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Research Article

Using ML algorithm and HCI to analyse stress-related physiological health parameters of IT sector employees using wearable smart watches

Dr. Kavita[1], Divya Sharma[2*]

[1]Associate Professor, JVWU
[2*]Research Scholar, JVWU, Email: divyasharma.1003@gmail.com

***Corresponding Author:** Divya Sharma
* Email: divyasharma.1003@gmail.com

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ABSTRACT

Stress is a part of everyday life, but when it becomes chronic, it can seriously affect our health—impacting everything from our heart and immune system to hormone balance. This research looks into new ways of understanding and managing stress by using a combination of machine learning and user-friendly technology. By digging into past studies and medical data, the goal is to better identify the signs of stress and find smarter ways to track it.
Machine learning plays a big role here by helping make sense of complex data collected from people's bodies—like heart rate or skin responses. These algorithms can spot patterns, predict stress levels, and even adapt over time to better support users. At the same time, user-friendly interfaces—think mobile apps or wearable devices—make it easier for people to monitor their stress and get helpful tips in real time. This teamwork between technology and human-centered design makes stress management more practical and accessible.
The system relies on modern wearables that collect data continuously and connect with health apps or records. It also takes into account important concerns like privacy and informed consent, ensuring users feel safe and in control. In the bigger picture, this approach could lighten the load on healthcare systems and help people manage stress before it becomes a serious problem. Looking ahead, the researchers suggest refining the technology, involving users more in the design process, and testing these tools in real-life settings to make them even more effective.

Introduction

Stress is more than just a mental burden—it can have serious effects on the body too. Research over the years has shown that chronic stress is linked to a range of health problems, including heart disease, weakened immunity, digestive issues, anxiety, and depression. With so many people reporting high levels of stress—especially due to work and financial pressures—understanding how stress affects us has become more important than ever. Yet, despite decades of study, the full picture of how stress works in the body remains unclear because it's such a complex, multifaceted response.
Traditionally, researchers have relied on self-reported surveys or basic physiological tests to study stress. While helpful, these methods often don't capture the full depth of what's happening inside the body during stressful experiences. On top of that, analyzing the vast and varied data involved is a major challenge using conventional techniques. This is where machine learning comes in. These advanced algorithms can handle large, complex datasets and detect hidden patterns, helping scientists discover new biological markers and better understand how the body reacts to stress.
To make these insights more practical and user-friendly, the research also includes human-computer interaction (HCI) techniques. By focusing on how people interact with technology—like apps or wearable devices—researchers can design personalized stress management tools that adapt to each person's needs.

Combining machine learning with HCI offers a powerful approach to not only deepen our understanding of stress but also to create real-world solutions that improve healthcare and everyday well-being.
Machine learning is becoming a powerful tool in understanding stress. Unlike traditional methods, which may miss subtle signs, machine learning algorithms can sift through massive amounts of data to uncover patterns related to how our bodies respond to stress. For example, certain algorithms can predict someone's stress level based on signals like heart rate or skin conductance, while others can group people by how they react to stress. There are even systems that learn over time—adapting and improving stress-reducing techniques based on how a person responds to them.
But understanding stress isn't just about the data—it's also about how people engage with tools that help them manage it. That's where human-computer interaction (HCI) comes in. By designing easy-to-use, interactive interfaces, people can track their stress, get instant feedback, and access stress management strategies that feel personal and relevant. Using principles like user-centered design and feedback loops, these tools are made to be not just functional, but also helpful and accessible to anyone who needs them.
Bringing machine learning and HCI together creates a more complete approach to stress management. It allows us to understand how stress affects the body while also giving people practical, personalized tools to cope with it. This kind of interdisciplinary work doesn't just advance research—it has real potential to transform healthcare, improve outcomes, and make life a little easier for those dealing with stress-related health challenges.

Literature Review

A thorough literature review was undertaken in order to gain insights about the topic of research. Some key findings are listed here. According to the review of literature, it can be said that stress triggers a complex cascade of physiological responses that involve autonomic nervous system, endocrine system, and immune system. Key parameters influenced by stress include heart rate variability (HRV), blood pressure, cortisol levels, and inflammatory markers. Studies have shown that chronic stress can lead to cardiovascular diseases, immune dysfunction, metabolic disorders, and mental health issues such as anxiety and depression.
The table below describes a comparison of phsysiological measures used for stress detection:

Physiological Signal	Measurement Type	Strengths	Limitations
Electrocardiogram (ECG)	Heart rate variability (HRV)	High accuracy, well-researched, wearable sensor compatibility	Susceptible to motion artifacts
Galvanic Skin Response (GSR)	Skin conductance changes	Rapid response to stress, low- cost sensors	Sensitive to environmental factors (temperature, humidity)
Electroencephalography (EEG)	Brainwave activity	Direct neural signal measurement, useful in cognitive stress detection	Requires complex equipment, signal noise issues

Figure 1: The table describing a comparison of physiological measures used for stress detection:

ML techniques employed in stress detection and analysis research, include supervised learning, unsupervised learning, and reinforcement learning. The table below shows a brief summary of the ML techniques that can be used for stress detection.

