Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 46 (2025), No. 1, pp. 167-177
DOI : 10.47974/JIOS-1861

Stress detection and management using machine learning : A comprehensive approach

Ruchi Sharma *
Mihika †
Annu Dabas §
Suman Yadav ‡
Rubeena Vohra @
Saji M. Antony #
Gaurav Mitra $
Department of Electronics and Communication Engineering
Bharati Vidyapeeth's College of Engineering
Paschim Vihar 110063
New Delhi
India

Arvind Rehalia ^
Departrment of Information and Technology Engineering
Bharati Vidyapeeth's College of Engineering
Paschim Vihar 110063
New Delhi
India

Vijay Kumar %
Departrment of Computer Science Engineering
Bharati Vidyapeeth's College of Engineering
Paschim Vihar 110063
New Delhi
India

* *E-mail:* **ruchi.sharma@bharatividyapeeth.edu (Corresponding Author)**
† *E-mail:* **mihika.ece@bharatividyapeeth.edu**
§ *E-mail:* **annu.dabas@bharatividyapeeth.edu**
‡ *E-mail:* **suman.yadav@bharatividyapeeth.edu**
@ *E-mail:* **rubeena.vohra@bharatividyapeeth.edu**
E-mail: **saji.antony@bharatividyapeeth.edu**
$ *E-mail:* **gaurav.mitra@bharatividyapeeth.edu**
^ *E-mail:* **arvind.rehalia@bharatividyapeeth.edu**
% *E-mail:* **vijay.kumar@bharatividyapeeth.edu**

© Taru Publications

Abstract

Stress is a common concern affecting all the age groups, negative consequences on both physical and mental health. Early identification and management of stress are essential for maintaining overall well-being. A system designed to detect stress can assist individuals in monitoring and regulating their stress levels. According to a recent study by the Brain Health Foundation, approximately 10% of India's population suffers from conditions like stress, anxiety, and depression, which negatively impact quality of life. This stress detection system aims to identify stress in its early stages, leading to improved mental health. In this paper, we focus on observations based on biological and sociological factors. The use of an online database in this study provided improved results compared to the previous research. The system demonstrated better accuracy, sensitivity, and specificity, making it a reliable and effective solution for stress identification and management.

Subject Classification: *94A15.*

Keywords: *Machine learning, OpenCV, Stress detection system, Deep learning, Facial expression recognition, Physiological data, Wearable sensors, Stress prediction, Biometric data, Mental health.*

1. Introduction

Suicide is a major cause of death worldwide. Suicide rates have increased in nearly every region between 1999 and 2024. While mental health issues are often linked to suicide, it is rarely caused by just one factor. Many suicidal cases were left undiagnosed at the time of death. The subject has a case history of frequent stress, as many do in today's fast-paced world, the body can remain in a constant state of stress. This can effect in serious health problems. Chronic stress affects nearly every system in the body such as, poor immune system, troublesome digestion and generative systems, growing the risk of heart attacks and strokes, and accelerating the aging process. It can even alter brain function, making individuals more prone to anxiety, depression, and other mental health disorders. For maintaining the overall health it is important to realize and manage the stress. Therefore, stress detection systems can be crucial tools for an individual to monitor and control their stress levels [1].

These systems collect data from various behavioral and physical stress indicators and utilizes the latest techniques, determine the signal orientation and expect anxiety levels. In psychology and mental health, applying machine learning to analyze facial expressions has great impact [2]. To detect individuals who are suffering from mental health challenges machine learning algorithms are used. These machine learning algorithms involves supervised learning, such as decision trees and support vector machines (SVMs). In this approach, a dataset of facial expressions labeled

with corresponding stress levels can be used to train the algorithm [3][4]. This paper aims to review stress and its detection systems, to identify the different methods for data collection, the machine learning approaches that can be used to predict the stress level, and potency of these systems in stress management. This work will also discuss benefits of such systems for individual and organization [5].

