Proceedings of the 5th International Conference on Pervasive Computing and Social Networking (ICPCSN-2025)
IEEE Xplore Part Number: CFP25EZ5-ART; ISBN: 979-8-3315-3519-3

2025 5th International Conference on Pervasive Computing and Social Networking (ICPCSN) | 979-8-3315-3519-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICPCSN65854.2025.11036077

# Artificial Intelligence – Powered Stress Monitoring and Adaptive Solution

1st Suji Priya J
*Master of Computer Applications*
*Sona College of Technology*
Salem, India
sujipriya@sonatech.ac.in

2nd Pragadeshwari H
*Master of Computer Applications*
*Sona College of Technology*
Salem, India
pragadeshwari.23cap@sonatech.ac.in

3rd 4Subhanitha K
*Master of Computer Applications*
*Sona College of Technology*
Salem, India
subhanitha.23cap@sonatech.ac.in

4th Thaparish T
*Master of Computer Applications*
*Sona College of Technology*
Salem, India
thaparish.23cap@sonatech.ac.in

***Abstract*—Stress is a major problem today, especially among young people. Life once considered carefree is now filled with stress, causing illnesses like depression, heart attacks, and suicide. In this work, It is working to predict stress levels among IT professionals and students based on their facial expressions, focusing on groups that often experience high stress. Our goal is to detect stress in real time by analyzing facial features like eye movement, tension in mouth, position of eyebrows, and tension in muscles. It can use a real-time camera output to capture such a face expression, and these are analyzed through convolutional neural networks (CNNs)—a kind of model trained to recognize patterns in stress in face images. The dataset for training includes facial images showing different stress levels. By using CNNs, the system can tell the difference between relaxed and stressed states. Real-time image processing allows the system to quickly respond, making it effective in active environments like workplaces and schools. After the system detects stress, it offers suggestions to help reduce it. If a user has mild stress, they may be recommended to try short breathing exercises, while someone with high stress may be advised to take a longer break or meditate. A number of simple and effective methods for reducing stress are based on psychological research on stress management. In this work, image processing and machine learning are combined to provide a non-intrusive, real-time solution for stress management. Creating healthier, more productive environments can be made easier by early stress detection. In this system, users are able to manage their stress in real-time through facial analysis to support mental health.**

***Keywords*— *Stress, Live Camera, Facial Expressions, Convolutional Neural Network (CNN), Recommendation Algorithm.***

## I. Introduction

This work is intended to help students and IT workers manage stress, especially when they experience high levels of stress frequently. With the help of machine learning and image processing, the system uses a live camera feed to study stress through facial expressions. The system is used to observe key facial features like eye movements, mouth tension, eyebrow position, and muscle tension as signs of stress. Different levels of stress can be identified quickly by tracking small changes in these features.

The system offers immediate feedback on stress levels and it provide a simple way to relieve stress. It may recommend breathing exercises, stretching, meditation, or short breaks for relaxation based on the level of stress it detects. By using this tool, workplaces and schools can build a healthy and positive working environment through early stress detection. In this study, AI is demonstrated as a potential support for mental health by helping people manage their stress in real-time.

## II. Literature Survey

Deep learning algorithms have been used in recent years to make great progress in the identification of stress. Notably, R. Ahuja et al. (2019) addressed mental stress in students at university level using machine learning algorithms. They have taken into consideration datasets of both behavior and physiology and have used classifiers including Support Vector Machines and k-Nearest Neighbors. The work emphasized feature selection and preprocessing of datasets for accuracy in classification. The work aided in developing specific interventions for controlling stress in educational environments [1]. The N. K. Jha et al. (2017) have designed SODA system, a system with both stress detection and its remedy incorporated in it. Wearable sensors have been utilized for collecting physiological data such as heart rate and conductance of skin, and processing through algorithms in machines have been conducted. Real-time stress-relief recommendations have even been incorporated in the system, providing a whole-brain picture of tracking and managing stress in real life [2].