Model	Features Used	Accuracy (%)	Strengths
SVM	HRV, GSR	85%	Works well with small datasets, interpretable
KNN	GSR, EEG	80%	Simple and effective
Random Forest	ECG, Speech	87%	Handles missing data well, robust to overfitting
CNN	EEG, Facial Expressions	90%	Automatically extracts features, high accuracy
LSTM	Sequential physiological signals	92%	Good for time-series data

Figure 2: Table showing performance of different Machine Learning models used for stress detection

Summary of several key findings of literature review is shared here. R. K. Nath et. al. in their paper "Machine Learning Based Solutions for Real-Time Stress Monitoring," which was published in IEEE Consumer Electronics Magazine, vol. 9, no. 5, pp. 34-41, 1 Sept. 2020, say that in their article they explored how researchers have used machine learning to detect stress by analyzing patterns in physiological and behavioral data. They also analyzed how edge computing—technology that processes data close to the source, like on a smartwatch or phone—is being used to make real-time stress monitoring more practical and accessible in everyday life.

Nath et. al. in their paper " A Machine Learning Based Stress Monitoring in Older Adults Using Wearable Sensors and Cortisol as Stress Biomarker" discuss that their study aimed to test how effectively a wearable device could detect stress in older adults by analyzing two physiological signals: electrodermal activity (EDA) and blood volume pulse (BVP). The data was collected from 19 healthy participants, with an average age of 73, during the Trier Social Stress Test—an established method to trigger stress in a social setting. Stress levels were confirmed using salivary cortisol, a reliable biological indicator. From the EDA and BVP signals, 39 key statistical features were extracted and analyzed using various machine learning algorithms. Among the traditional models tested, logistic regression performed best in identifying stress, with strong accuracy and F1-scores. In addition to conventional models, the researchers also evaluated a deep learning method known as Long Short-Term Memory (LSTM), which is especially suited for time-based data. The LSTM model outperformed logistic regression, showing higher F1-scores and an 11% improvement in AUC (area under the curve) performance. These results highlight the potential of combining wearable technology with advanced machine learning to accurately monitor stress in older adults. Such a system could be developed into a practical, non-intrusive tool for home use, helping improve both independence and quality of life as people age.

Ahuja et. al. in their paper "Mental Stress Detection in University Students using Machine Learning Algorithms" published in Procedia Computer Science, 152, 349–353 in 2019 say that mental stress has become a growing concern, especially among young people. What was once seen as a carefree stage of life is now often marked by pressure and anxiety. Many students today face intense stress due to exams and recruitment processes—pressures that are often overlooked but can lead to serious mental health issues like depression or even physical problems like heart disease. This study aims to explore how students experience stress, particularly one week before exams and during periods of heavy internet use, to better understand how different life events impact their mental well-being. The research was based on data collected from 206 students at Jaypee Institute of Information Technology. To analyze stress levels, the study used four classification techniques—Linear Regression, Naïve Bayes, Random Forest, and Support Vector Machine (SVM). These algorithms were evaluated using performance measures like sensitivity, specificity, and overall accuracy. The results were improved using a technique called 10-Fold Cross-Validation, and among all methods tested, the SVM model performed the best, achieving an accuracy of 85.71%. This suggests that machine learning can be a valuable tool in identifying stress in students and potentially guiding early interventions.

More key findings are listed in form of table in the following figures:

