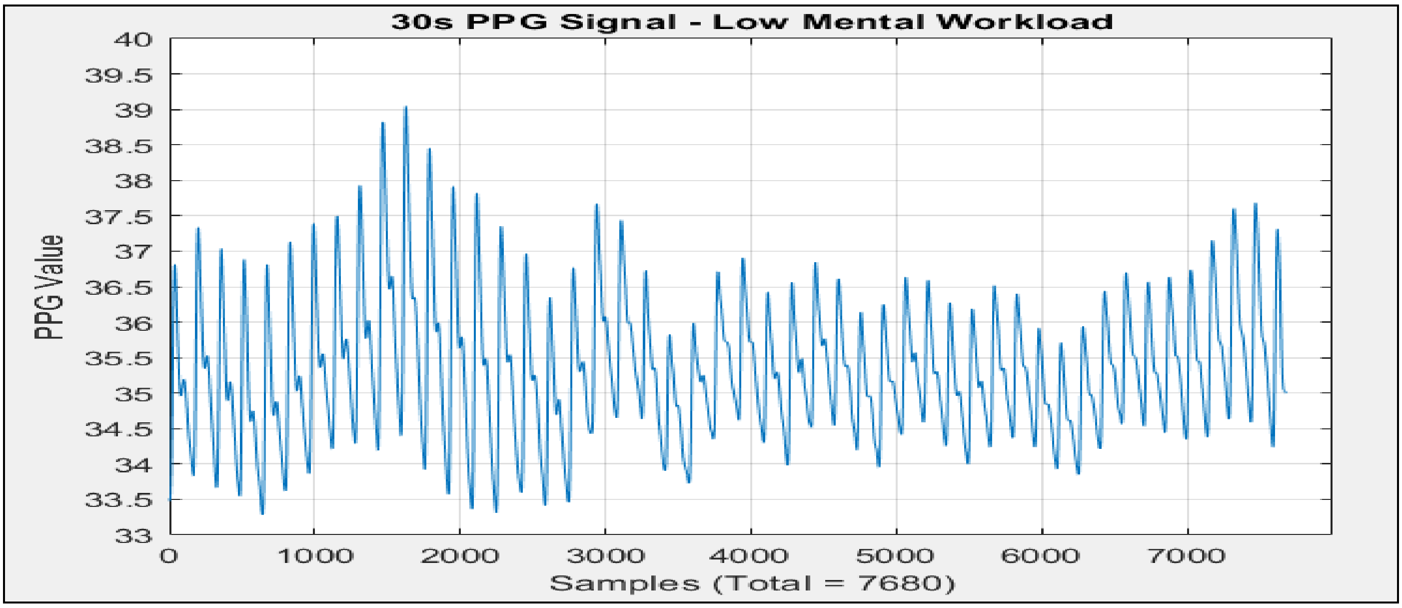

Fig 6 Plot of 30 Sec PPG Low Mental Workload

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➢ *Feature Extraction*

ECG and PPG signals were segmented into 10-second intervals. Following epoching, a total of 50 features were extracted from the time domain, comprising 25 from the ECG signal and 25 from the PPG signal. The extracted features have been presented in Table 1 over three columns: feature number, feature, and formula. The variable x in the equations denotes the signal. The equations demonstrate the variances. S^2 indicates the variance of the x signals, S_1^2 indicates the variances of first derivative of the x signal and S_2^2 indicates the variance of the second derivative of the x signal.