A. Alberdi et al. (2018) conducted a study of predicting work-related stress in smart work environments. In a study, ambient environment information (e.g., sound and level of light) and physiologic signals have been blended together for enhancing prediction models for stress. By fusing such multimodal datasets, prediction accuracy rose incredibly and exhibited smart environments' potential for workplace stress management [3]. I. Bichindaritz, C. Breen et al. (2017) have performed ECG signal analysis for stress analysis. With feature selection and machine learning, a multilevel model for stress detection is proposed by the authors. In multiscale ECG feature analysis, accuracy in stress detection, particularly in medical care monitor environments, is increased according to them[4].

Crosswell et al. (2020) gave a review of best practice in psychological stress measurement in studies in health. Crosswell and Lockwood addressed measurement approaches for stress, including self-rated and physiological markers. Crosswell and Lockwood's work formed a basis for testing and norming tools in studies of stress [5]. Y. Hasanpoor et al. (2024) developed a deep neural network model, combining Convolutional Neural Networks (CNN) and Multilayer Perceptron (MLP), for identifying stress via Photoplethysmogram (PPG) signals. Their model performed with high accuracy in classification, confirming that deep learning can function effectively in wearable-based stress tracking systems [6]. M. Bolpagni et al. (2024) discussed personalized stress detection using biosignals from wearable devices. Their scoping review identified key requirements for developing context-aware and user-dependent models, proposing future directions for more effective and flexible stress monitoring solutions using wearable [7].

T. Islam et al. (2023) analyzed multimodal data for personalized prediction of recurrent stress events. By employing self-supervised learning on time-series data, the study demonstrated increased robustness and accuracy in predicting stress by integrating multiple physiological markers [8]. M. Hosseini et al. (2023) explored multimodal stress detection using facial landmarks and biometric signals. Their study utilized machine learning algorithms for real-time stress recognition based on facial expressions and physiological data, highlighting the importance of multimodal approaches in stress analysis [9].

H. Zhang et al. (2023) proposed hybrid machine learning frameworks for predicting stress using smartphone behavior information. By fusing smartphone behavior (e.g., typing speed and app usage) with traditional physiologic information, the work achieved high-performance stress detection. In this work, ubiquitous device capabilities in real-life stress tracking have been stressed [10]. A. Sharma et al. (2021) discussed the application of Electroencephalogram (EEG) signals in identifying stress levels. In their work, deep learning algorithms, such as Long Short-Term Memory (LSTM) networks, were utilized for distinguishing between brainwave patterns and stress. High accuracy in classification, according to the results, showed that EEG-based stress tracking can have significant use in medical and work settings [11].

M. G. Jenifel et al. (2023) developed a multimodal stress detection system using wearable sensors and machine learning techniques. By integrating HRV, GSR, and accelerometer data, the system was able to analyze trends in stress, proposing a viable model for real-time, continuous stress monitoring [12]. G. S. Kumar et al. (2025) explored stress detection using Photoplethysmography (PPG) signals with a hybrid Conv-XGBoost model. By combining CNN-based feature extraction with XGBoost classification, their approach improved stress prediction. The study emphasized the model's robustness in handling high-dimensional PPG features, showcasing its potential for real-time physiological stress monitoring [13].

J. Kim et al. (2024) analyzed micro-facial expression as a marker for stress detection. Computer vision techniques have been used in the work for identifying minor face-related changes in relation to reaction to stress. With integration of deep algorithms such as CNNs, high accuracy in stress classification was achieved. In their work, face recognition technology and its application in nonintrusive stress detection have been emphasized [14]. N. Balakrishnan et al. (2014) proposed an intensity histogram equalization algorithm for improving an image through de-noising. The algorithm improves an image's quality through suppression of noise and contrast improvement with no loss of structural information. The algorithm can be utilized in medical imaging and satellite image processing. [15].