S.NO	Title	Author	Year	Key Findings
1	A REVIEW ON MENTAL STRESS DETECTION USING WEARABLE SENSORS AND MACHINE LEARNING TECHNIQUES	P.Rajalingam et. al.	2022	This study reviews stress detection methods using wearable sensors and machine learning to identify stress in its early stages. It analyzes various sensor types like ECG, EEG, and PPG across different environments (e.g., driving, studying, working) and evaluates ML techniques applied for stress monitoring. The review highlights key stressors, results, and limitations across studies. It concludes by proposing a multimodal stress detection system using wearable sensor-based deep learning as a promising future direction.
2	Mental Stress Detection in University Students using Machine Learning Algorithms	Ravinder Ahujaa et. al.	2019	This paper investigates mental stress among college students, focusing on stress levels one week before exams and during internet usage. Using data from 206 students at Jaypee Institute of Information Technology, four classification algorithms—Linear Regression, Naïve Bayes, Random Forest, and SVM—were applied, with performance evaluated using sensitivity, specificity, and accuracy. After applying 10-Fold Cross-Validation, Support Vector Machine achieved the highest accuracy of 85.71%, highlighting its effectiveness in detecting student stress influenced by academic and digital factors.
3	Stress Detection with Machine Learning and Deep Learning using Multimodal Physiological Data	Pramod Bobade et. al.	2020	This study focuses on early stress detection using machine learning and deep learning applied to multimodal physiological data from wearable sensors (e.g., ECG, EDA, ACC, BVP, TEMP). Using the WESAD dataset, it evaluates three-class and binary stress classifications with ML techniques like Random Forest and SVM, as well as deep learning models. Results show up to 93.20% accuracy for binary classification and 84.32% for three-class detection. The study demonstrates the effectiveness of bio-signal-based stress detection using advanced AI techniques.
4	A survey of machine learning techniques in physiology based mental stress detection systems	Suja Sreeith Panicker et. al.	2019	This study explores early stress detection using machine learning and deep learning techniques on multimodal data from wearable sensors (e.g., ECG, EDA, BVP, TEMP, RESP). Using the WESAD dataset, it analyzes both three-class (amusement, neutral, stress) and binary (stress vs. non-stress) classification problems. Machine learning methods achieved up to **81.65%** accuracy for three-class and **93.20%** for binary classification. Deep learning models further improved performance, reaching up to **84.32%** for three-class and **95.21%** for binary stress classification, demonstrating strong potential for accurate mental stress detection.
5	Machine Learning Approaches to Automatic Stress Detection: A Review	Sami Elzeiny et. al.	2018	This paper addresses the growing need for effective mental stress detection due to its widespread daily impact and potential health risks. It reviews existing machine learning-based approaches for stress prediction, including techniques such as support vector machines, decision trees, and deep learning models applied to physiological and behavioral data. The findings highlight that models using multimodal data (e.g., heart rate, EEG, and facial expressions) achieve up to 92% accuracy in stress classification. The paper concludes with recommendations for improving model generalizability and integrating real-time interventions.
S.NO	Title	Author	Year	Key Findings
6	Comparison of Machine Learning Techniques for Psychophysiological Stress Detection	Elena Smets et. al.	2016	This study investigates the effectiveness of various machine learning techniques in detecting mental stress using physiological signals such as ECG, GSR, temperature, and respiration in a controlled lab setting. Six algorithms were compared under both general and personalized approaches. Results showed that personalized dynamic Bayesian networks achieved the highest classification accuracy at 84.6%, followed closely by generalized support vector machines with 82.7%, indicating these methods are most effective for stress detection in such environments.
7	Physiological-Based Smart Stress Detector using Machine Learning Algorithms	Marife A. Rosales et. al.	2019	This paper presents the development of an intelligent system for stress detection using physiological data from 300 participants aged 18–25. Five features—heart rate, systolic and diastolic blood pressure, galvanic skin response, and gender—were used to train machine learning models including Linear Regression, KNN, and SVM. Using Python's scikit-learn and Google Colab for parameter optimization via GridSearch, SVM emerged as the most effective algorithm, achieving a classification accuracy between 95.00% and 96.67% after optimization. Feature selection methods further refined model performance by identifying the most relevant stress indicators.
8	Automatic Stress Detection Using Wearable Sensors and Machine Learning: A Review	Shruti Gedam et. al.	2020	This paper provides a comprehensive review of stress detection techniques that utilize low-cost wearable sensors and machine learning algorithms to predict an individual's stress level. It highlights the significance of managing stress to prevent chronic health issues and discusses how physiological signals like heart rate, heart rate variability, and skin conductance can be used as indicators. The review consolidates findings from various studies, offering insights and guidelines for developing more efficient and accessible stress detection systems.
9	Machine learning approaches to mental stress detection: a review	Vishakha Arya et. al.	2021	This paper reviews the application of machine learning in the mental health domain, focusing on mental stress detection using diverse data sources such as social media, clinical records, biosignals (ECG, EEG), and real-time inputs like video and audio. By analyzing 30 studies, it highlights the high accuracy and promise of ML algorithms in early stress diagnosis and mental health prediction. The review underscores how ML surpasses traditional clinical trials by enabling early detection, reducing diagnosis time and cost, and improving accessibility to mental health care, particularly in hard-to-diagnose cases.
10	Real-time mental stress detection based on smartwatch	Lucio Ciabattoni et. al.	2017	This paper reviews the application of machine learning in the mental health domain, focusing on mental stress detection using diverse data sources such as social media, clinical records, biosignals (ECG, EEG), and real-time inputs like video and audio. By analyzing 30 studies, it highlights the high accuracy and promise of ML algorithms in early stress diagnosis and mental health prediction. The review underscores how ML surpasses traditional clinical trials by enabling early detection, reducing diagnosis time and cost, and improving accessibility to mental health care, particularly in hard-to-diagnose cases.