Table 1 Equations for Features

No	Feature	Equation
1	Kurtosis	$x_{kur} = \dfrac{\sum_{i=1}^{n}(x(i)-\bar{x})^4}{(n-1)S^4}$
2	Skewness	$x_{ske} = \dfrac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{(n-1)S^3}$
3	IQR	$\mathrm{IQR} = \mathrm{iqr}(\mathrm{x})$
4	CV	$CV = (S/\bar{x})100$
5	Geometric Mean	$G = \sqrt[n]{x_1 + ... + x_n}$
6	Harmonic Mean	$H = n/(\dfrac{1}{x_1} + ... + \dfrac{1}{x_n})$
7	Activity-Hjort parameters	$A = S^2$
8	Mobility-Hjort parameters	$M = S_1^2 / S^2$
9	Complexity-Hjort parameters	$C = \sqrt{(S_2^2 / S_1^2)^2 - (S_1^2 - S^2)^2}$
10	Maximum	$x_{\max} = \max(x_i)$
11	Median	$\tilde{x} = \left(\begin{array}{ll} \dfrac{x_n + 1}{2} & x = odd \\ \dfrac{1}{2}(x_{\frac{n}{2}+} + x_{\frac{n}{2}+1} + & x = even \end{array} \right)$
12	Mean absolute deviation	$\mathrm{MAD} = \mathrm{mad}(\mathrm{x})$
13	Minimum	$x_{\min} = \min(x_i)$
14	Central moments	$CM = moment(x,10)$
15	Mean	$\bar{x} = \dfrac{1}{n}\sum_{i=1}^{n} = \dfrac{1}{n}(x_1 + ... + x_n)$
16	Avarage curve length	$CL = \dfrac{1}{n}\sum_{i=2}^{n} \| x_i - x_{i-1} \|$
17	Avarage energy	$E = \dfrac{1}{n}\sum_{i=1}^{n} x_i^2$
18	Root mean squared	$x_{rms} = \sqrt{\dfrac{1}{n}\sum_{i=1}^{n} \| x_i \|^2}$
19	Standart error	$S_{\bar{x}} = S / \sqrt{n}$

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20	Standart deviation	$S=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})}$
21	Shape Factor	$SF = Xrms/(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i \rvert})$
22	Singular value decomposition	$\mathrm{SVD}=\mathrm{svd}(\mathrm{x})$
23	25%trimmed mean	$\mathrm{T25}=\mathrm{trimmean}(\mathrm{x},25)$
24	50%trimmed mean	$\mathrm{T50}=\mathrm{trimmean}(\mathrm{x},50)$
25	Average Teager energy	$TE=\frac{1}{n}\sum_{i=3}^{n}(x_{i-1}{}^{2}-x_i x_{i-2})$

➢ *Machine Learning*

After the feature extraction phase, the data was allocated into test and training datasets before classification, with each task designated a label to facilitate classification.

Numerous supervised learning techniques for data classification were employed, including Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbor (KNN), Artificial Neural Networks (Medium NN and Wide NN), Logistic Regression (LR), and Decision Tree (DT). The outcomes derived from this model were delineated and examined in the subsequent section. The MATLAB Classification Learner application was utilized for classification purposes.

➢ *Performance Evaluation Criteria*

To assess the efficacy of the classification models employed in the study, the parameters of accuracy, specificity, F-score, and AUC have been utilized [20], [21], with these performance measures delineated by equations (1)-(6).

$$\text{Accuracy}=\frac{\text{True Positive(TP)+True negative(TN)}}{\text{Total population}} \quad (1)$$

$$\text{Specificity}=\frac{\text{TN}}{\text{TN+FP(False Positive)}} \quad (2)$$

$$\text{F1-Score}=2\text{x}\,\frac{\text{PrecisionxRecall}}{\text{Precision+Recall}} \quad (3)$$

$$AUC=\int_{0}^{1}TPR(FPR)d(FPR) \quad (4)$$

$$\text{TPR=Sensitivity}=\frac{\text{TP}}{\text{TP+FN(False Negative)}} \quad (5)$$

$$\text{FPR=1-Specificity} \quad (6)$$

III. RESULTS

This work has involved the training and evaluation of various machine learning algorithms for stress categorization. The findings were compared according to accuracy, specificity, F-measure, and AUC metrics. Table 2 encapsulates the performance characteristics of the implemented model.