## III. Dataset and Pre-Processing

The dataset for this study consists of a group of labelled face photos with a variety of intensity of stress, captured with students and IT professionals. Each image represents a specific emotion such as "Happy," "Surprise," "Sad," "Angry," "Disgust," "Fear," or "Neutral," Images were pre-processed for model performance enhancement, utilizing operations including resizing, normalization, and filtering out noise. All of them contribute to uniformity in all input information, critical for training a proper CNN model. In addition, operations including flipping, rotation, and zooming for data augmentation have been utilized for enriching the dataset and enriching model generalizability over a range of face expressions and symptoms of stress.

To label photos, it can refer to brow furrowing, tension in eyes, and tension in mouth, cues derived in psychological studies, and tags them according to respective categories of stress, such that the dataset accurately reflects each one of them.

The Convolutional Neural Network (CNN) model was trained with such a preprocessed dataset. With CNNs, a low-cost, nonintrusive real-time monitor for tracking stress can be attained with early warnings and interventions for mental wellness.

## IV. Proposed System

In this article, a real-time, nonintrusive face expression level estimation system via computer vision and machine learning is presented. With a use of a trained convolutional neural network (CNNs) for the specific purpose of identifying face expression indicative of stress, real-time camera feeds are processed for tracking subtle variation in face expression. The expression is then detected and sorted under "Happy," "Surprise," "Sad," "Angry," "Disgust," "Fear," and "Neutral" categories, and these categories act as strong markers for stress.

The non-intrusive model employs a single camera, abandoning wearer sensors and direct intervention, and IT can be placed in environment such as workplace and school environments. On measured stress, then, the system creates personalized recommendations for stress management, such as short break times, deep breathing, guided meditation, and long resting times.

Designed to work for IT professionals, students, and workers in similar high-strain jobs, this solution helps continuous tracking and early intervention, and its use helps its users preserve their well-being and counteract burnout. Suggestion for stress relief is backed with psychological studies, offering long-term well-being with recommendations backed with evidence. With high-tech image processing and machine learning, continuous, real-time tracking of stress is facilitated through this paper, with maintenance of well-being in high-strain settings. It is an effective and accessible tool for mental care improvement.

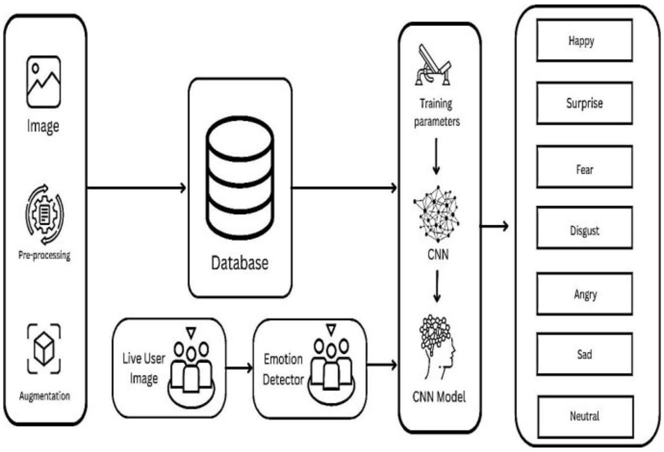



Fig.1. Architecture Diagram

The above Fig 1. shows the architecture for the emotion classification by using Convolutional Neural Network.

## V. Model Training and Testing

*A. CNN Model Setup:*

Convolutional Neural Network (CNN) process face images through a collection of parameters in terms of convolutional layers. It learns to detect stress cues, including eye motion, tension in the lips, and motion in eyebrows through a collection of face expression datasets.

*B. Real-Time Image Processing:*

Real-time processing of a user's web camera video is performed through CNN during testing. Video frames are normalized to adapt to what the model is trained for, and it runs seamlessly and precisely.

*C. Recommendation System:*

When the system detects a certain level of stress, it will provide personalized recommendation. For example, deep breathing or mindfulness.

In combination, these steps enable the model to accurately measures stress in real time and offer users practical advice on how to manage it.