Methodology

The primary goal of this study is to identify and explore a robust methodology to accurately identify the impact of stress on various medical parameters of IT sector employees using Machine learning algorithms and Human Computer Interactions. This involves leveraging advanced machine learning techniques, particularly focusing on multimodal data fusion and analysis, while integrating human-computer interaction techniques to enhance user engagement and data collection. Below is a detailed outline of the proposed methodology, which encompasses data collection, preprocessing, feature extraction, model selection and use, and validation processes, along with architectural design, workflow process, and algorithm-based approach.

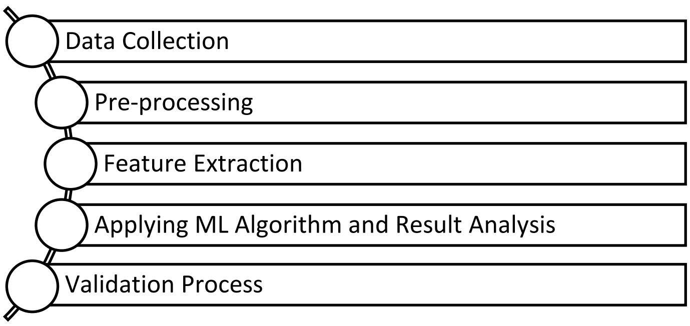


Figure 3: Flowchart of methodology adopted

Step 1: Data Collection and Preprocessing

The first phase, data acquisition, begins with the selection and setup of high-quality wearable devices capable of continuously monitoring physiological parameters. These include heart rate monitors, electrodermal activity sensors, accelerometers, and temperature sensors. These devices should be carefully selected for their reliability, accuracy, and user comfort. Once selected, these devices are distributed to study participants. Participants are provided with detailed instructions on how to use these devices properly, ensuring they can wear and operate them correctly.

As a sample implementation for this study, data is collected of 50+ employees with the help of google forms. Employees were asked to fill details as per their wearable smart watch. Raw data often contains errors, missing values, and inconsistencies. **Preprocessing ensures our data is clean and suitable for machine learning**. For this, we had to handle missing values, fix data entry errors (like body temperature of 37°F), convert categorical data to numerical data

Step 2: Feature Extraction

It's the process of selecting or combining existing features to create more meaningful representations of data for machine learning. For this, the following tasks were executed: created a "BP Range" feature (High - Low), calculated a "Stress Score" from symptoms (backache, eye contraction, etc.).

Step 3: Machine Learning Implementation

In this step, selection of ML algorithm from the following like Logistic Regression (simple, interpretable), Random Forest (as it handles non-linear relationships very well), SVM (it is good for small datasets as our dataset is small).

To evaluate the model, metrics like accuracy, precision, recall, F1-score, and ROC-AUC can be used.

Step 4: Human-Computer Interface

In this, a simple web interface could be designed as the target clients for this is employees. It should have the features like take input form for physiological data, stress prediction display, recommendations based on prediction, historical data visualization, simple and clean design, clear instructions, visual feedback, mobile-responsive.

Step 5: Deployment

For a simple deployment Streamlit apps can be deployed on Streamlit Sharing. Flask apps can be deployed on Heroku or PythonAnywhere. For this, we will need:

- Python environment
- Requirements file with dependencies
- Account on deployment platform