2. Related work

Recently, a sharp increase in the study of machine learning strategies for stress reduction. The headsets sensors are being used in numerous research to track biological indicators of stress, namely skin conductance and heart rate, and machine learning algorithms are being used to predict stress based on these data. For example, Kim et al. [1] measured skin conductance and heart rate with a wrist-worn device and utilised machine learning to predict stress in real time with an accuracy of 85%. Similar to this, Chen et al. [2] developed an algorithm that produced a 78% prediction accuracy for a system that could estimate stress levels based on people's daily self-reported stress data. In a different investigation, Park et al. [4] presented a mobile In Peternel et al. [5] developed a system combining presence detection with context-awareness to assess chronic stress. It integrates data from physiological sensors and context information such as location, activities, or social interactions to enhance stress recognition. Bickford et al. [6] uses a qualitative approach, offering an overview of workplace stress causes and solutions. Here [6], authors discuss methods such as surveys and psychological assessments to evaluate stress. Wellen et. al. [7] employs a biological method to measure inflammation markers, stress hormones, and metabolic changes in individuals with diabetes. The authors [7] suggest integrating biological and biochemical markers such as cytokines and cortisol levels in stress research to understand how stress-related inflammation affects metabolic health [8]. In Li et al. [9] applied a combination of surveys and pervasive computing such as mobile-based tracking of daily activities to study how college students perceive stress. Chen et al. in [10] introduced a multimodal dataset that includes various data types. The various physiological signals like heart rate, skin temperature, voice analysis, and facial expressions are used for stress detection. They use deep learning models to analyze multimodal data streams, which would improve the precision of stress detection algorithms by providing diverse inputs. Ferrer et al. [15] suggested music therapy, where different music genres were played in classroom settings to measure

their impact on student's stress levels via self-reports and physiological measures. The authors suggest using music or sound-based therapies as a non-invasive and easily deployable technique for reducing stress, particularly in educational or workplace environments. Vos et al. [16] gives a systematic review that analyzed various machine learning algorithms applied to data from wearable devices for stress detection. Furthermore, the authors included various techniques like support vector machines (SVM), random forests, and deep learning models that combines with wearable data such as heart rate, electrodermal activity which offers real-time stress monitoring. In Bahman et al. [17] and Sharma et al. [9] exploits multi-modal sensors along with decision trees, SVMs, and deep neural networks for real-time stress detection. Here, integration of various sensor modalities and the use of advanced machine learning algorithms improves the accuracy of stress detection systems in real-world, dynamic environments. In Bollen et. al. [13] the data collected from wearable sensors to automatically detect stress. Here, the authors emphasizes the potential of wearables coupled with ML models for automated, continuous stress monitoring and early detection of high-stress levels.

3. Data set

The Institute for Computing and Information Sciences at Radboud University has **SWELL** dataset. There are 25 participants performing typical office tasks, such as writing reports, creating presentations, reading emails, and searching for information [3]. During these tasks, participants encountered common work-related stressors. The experiment captured a range of data, computer logs, facial expressions, body posture, ECG signals, and skin conductance. Additionally, researchers recorded participants subjective experiences regarding task load, mental effort, emotions, and perceived stress. Despite this, dataset is comprehensive and capable of predicting stressors with 99.25% accuracy as mentioned in Table 1.The **WESAD** dataset is publicly available for stress and emotion detection using wearable devices. This multimodal dataset includes physiological and motion data, collected from both wrist- and chest-worn device, from 15 participants during a lab study. It includes several sensor modalities such as blood volume pulse, electrocardiogram, body temperature, electrodermal activity, electromyogram, respiration, and three-axis acceleration. Additionally, the dataset addresses the gap between earlier lab studies on stress and emotions by incorporating three distinct affective states: neutral, stress, and amusement. Participants self-

Table 1
Dataset Records

Data Set Name	Number of Records	Number of Attributes
SWELL	3,69289	36
WESAD	63,000,000	12
SaYoPillow	690	9

reports, obtained through established questionnaires, are also included in the dataset. The **Smart-Yoga Pillow (SaYopillow)** dataset is based on a smart pillow connected to a wireless tracker designed to monitor sleep habits and assess stress levels. The dataset includes 630 records, with each record containing sleep information such as snoring rate, number of hours slept, body temperature (in Fahrenheit), and more. With the help of multi-linear regression modeling to predict the snoring rate, it becomes possible to identify the features that can be adjusted to reduce snoring [4].