## VI. Algorithm and Layers

1. Convolutional Neural Network (CNN):

The proposed system utilizes a Convolutional Neural Network (CNN) for processing face expression and real-time stress level analysis. CNNs best work for recognitions in terms of images, specifically in processing complex face feature mappings to a variety of emotion, including stress. Live camera streaming is processed in such an algorithm for face feature tracking and face feature identification such as eye motion, brow tension, and mouth position, and these face features act as key markers for stress. The CNN identifies and isolates such face features and labels them into individual emotion categories for stress analysis.

2. Layers of the Convolutional Neural Network (CNN):

The CNN model involves several layers that increasingly extract increasingly complex and high-level features out of the input face images. There is a decomposition of the most important layers in the model below:

1. Input Layer: It takes in grayscale face images with a resolution of 48x48 pixels. It processes and prepares the information for processing via the following convolutional layers.

2. Convolutional Layer 1: Conv1 takes 32 3x3 filters and applies them to the input picture. 3x3 32 filters detect low level feature such as textures and edges. ReLU activation function is used in the layer for delivering non-linearity and allowing complex feature learning in the model.

3. Pooling Layer 1: Max-pooling is then conducted after the first convolutional layer in an attempt to down sample the feature map's dimensions in a spatial manner. Pooling layer retains most important features and simplifies computation through a drop in information dimensions.

4. Convolutional Layer 2: In this layer, even more complex face features are extracted with 64 3x3 filters. ReLU is again used in this first and second convolutional layer for delivering non-linearity, allowing the network to learn about even more complex face expression information.

5. Pooling Layer 2: There is a secondary max-pooling layer following the second layer of convolution in an attempt to

downsize the feature map in terms of its spatial dimensions but maintain its most significant features.

6. Convolutional Layer 3: Convolutional layer 3 utilizes 128 filters in a quest for high-level feature information. Convolutional layer 3 carries out deeper analysis, with a purpose of working with even more complex patterns in an image that will work towards determination of stress and emotionality.

7. Pooling Layer 3: There is a secondary max-pooling layer, reducing feature map dimensions even smaller but with most critical information retained.

8. Flatten Layer: After between a pool and a convolutional layer, feature maps are flattened in 1D vector form. Flattened information is then consumed as an input for successive full-connected layers.

9. Fully Connected (Dense) Layers: Flattened information is then processed through fully connected layers, whose function is to learn high-level feature and make prediction. Fully connected layers combine the abstracted feature extracted in the convolutional layers in an attempt to classify a state of emotion in a user.

10. Output Layer: In the output layer, a softmax function is used, and it converts raw prediction values into probabilities for all seven emotion categories (e.g., Happy, Sad, Angry, etc.). The predicted emotion is calculated with the most likely class having a largest value.

11. Dropout Layer: There is a dropout layer with 50% dropout added in an attempt to counteract overfitting and chance to zero out 50% of the neurons during training at a random basis. It helps in generalization to new, unseen information.

Each layer in a model of a CNN is important in sequentially processing and classifying face expression in a bid to detect stress, and in such a way, allow effective working in real-time environments.

## VII. Adaptive Stress Management and Recommendation

The paper introduces a real-time, nonintrusive monitor for stress level with a deep model-based system. It processes and takes real-time face expression with computer vision and machine learning and identifies significant face features such as eye movement, brow position, and mouth tension and labels them with stress. It separates between a happy, sad, surprised, and angry, and a neutral level, and provides a rich level of information about a state of emotion for a user.

The system incorporates an adaptability module for dealing with stress, employing real-time tracking of emotion for individualized guidance in dealing with stress. It recognizes detected stress via face expression and then suggests individualized guidance for efficient dealing with such detected stress, whose guidance is derived in terms of intensity and type of detected stress, and in such a form that it can adapt its guidance in terms of individual needs of the individual.

These recommendations will vary with detected level of emotions and it can include simple recommendations techniques such as deep breathing, mindfulness, and break suggestions. By using this tool, workplaces and schools can build a healthy and positive working environment through early stress detection.

## I. Results and Discussions

This work developed a real-time, non-intrusive system for facial expression capture, processing, and analysis for stress detection using computer vision and machine learning approaches. The system identifies key face features including eye movement, brow position, and mouth tension, with a relation to stress. A trained model then identifies stress in terms of happy, sad, surprised, angry, and neutral, respectively, through face analysis.