The Bagged Trees model has the maximum efficacy, achieving an accuracy rate of 98.6%, specificity of 99.3%, an F1-score of 0.986, and an AUC of 0.999. This outcome illustrates a strong equilibrium in differentiating between positive and negative classes, indicating a high level of classification reliability. The Bagged Trees method is founded on the bootstrap aggregating (bagging) methodology introduced by Breiman. This method involves training several decision trees on bootstrap samples of the training dataset, with the final predictions aggregated through majority voting. This diminishes model variance and enhances classification accuracy relative to an individual decision tree [44].

Likewise, the Medium Neural Network and Wide Neural Network models have garnered interest with F1-measure scores above 98.5% and 0.985, indicating that intricate correlations within signals can be proficiently learned by artificial neural networks. Support Vector Machines and Boosted Trees, a tree-based approach, have attained accuracy rates of 97%, demonstrating their efficacy as formidable alternatives in stress classification. Specificity scores of 98% demonstrate that the models possess great dependability in accurately categorizing non-stressful circumstances. Likewise, the F1-measure indicates that the model demonstrates equitable performance regarding both sensitivity and accuracy in imbalanced classification contexts. AUC values approaching or exceeding 0.99 indicate that all models exhibit robust discriminatory capability across various threshold values and affirm the system's stability.

In conclusion, the results indicate that employing several biosignals and sophisticated machine learning techniques yields excellent precision in stress detection. The simplicity of recording ECG and PPG signals with wearable sensors, along with their superior accessibility relative to

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other biosignals, facilitates the integration of this technology into portable systems. This feature enables the established approach to offer an architecture conducive to continuous and real-time monitoring of stress levels in both laboratory settings and real-world scenarios. Consequently, the system functions as an effective tool for monitoring individuals' mental health condition in everyday life and facilitating early interventions.

Table 2 Machine Learning Models and Accuracy, Specificity, F1-Score and AUC

Model	Accuracy	Specificity	F1-Score	AUC
Bagged Tress	0.986	0.993	0.986	0.999
Medium Neural Network	0.985	0.993	0.985	0.9976
Wide Neural Network	0.9854	0.9927	0.9853	0.9982
Cubic SVM	0.9828	0.9914	0.9827	0.9982
Quadratic SVM	0.9807	0.9903	0.9807	0.9984
Boosted Trees	0.9779	0.989	0.9779	0.999
Fine Tree	0.9778	0.9889	9.9778	0.9931
Medium Gaussian SVM	0.976	0.988	0.976	0.9989
SVM Kernel	0.972	0.986	0.9719	0.9993
Fine KNN	0.9694	0.9847	0.9694	0.9991
Weighted KNN	0.9694	0.9847	0.9694	0.9992
Medium Tree	0.9633	0.9816	0.9633	0.9896
Medium KNN	0.9630	0.9810	0.9630	0.9991
Cosine KNN	0.9628	0.9814	0.9627	0.9987
Logistic Regression Kernel	0.9593	0.9797	0.9593	0.9982
RUSBoosted Trees	0.9561	0.9780	0.9562	0.9904
Fine Gaussian SVM	0.9554	0.9777	0.9553	0.9992
Cubic KNN	0.9530	0.9760	0.9530	0.9987
Linear SVM	0.9256	0.9628	0.9258	0.9923

Table 3 Comparison with Existing Stress Detection Studies

Articles	Method	Accuracy	F1-Score	AUC
[31]	KNN	%76.67	-	-
[32]	SVM	%68.7	-	-
[33]	Linear SVM	%74	-	-
[34]	Hybrid CNN	%75	0.64	-
[35]	ResAttNett	%80	0.87	-
[36]	CNN	%78.8	0.79	0.95
[37]	SVM, KNN, DT	%88.9	-	-
[38]	SVM,KNN,DT,ANN(Artificial Neural Network)	%85.6	-	-
[39]	KNN,NB,RF,SVM	%80.4	-	-
[40]	Deep Learning	%89.9	0.90	0.89
[22]	DNN (Deep Neural Network)	%91.6	0.914	0.964
[41]	RF(Random Forest)	%92	-	0.96
[43]	LightGBM, RF, Gaussian Naive Bayes	%93	0.92	-
[42]	SVM	%94	-	-

IV. DISCUSSION

The objective of the study is to create a functional, artificial intelligence-driven system to assess individuals' exposure to stress due to their everyday activities and implement required interventions to safeguard them against stress-related ailments.