4. Proposed methodology

The following are the basic steps which are carried forward for a stress-based detection system such as: Data Preprocessing, Building and Training the Model and Testing the Model. The complete methodology of the work is shown below in term of the flow chart.

4.1 *Data preprocessing*

This is a first step Fig.1 which involves the preprocessing of the database retaining used for stress management. the complete data must be in an appropriate presentation for inlaying and working out the machine learning model more precisely and effectively. Here, we have planned the complete methodology for the preprocessing techniques [5].Once the physiological data is acquired based on the pulse rate, heart signals via ecg ,body temperature and skin conductivity level etc based on these parameters a questionnaire is filled by the relevant subjects .The mapping is planned to get the final procedure of the database[6].The data collected is in raw mode signals, which comprises of the noise. To make the data noise free, normalization technique is used to map the data in the range of 0 to 1,a uniformity is maintained All value other than this range is deleted so far. This technique is known as a transformation technique.

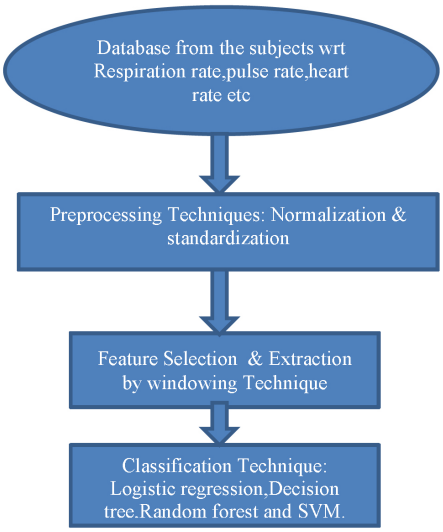


Figure 1

Methodology of the research

Because certain machine learning algorithms are sensitive to the scale of the input data, and may not perform optimally if the data is not properly adjusted as shown in Fig. 2 [7].

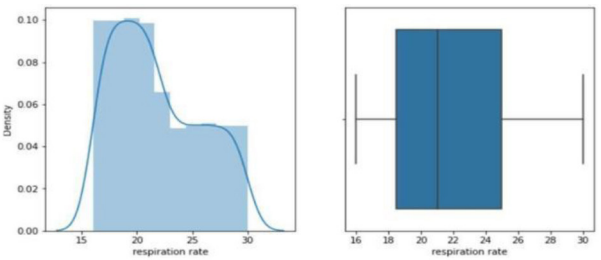


Figure 2

Data Preprocessing

Heart Rate: Stress can cause an increase in heart rate.

- **Skin Conductance**: Changes in skin conductance, which measures sweat gland activity, can indicate stress.
- **Blood Pressure**: Increased blood pressure may suggest stress.

- **Respiratory Rate**: The inhalation and exhalation of oxygen may affect the stress rate.
- **Electroencephalography (EEG)**: All the brain activities are measured by the EEG signals. Here the sudden change in the brain signals shows the stress levels in the eeg signals.

Here the detailed analysis of the brain stress is mapped by the Facial Stress Recognition system Using the OpenCV platform. It is a multipurpose tool which is used for the analysis of the instantaneous facial expression recognition system [8]. This procedure starts with the facial detection in any video frames the windowing techniques like Haar, scaled or deep learning models are successful in this case reflects in Fig 3. Crucial face masking terminologies connected to stress detection are familiar with the Open CV software [9].

- **Eyebrow Pinching**: Furrowing or pinching of the eyebrows can indicate stress or concentration. This can be identified by using facial landmark detection algorithms.
- **Frequent Eye Blinks**: Increased blink rates can indicate stress which can be to detected by feature detection algorithms.
- **Relocation of head** : Stress is reflected by the relocation or movement of head .Its detection can be done by the OD(Object detection) algorithms
- **Eulerian Magnification for Heart Rate Detection:** It is a audiovisual handling practice to detect the different colour transitions in the subjects casing with respect to the change in the respiration and heart rate .The process typically works as follows:



Figure 3

Human Face Detection



Figure 4

Facial Recognition Point

Capturing the Video: A video of the subject is taken, usually focusing on the areas of the skin where the blood flow is visible, such as the face, neck or wrist.