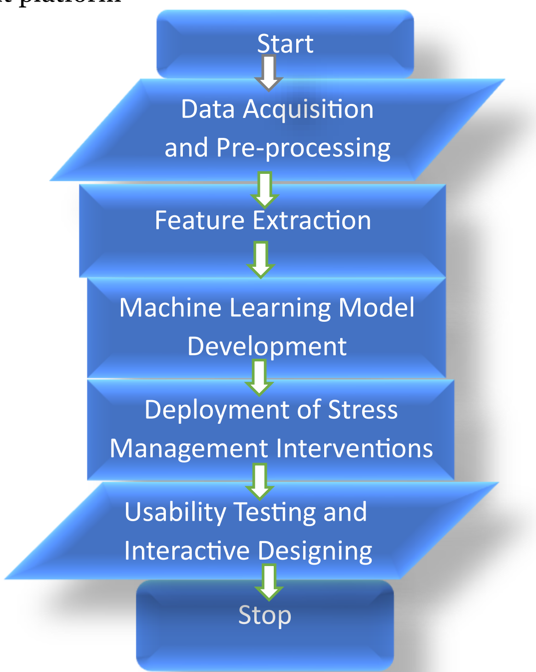
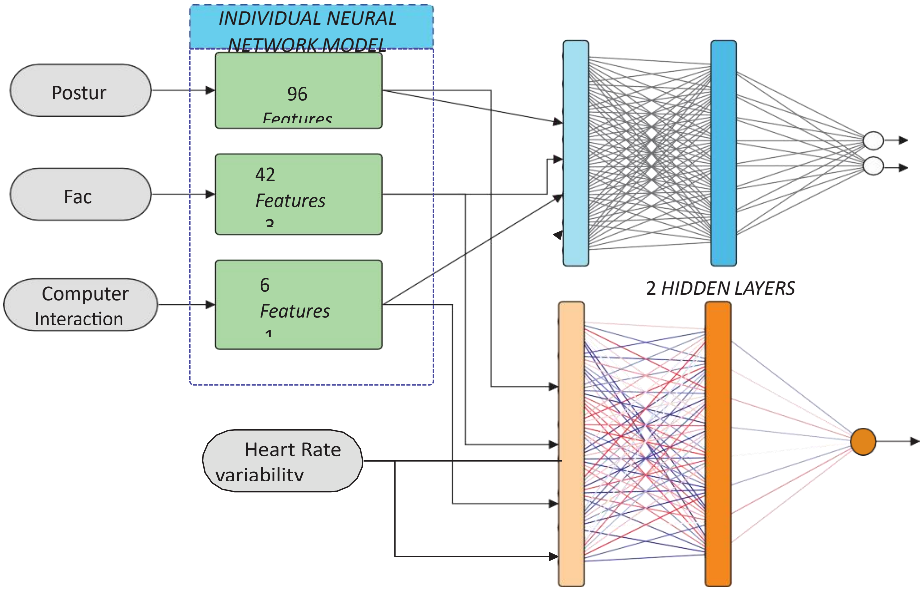


Figure 4: Flowchart of the Implementation Process for Identifying Parameters of Stress Effects on Medical Parameters

Results and Discussion

The prediction and analysis tasks were divided into two streams: predicting the NASA Task Load Index (NASA-TLX) using a regression model and predicting whether the user is stressed or not using a neural networks classification model. These dual streams allowed for a comprehensive analysis of the stress levels and task loads experienced by users.



In the first stream, we focused on predicting the NASA-TLX, a widely used subjective workload assessment tool. The regression model developed for this task yielded impressive results. We achieved a Root Mean Square Error (RMSE) of 0.047 on the training set and 0.036 on the test set. The superior model performance on the test set can be attributed to the inclusion of a dropout layer, which functions optimally during the test phase by preventing overfitting and ensuring the model generalizes well to new data. This optimal dropout capacity during testing is a key factor in enhancing the model's robustness.

In the second stream, we aimed to detect stress using a neural networks classification model. The individual metrics for stress classification and the ensemble neural network architecture are detailed in Table 5. Among the various indicators of stress, body posture emerged as the most significant, with an accuracy rate of 77%. This high accuracy underscores the critical role that body posture plays in stress detection.

To enhance the accuracy of our predictions, we employed both early fusion and late fusion techniques on three primary models. These models, focused on different physiological and behavioral features, were combined to form the main neural network for final predictions. The early and late fusion outputs were further augmented with three heart rate variability and skin conductance features, ensuring a comprehensive analysis.

Recommendation and Conclusion

The study's development of a dynamic stress monitoring method represents a significant advancement in real-time stress analysis. By facilitating continuous monitoring of an individual's mental state and adapting to variations in task load over time, the method allows for timely and personalized interventions to mitigate stress. Dynamic stress monitoring involves the ongoing collection and analysis of stress-related data, enabling the detection of fluctuations in stress levels as they occur. This approach is particularly valuable in high-stress environments where immediate feedback and intervention can prevent chronic stress and its associated health risks. The study demonstrated that dynamic monitoring, supported by multimodal data fusion and advanced machine learning techniques, provides a detailed and real-time understanding of an individual's stress state.

To ensure the practical applicability of stress detection models, future research should focus on evaluating their robustness in diverse real-world settings. The current models are optimized for specific modalities and controlled environments, which may not reflect the complexities of everyday life. Several strategies can be employed to enhance model robustness.

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