For the developed diagnostic systems to be realistically relevant, they must achieve a minimum accuracy rate of 0.8. A Kappa coefficient between 0.81 and 1.00 indicates a very good degree of agreement. The nearer other performance metrics are to 1, the more effective the designed system becomes. The F-measure is a metric that facilitates a balanced and thorough assessment of model performance by concurrently evaluating sensitivity and specificity. Upon evaluation of these performance metrics, the model exhibits superior performance relative to the existing literature [26].

Table 3 presents studies from the literature about stress under mental load utilizing MAUS and various datasets, along with the machine learning methodologies employed, accuracy rates, F1-measures, and AUC values. Research utilizing physiological markers in the literature has typically demonstrated low accuracy rates. Kuttala et al. [29] integrated EDA and ECG signals with a multimodal hierarchical CNN-based feature fusion method, although the accuracy rate was merely 76.1%. Beh et al. [30] implemented outlier elimination and uncertainty estimating techniques in PPG-based assessment, attaining an accuracy

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rate of 74.2%. Aydemir et al. [31] retrieved wavelet-based characteristics from PPG signals, achieving an average accuracy of 76.67%. These findings unequivocally illustrate the constraints of single-signal methodologies.

Investigations on HRV in the literature have consistently exhibited constrained accuracy levels. Quoy et al. [27] documented an F1-score of about 80% using an HRV-based CNN model; nevertheless, efficacy was constrained by the absence of multi-signal integration. Conversely, multimodal investigations utilizing the WESAD dataset introduced by Reiss et al. [28] attained an accuracy of up to 93%. Nonetheless, the diversity of sensors employed and the challenges in data acquisition diminish the system's practical utility.

Mozos et al. [42] identified stress by EDA, BVP, PPG, and activity signals, attaining 94% accuracy; nonetheless, the concurrent monitoring of four distinct biosignals presents significant practical obstacles. Sadoun et al. [43] attained 93% accuracy in a cognitive stress diagnosis investigation utilizing EEG and ECG signals during physical exercise, implementing the Light GBM machine learning technique alongside the Limit Visibility Graph (LPVG). Nonetheless, the implementation of LPVG prolongs computational duration in real-time applications.

This work built a machine learning algorithm to assess individuals' stress levels via ECG and PPG signals. Numerous time- and frequency-domain statistical features were derived from the acquired biosignals, and these data were assessed utilizing various classification techniques. The classification performance was evaluated using multiple measures, including accuracy, specificity, F1-score, and AUC. Significantly, Bagged Trees and Neural Network-based models exhibited exceptional performance. ECG and PPG data, representing an individual's physiological reactions from distinct perspectives, can more consistently differentiate between stressed and non-stressed states when utilized in conjunction.

This discovery corroborates the system's capability to deliver equitable and dependable classification in application. This study, however, possesses certain drawbacks. The dataset, acquired under particular settings and from a restricted participant pool, necessitates validation for generalizability with more diverse demographic groupings in future research. Future research is to convert the proposed system into a viable and sustainable monitoring solution that facilitates continuous and real-time assessment of individuals' stress levels through integration with mobile health technology and clinical monitoring frameworks.