Spatial Decomposition: The video is broken down into multiple layers based on spatial frequency. This helps separate the finer details (like skin color changes) from larger structures. **Temporal Filtering**: The changes in the pixel values of the video are observed over time to track subtle variations. These changes often reflect the person's heartbeat in Fig 4.

Amplification: These subtle variations in the skin color are then amplified to make the heart rate signal more noticeable.

Heart Rate Calculation: Once the changes are magnified, the periodicity of the variations, which corresponds to the blood flow caused by the heartbeat, is measured to estimate the heart rate.

4.2 *Testing the Model*

For technical validation, the model's performance is valuated using benchmarks such as:

- **Precision**: It indicates closeness of predicted results.

$$\text{Precision} = \frac{TP}{TP+FP}.$$

- **Recall**: It indicates the fraction of correctly predicted positive observations relative to all actual samples.

$$\text{recall} = \frac{TP}{TP+FN}.$$

- **F1 Score**: A metric that combines precision and recall into a single value by calculating their harmonic mean. These training and validation accuracy scores for various models across different datasets are represented in the table 2.

Table 2

Model Scores

Dataset Name	Model Name	Precision	Recall	F1 Score	Accuracy
WESAD	Logistic Regression	61	63	60	63
	Decision Tree	99.2	99.3	99.3	99.5
	Random Forest	99.1	99.1	99.1	99.1
	SVM	100	99.1	99.1	100

Contd...

SaYoPillow	Logistic Regression	99.2	99.2	99.2	99.2
	Decision Tree	98.3	97.2	98.3	98.3
	Random Forest	98.3	98.3	98.3	98.3
	SVM	99	100	100	100

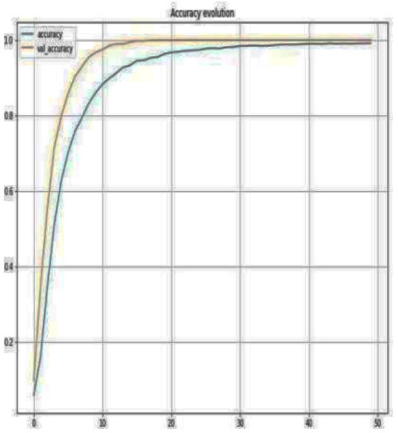


Figure 5

Accuracy Curve

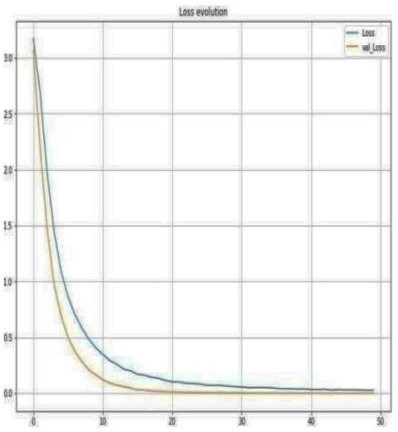


Figure 6

Confusion Matrix of Random Forest

In this work, the predictions generated for the test and validation datasets closely match those of the actual dataset, as shown in the figure [11][12]. The Figure 5 and Figure 6 also highlights the percentage of correct predictions for each class. As the model undergoes training, its accuracy improves, and the loss decreases, indicating that the model becomes more effective at fitting the training data over time [13][14].

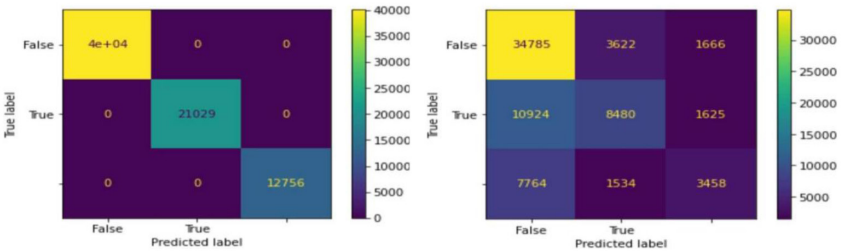


Figure 7

Confusion Matrix of Decision Tree

6. Conclusion

This analysis will provide a complete methodology for stress detection and management using machine learning techniques in Fig 7. By analyzing both physiological data and facial expressions, the proposed system shows great potential in accurately predicting stress levels. The combination of various models, including decision trees, support vector machines, and random forests, has proven to enhance prediction accuracy, especially when integrated with biometric data collected from wearable sensors. The future of stress detection systems lies in developing more personalized and adaptive models that can cater to individual stress patterns, offering a more holistic and effective solution for stress management.