The system provides personalized and adaptable options for managing stress in relation to its detected level, for effective management and reduction of its level in its users. It seeks to enhance mental wellness and productivity in both academic and work environments, with accuracy, usability for its users.

The AI-driven platform is an unobtrusive, effective tool for diagnosing stress in high-stress settings, such as schools and workplace settings, in a format that can contribute to healthier, more productive settings through early intervention. The work values immediate feedback and personalized guidance, such as through breathing techniques, through psychological studies for long-term well-being.

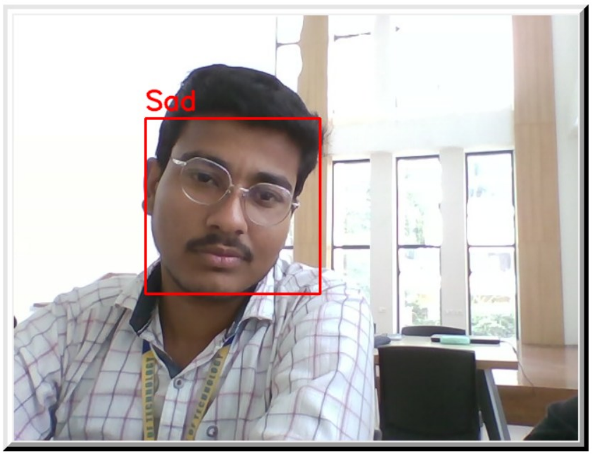
The system stands out by eliminating the need for additional devices like sensors or wearable,relying solely on a camera for analysis, thus simplifying setup and making it accessible and user-friendly. This comprehensive solution not only improves detection accuracy but also ensures enhanced accessibility and ease of use, making it a practical tool for stress managementin daily life.

As shown in Figure 2 and Figure 3, if the person is found to be at a certain stress level such as sadness, they will receive personalized recommendations, such as “Try some deep breathing exercises”, “Take a short walk” or “Get some fresh air”.

As depicted in Figure 4 and Figure 5, if the person is angry, it will provide personalized recommendations such as “Practice mindfulness” or “Write down your feelings”. If the person is fear as shown in Figure 6 and Figure 7, it will provide recommendations such as, “Think of something that makes you feel safe and happy”, “Listening to calm music or podcasts” or “Journaling”.

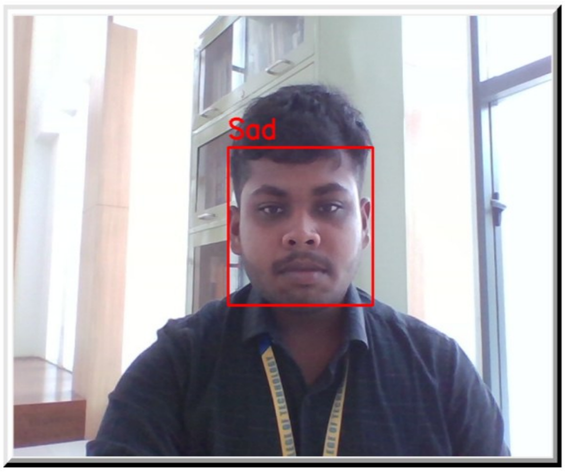
As shown in Figure 8, if the person is found to be at an emotion such as surprise, it will give recommendations like “Wow! Life is full of surprises – enjoy every moment” or Celebrate the moment. As shown in Figure 9 , if the person is found to be at an emotion such as Neutral , the person will get a recommendations such as “Every day brings new opportunities, embrace them with a smile!” or “Engage in a new activity”.

As shown in Figure 10, if the person is found to be at a certain emotion level such as Happy, It will provide personalized recommendations such as “Feeling good? Spread the joy! Happiness is contagious” or “Keep this positive energy going! It brightens up everyone’s day”.