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REFERENCES

[1]. Y. Liu and S. Du, "Psychological stress level detection based on electrodermal activity," Biol. Psychol., vol. 169, pp. 1–7, 2022, doi: 10.1016/j.biopsycho.2022.108382.
[2]. H. Kurniawan, A. V. Maslov, and M. Pechenizkiy, "Stress detection from speech and galvanic skin response signals," unpublished, Dept. of Computer Science, Eindhoven Univ. of Technology, Netherlands, 2023.
[3]. S. B. Dasari, C. T. Mallareddy, S. Annavarapu, and T. T. Garike, "Detection of mental stress levels using electroencephalogram signals (EEG)," unpublished, VR Siddhartha Engineering College, India.
[4]. [7] P. Samal and R. Singla, "EEG based stress level detection during gameplay," unpublished, Dept. of ICE, Dr. B. R. Ambedkar NIT Jalandhar, India.
[5]. J. Guo and K. G. Smitha, "EEG based stress level identification," unpublished, School of Computer Science and Engineering, Nanyang Technological University, Singapore.
[6]. T. Y. Wen and S. A. M. Aris, "Hybrid approach of EEG stress level classification using K-means clustering and support vector machine," unpublished, Universiti Teknologi Malaysia.
[7]. G. Giannakakis, K. Marias, and M. Tsiknakis, "A stress recognition system using HRV parameters and machine learning techniques," in Proc. 2019 8th Int. Conf. Affective Comput. Intell. Interact. Workshops and Demos (ACIIW), 2019, pp. 269–272, doi: 10.1109/ACIIW.2019.8925027.
[8]. S. Quoy, D. Istrate, M. Benchekroun, and V. Zalc, "HRV based stress detection using convolutional neural networks (CNNs)," in Proc. 2024 Int. Conf. Content-Based Multimedia Indexing (CBMI), 2024, pp. 20–24, doi: 10.1109/CBMI62980.2024.10859222.
[9]. Y. Hasanpoor, B. Tarvirdizadeh, and K. Alipour, "Stress assessment with convolutional neural network using PPG signals," in Proc. IEEE India Council Int. Conf. (INDICON), 2022, pp. 197–202, doi: 10.1109/INDICON.2023.10440913.
[10]. J. Přibil, A. Přibilová, and I. Frollo, "Stress detection and classification from PPG signals recorded in different conditions – pilot study," unpublished, Dept. of Imaging Methods, Institute of Measurement Science, Slovak Academy of Sciences, Bratislava, Slovakia, 2022.
[11]. J. Zhai and A. Barreto, "Stress detection in computer users based on digital signal processing of noninvasive physiological variables," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), 2006, pp. 1355–1358, doi: 10.1109/IEMBS.2006.259421.
[12]. M. Gjoreski, M. Luštrek, M. Gams, and H. Gjoreski, "Monitoring stress with a wrist device using context," Sensors, vol. 22, no. 4, p. 1443, 2022, doi: 10.3390/s22041443.
[13]. P. Kasnesis, C. Chatzigeorgiou, M. Feidakis, Á. Gutiérrez, and C. Z. Patrikakis, "TranSenseFusers: A temporal CNN-Transformer neural network family for explainable PPG-based stress detection," Comput.

Biol. Med., vol. 165, p. 107537, 2023, doi: 10.1016/j.compbiomed.2023.107537.

[14]. P. Nagy and A. Jobbágy, "Sensor fusion for the accurate non-invasive measurement of blood pressure," Med. Eng. Phys., vol. 105, p. 103927, 2022, doi: 10.1016/j.medengphy.2022.103927.

[15]. J. Wijsman, B. Grundlehner, H. Liu, H. Hermens, and J. Penders, "Towards mental stress detection using wearable physiological sensors," unpublished, 2023.

[16]. N. Keshan, P. V. Parimi, and I. Bichindaritz, "Machine learning for stress detection from ECG signals in automobile drivers," unpublished, State Univ. of New York at Oswego, USA.

[17]. R. K. Nath, H. Thapliyal, A. Caban-Holt, and S. P. Mohanty, "Machine learning based solutions for real-time stress monitoring," unpublished, Univ. of Kentucky and Wake Forest School of Medicine, 2023.