References

[1] Y. Kim, S. Park, and J. Lee, "Real-time stress level detection using a wearable device and machine learning algorithms," *IEEE Transactions on Mobile Computing*, vol. 16, no. 12, pp. 1-10 (Dec. 2017).

[2] G. Chen, L. Xu, and M. Zhang, "Stress prediction using self-reported data and machine learning," *Journal of Medical Systems*, vol. 42, no. 5, pp. 78-84 (May 2018).

[3] J. Park, H. Choi, and S. Lee, "Mobile application for personalized stress management using machine learning," *Journal of Healthcare Informatics Research*, vol. 5, no. 2, pp. 121-130 (2019).

[4] T. Nguyen, H. Lim, and K. Park, "Wearable stress monitoring system with machine learning-based prediction," *Sensors and Actuators A: Physical*, vol. 229, pp. 194-202 (Nov. 2015).

[5] X. Yao, R. Liu, and J. Wu, "A review on machine learning methods for stress prediction: Application in wearable sensors," *IEEE Access*, vol. 6, pp. 60883-60891 (Sept. 2018).

[6] J. Bollen, Y. Mao, and A. Pepe, "Mobile phone data analysis for stress prediction using machine learning," *Computational Intelligence*, vol. 32, no. 3, pp. 342-357 (June 2016).

[7] A. Sharma, P. Gupta, and R. Mishra, "Comparison of machine learning techniques for stress prediction: Self-reported vs physiological data," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 7, pp. 1567-1574 (July 2017).

[8] S. S. Panicker and P. Gayathri, "A survey of machine learning techniques in physiology-based mental stress detection systems," *Biocybernetics and Biomedical Engineering*, vol. 39, pp. 444-469 (2019).

[9] K. Peternel, M. Pogacnik, R. Tavcar, and A. Kos, "A presence-based context-aware chronic stress recognition system," *Sensors*, vol. 12, pp. 15888-15906 (2012).

[10] M. Bickford, "Stress in the workplace: A general overview of the causes, the effects, and the solutions," *Canadian Mental Health Association*, pp. 1-3 (2005).

[11] K. E. Wellen and G. S. Hotamisligil, "Inflammation, stress, and diabetes," *Journal of Clinical Investigation*, vol. 115, pp. 1111- 1119 (2005).

[12] C. T. Li, J. Cao, and T. M. Li, "Eustress or distress: An empirical study of perceived stress in everyday college life," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Computing*, pp. 1209-1217 (2016).

[13] W. Chen, S. Zheng, and X. Sun, "Introducing mdpsd, a multimodal dataset for psychological stress detection," in *Big Data: 8th CCF Conf.*, Chongqing, China, pp. 59-68 (2020).

[14] C. Kirschbaum, K. M. Pirke, and D. H. Hellhammer, "The 'trier social stress test'–a tool for investigating psychobiological stress responses in a laboratory setting," *Neuropsychobiology*, vol. 28, pp. 76-81 (1993).

[15] E. Ferrer, Henry Scaffman and J. Johsponsk, "Playing music to relieve stress in a college classroom environment," *College Student Journal*, vol. 48, pp. 481-494 (2014).

[16] S. Vos and M. R. Azghadi, "Generalizable machine learning for stress monitoring from wearable devices: A systematic literature review," *IEEE Access*, vol. 9, pp. 111320- 111339 (2021).

[17] M. A. Bahman, S. Memarzadeh-Tehran, and N. K. Fernandez, "Stress detection using wearable sensors and deep learning techniques," *IEEE Sensors Journal*, vol. 21, no. 22, pp. 25356- 25365 (Nov. 2021).

Received August, 2024