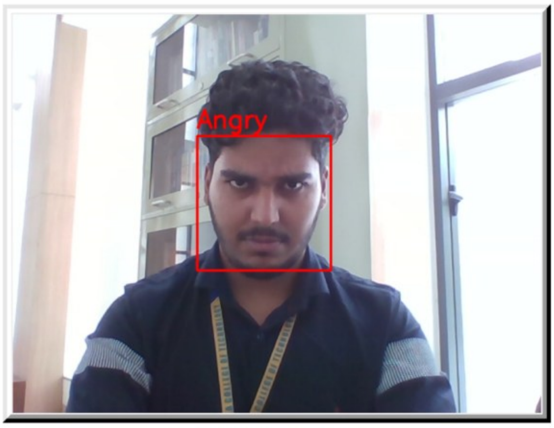

Tip: Try some deep breathing exercises

Fig.2. Sad




Tip: Take a Short walk

Fig.3. Sad




Tip: Write down your feelings

Fig.4. Angry

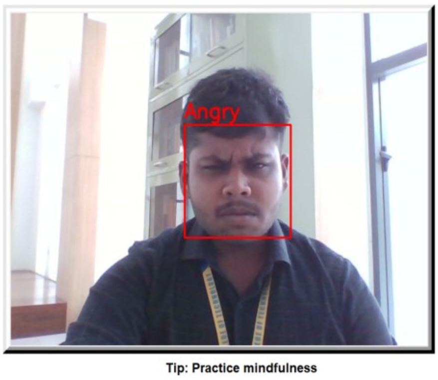



Fig.5. Angry


Fig.6. Fear


Fig.7. Fear


Fig.8. Surprise

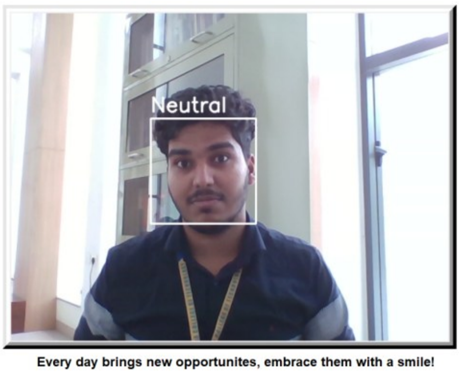



Fig.9. Neutral


Fig.10. Happy

## II. Conclusion and Future Scope

In conclusion, the proposed work in this thesis introduces a real-time, nonintrusive stress level estimation system powered with a deep model of learning. Live face expression is detected and processed with computer vision and machine learning in order to detect important face features with a relation with stress, such as eye motion, brow position, and mouth tension. Through emotion classification such as "Happy," "Sad," "Surprised," "Angry," "Disgust," "Fear," and "Neutral," the system provides a deep analysis of the state of emotion of the user.

The core output of such work is presented through an accessible web interface. The interface utilizes a single live camera, and hence, it is convenient and simple to use in any environment, for instance, in schools and working environments. The interface utilizes a trained model for face analysis for classification of a stress level and offering personalized tips for stress management, such as deep breathing, according to individual requirements. User experience is at the focal point of proposed work, with an intention to make access easier for people in getting insights and managing stress without having to utilize any additional device or sensors. All such ease comes through robust back-end processes for face expression analysis, classification of a stress level, and presenting a result.

This AI-driven work sees future potential in utilizing nonintrusive technology in real-time stress management, providing beneficial feedback and information for effective management of one's stress level. By enhancing mental wellness and productivity in high-stress environments, such as work and school, this work sees future potential in new trends in stress detection and management in developing a healthy and productive environment.

To further develop the stress detection system, a proposed expansion of our dataset with a larger variety of facial expression and markers for stress, and a model with a high accuracy and robustness level. With expansion, the system will generalize well in a range of populations and real-life settings. In addition, an intention to implement a feature for sending a notification to a user's caregiver or senior administrator in case of high-level detections of stress. With such a feature, timely intervention and proper care will be facilitated, and in the long run, make the system even more effective in controlling and preventing stress and improving well-being.