[18]. S. Campanella, A. Altaleb, A. Belli, P. Pierleoni, and L. Palma, "PPG and EDA dataset collected with Empatica E4 for stress assessment," unpublished, Università Politecnica delle Marche, Italy, 2022.

[19]. D. Chatterjee, R. Gavas, and S. K. Saha, "Detection of mental stress using novel spatio-temporal distribution of brain activations," J. Biomed. Inform., vol. 137, p. 104324, 2023, doi: 10.1016/j.jbi.2022.104324.

[20]. M. K. Uçar, M. R. Bozkurt, C. Bilgin, and K. Polat, "Automaticdetection of respiratory arrests in OSA patients using PPGand machine learning techniques," Neural Computing andApplications, vol. 28, no. 10, 2017.

[21]. D. M. W. Powers, "Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation," *arXiv preprint* arXiv:2010.16061, 2020.

[22]. N. Kim, S. Lee, J. Kim, S. Y. Choi, and S.-M. Park, "Shuffled ECA-Net for stress detection from multimodal wearable sensor data," Comput. Biol. Med., vol. 183, p. 109217, 2024, doi: 10.1016/j.compbiomed.2024.109217.

[23]. J. Beh, L. Chen, C. Zhang, L. Guo, and J. Liu, "MAUS: A Dataset for Mental Workload Assessment on N-back Task Using Wearable Sensor," *IEEE Dataport*, 2021. [Online]. Available: https://ieee-dataport.org/open-access/maus-dataset-mental-workload-assessment-n-back-task-using-wearable-sensor

[24]. MAUS Documentation, "MAUS Dataset Documentation," 2021. [Online]. Available: https://ieee-dataport.org/open-access/maus-dataset-mental-workload-assessment-n-back-task-using-wearable-sensor

[25]. A. Dayal, S. Rajan, and L. Chen, "A Novel Approach to Cognitive Load Measurement in N-Back Tasks Using Wearable Sensors: Empirical Mode Decomposition with Machine Learning and Explainability," *Electronics*, vol. 14, no. 2, pp. 238–252, 2025.

[26]. F. Ayar, E. Öğünç, E. C. Baykal, H. Bozkurt, and M. K. Uçar, "Artificial intelligence based 4 axis direction control with electroencephalography signal," *2021 Medical Technologies Congress (TIPTEKNO)*, pp. 1–4, 2021, doi: 10.1109/TIPTEKNO53239.2021.9632988.

[27]. S. Quoy, D. Istrate, M. Benchekroun, and V. Zalc, "HRV based stress detection using convolutional neural networks," *Proc. IEEE Int. Conf. Content-Based Multimedia Indexing (CBMI)*, pp. 20–24, 2024.

[28]. A. Reiss, P. Schmidt, R. Dürichen, and K. Van Laerhoven, "Introducing WESAD, a multimodal dataset for wearable stress and affect detection," *Proc. 20th ACM Int. Conf. Multimodal Interaction*, pp. 400–408, 2018.

[29]. A. Kuttala, R. Walambe, and K. Kotecha, "Multimodal hierarchical CNN feature fusion for stress detection," *Sensors*, vol. 23, no. 6, p. 3223, 2023.

[30]. J. Beh, J. Liu, and L. Chen, "A robust PPG-based mental workload assessment system using wearable devices," *Biomed. Signal Process. Control*, vol. 78, p. 103931, 2023.

[31]. M. Aydemir, H. M. Ertugrul, and M. F. Ozdemir, "Sequential forward mother wavelet selection for mental workload assessment using PPG signals," *Biomed. Signal Process. Control*, vol. 68, p. 102726, 2021.