# REFERENCES


[1] R. Ahuja and A. Banga, "Mental stress detection in university students using machine learning algorithms," *Procedia Computer Science*, vol. 152, pp. 349–353, 2019. DOI: 10.1016/j.procs.2019.05.007.

[2] A. O. Akmandor and N. K. Jha, "Keep the stress away with soda: Stress detection and alleviation system," *IEEE Transactions on Multi-Scale Computing Systems*, vol. 3, no. 4, pp. 269–282, 2017. DOI: 10.1109/TMSCS.2017.2703613.

[3] A. Alberdi, A. Aztiria, A. Basarab, and D. J. Cook, "Using smart offices to predict occupational stress," *International Journal of Industrial Ergonomics*, vol. 67, pp. 13–26, 2018. DOI: 10.1016/j.ergon.2018.04.005.

[4] I. Bichindaritz, C. Breen, E. Cole, N. Keshan, and P. Parimi, "Feature selection and machine learning-based multilevel stress detection from ECG signals," in *Proc. Int. Conf. Innovation in Medicine and Healthcare*, Berlin, Germany, 2017, pp. 202–213.

[5] A. D. Crosswell and K. G. Lockwood, "Best practices for stress measurement: How to measure psychological stress in health research," *Health Psychology Open*, vol. 7, no. 2, pp. 2055102920933072, 2020. DOI: 10.1177/2055102920933072.

[6] Y. Hasanpoor, K. Motaman, B. Tarvirdizadeh, K. Alipour, and M. Ghamari, "Stress detection using PPG signal and combined deep CNN-MLP network," Biomedical Signal Processing and Control, vol. 82, pp. 105214, 2024. DOI: 10.1016/j.bspc.2024.105214.

[7] M. Bolpagni, S. Pardini, M. Dianti, and S. Gabrielli, "Personalized stress detection using biosignals from wearables: A scoping review," Sensors, vol. 24, no. 10, pp. 3221, 2024. DOI: 10.3390/s24103221.

[8] T. Islam and P. Washington, "Personalized prediction of recurrent stress events using self-supervised learning on multimodal time-series data," IEEE Access, vol. 12, pp. 22456–22472, 2023. DOI: 10.1109/ACCESS.2023.3315432.

[9] Hosseini, M., Bodaghi, M., Bhupatiraju, R.T., Maida, A., and Gottumukkala, R., "Multimodal stress detection using facial landmarks and biometric signals," arXiv preprint, arXiv:2311.03606, 2023.

[10] H. Zhang, J. Li, and L. Wang, "Hybrid machine learning frameworks for stress prediction using behavioral data from smartphones," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 345–358, 2023. DOI: 10.1007/s12652-023-04567-2.

[11] A. Sharma and P. Goyal, "Stress level detection using EEG signals and deep learning," Biomedical Signal Processing and Control, vol. 70, pp. 103091, 2021. DOI: 10.1016/j.bspc.2021.103091.

[12] M. G. Jenifel, P. Kanmani, K. S. Kumari, B. G. Geetha, S. S. S. Lakshmi, and D. Deepika, "A multimodal stress detection system with wearable sensors using machine learning and deep learning approaches," in Proceedings of the International Conference on Innovation, Sustainability, and Applied Sciences, Cham, Switzerland, Dec. 2023, pp. 313–320.

[13] G. S. Kumar and B. Ankayarkanni, "Leveraging Conv-XGBoost algorithm for perceived mental stress detection using photoplethysmography," Intelligence-Based Medicine, vol. 11, p. 100209, 2025. DOI: 10.1016/j.ibmed.2024.100209.

[14] J. Kim, Y. Choi, and H. Park, "Facial micro-expression analysis for stress detection using deep learning," Pattern Recognition Letters, vol. 168, pp. 45–54, 2024. DOI: 10.1016/j.patrec.2023.09.005.

[15] N.Balakrishnan, T.Ramkumar and S. P. Shantharajah, "An image de-noising method based on intensity histogram equalization technique for image enhancement," International Review on Computers and Software, vol. 9, no. 6, pp. 1022–1029, 2014.