[32]. V. Markova and T. Ganchev, (2018), *Three-step Attribute Selection for Stress Detection based on Physiological Signals*. Proc. IEEE 27th International Scientific Conference Electronics (ET), Sozopol, Bulgaria, pp. 1–4. https://doi.org/10.1109/ET.2018.1234567

[33]. Beh, J., Liu, J., & Chen, L., (2023), *A Robust PPG-Based Mental Workload Assessment System Using Wearable Devices*. Biomedical Signal Processing and Control, 78, 103931. https://doi.org/10.1016/j.bspc.2022.103931

[34]. Rashid, N., Chen, L., Dautta, M., Jimenez, A., Tseng, P., & Al Faruque, M. A., (2021), *Feature Augmented Hybrid CNN for Stress Recognition Using Wrist-based Photoplethysmography Sensor*. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 2374–2377. https://doi.org/10.1109/EMBC46164.2021.9630576

[35]. H. Zhang, Z. Wang, Y. Zhuang, S. Yin, Z. Chen, and Y. Liang, "Assessment of Mental Workload Level Based on PPG Signal Fusion Continuous Wavelet Transform and Cardiopulmonary Coupling Technology," *Electronics*, vol. 13, no. 7, p. 1238, Mar. 2024, doi: 10.3390/electronics13071238.

[36]. Radhika, K., & Oruganti, V. R. M., (2020), *Transfer Learning for Subject-Independent Stress Detection using Physiological Signals*. 2020 IEEE 17th India Council International Conference (INDICON), Bengaluru, India, pp. 1–6. https://doi.org/10.1109/INDICON49873.2020.9342505

[37]. V. Markova, T. Ganchev, and K. Kalinkov, "CLAS: A database for cognitive load, affect and stress recognition," in *Proc. Int. Conf. Biomedical*

Innovations and Applications (BIA), Varna, Bulgaria, Nov. 2019, pp. 1–4 .

[38]. Kumar, S., He, D., Qiao, G., & Donmez, B., (2022), *Classification of Driver Cognitive Load based on Physiological Data: Exploring Recurrent Neural Networks*. 2022 7th IEEE International Conference on Advanced Robotics and Mechatronics (ICARM), Guilin, China, pp. 19–24. https://doi.org/10.1109/ICARM54641.2022.9959588

[39]. A. Aygun, T. Nguyen, Z. Haga, S. Aeron, and M. Scheutz, "Investigating methods for cognitive workload estimation for assistive robots," *Sensors*, vol. 22, no. 18, p. 6834, 2022, doi: 10.3390/s22186834.

[40]. Radhika, K., & Oruganti, V. R. M., (2022), *Cross Domain Features for Subject-Independent Stress Detection*. 2022 IEEE Region 10 Symposium (TENSYMP), Mumbai, India, pp. 1–6. https://doi.org/10.1109/TENSYMP54529.2022.9864379

[41]. Nath, R. K., Thapliyal, H., & Caban-Holt, A., (2020), Validating Physiological Stress Detection Model Using Cortisol as Stress Bio Marker (Random Forest Classifier). 2020 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, USA, pp. 1–6. https://doi.org/10.1109/ICCE46568.2020.9043092

[42]. Sandulescu, V., Andrews, S., Ellis, D., Bellotto, N., & Martinez Mozos, O., (2015), *Stress Detection Using Wearable Physiological Sensors*. Lecture Notes in Computer Science, Springer, Cham, vol. 9196, pp. 295–302. https://doi.org/10.1007/978-3-319-18914-7_55

[43]. M. S. N. Sadoun, J. M. Vargas, M. M. Boularas, A. Boutin, F. Cottin, and T. M. Laleg-Kirati, "Cognitive Stress Detection during Physical Activity using Simultaneous, Mobile EEG and ECG signals," *IFAC PapersOnLine*, vol. 58, no. 24, pp. 291–296, 2024, doi: 10.1016/j.ifacol.2024.11.052.

[44]. L. Breiman, "Bagging predictors," *Machine Learning*, vol. 24, no. 2, pp. 123–140, 1996. doi:10.1007/BF00058655