Convergence of IoT and Machine Learning: A Survey of Real-time Stress Detection System

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***Abstract* -- In today's rapidly evolving environment, stress has emerged as a significant health concern across different age groups. Stress that isn't controlled, whether it comes from job responsibilities, health issues, or the never-ending news cycle, can have a negative effect on our well-being. The problem is further aggravated by the ongoing connection to technology. In this high-tech age, identifying and controlling stress is vital. In order to solve this health issue, the study focuses on three key metrics for stress detection: body temperature, heart rate, and galvanic skin response (GSR). These parameters along with the Support Vector Machine classifier assist the system to categorize stress into three groups: 1) Stressed, 2) Not stressed, and 3) Moderate stress. Proposed training model, a NodeMCU combined with particular sensors collects data in real-time and rapidly categorizes individuals based on their stress levels. Real-time stress detection is made possible by this creative combination of hardware and software.**

Keywords - Real time Stress detection, NodeMCU, Sensors, Heart-Rate, Galvanic skin, Body temperature, response (GSR), Support Vector Machine.

I. INTRODUCTION

According to research by the American Institute of Stress, 80% of employees report feeling stressed out at work on a daily basis and need assistance with stress management [1]. In today's rigorous work and academic situations, stress is common and has significant adverse effects on mental health. According to surveys, a significant portion of people report feeling stressed out, and stress at work is associated with higher levels of anxiety and depression. The seriousness of this problem is highlighted by the World Health Organization's report on the high rate of depression worldwide, which is made worse by pressures in the job and classroom. While a number of parameters can be used to identify stress, the combination of, Heart-rate, Galvanic Skin Response (GSR) and Temperature proves remarkably efficient in detecting stress.

Figure 1.1 represents the results of an extensive survey with one hundred participants, providing insight into the elements that lead to stress in daily life. "Current Work" and "Financial Stability" are two of the major stressors that have been found; the greatest proportion of respondents who reported feeling stressed out blamed these variables.

This well-written portrayal highlights the frequency and importance of work-related difficulties and money worries as major causes of stress for those who responded to the poll.

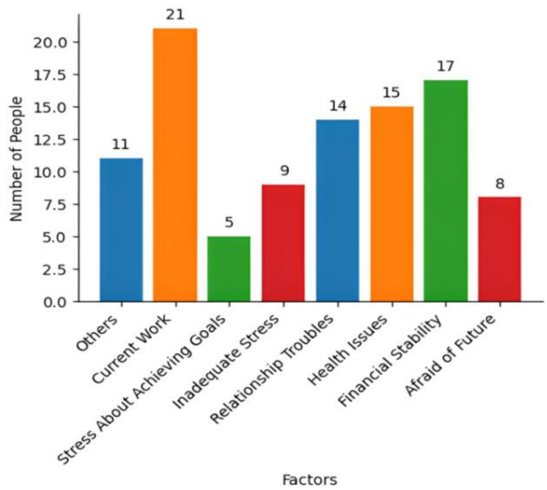

Fig 1.1: - Factors causing stress in day-to-day life

Stress can be identified by physiological markers such as EEG and ECG, or psychological tests. However, studies indicate that it is possible to recognize stress effectively in people by using indicators like, Heart-rate, Galvanic Skin Response (GSR) and Temperature [2]. Although stress can be identified with just one parameter, the model's overall performance and identification accuracy are greatly improved when heart rate, temperature, and GSR are included. When all three of these factors are use used together, stress detection accuracy is increased and a deeper, more complex understanding of a person's physiological reactions is produced [3].

Stress can be categorized into positive and negative forms, each yielding distinct outcomes. Positive stress acts as an alert mechanism, heightening awareness to potential dangers and ultimately contributing to performance enhancement. Conversely, negative stress manifests when individuals face continual challenges without adequate intervals for relaxation, resulting in notable mental and behavioural changes. It is essential to recognize that while positive stress can serve as a motivator, negative stress poses a risk to mental well-being, emphasizing the importance of managing stressors effectively to maintain a healthy balance in coping with life's demands [4].

II.LITERATURE REVIEW

[1] Zainudin, Z et al, demonstrated a machine learning and deep learning-based stress detection system. (IoT) sensors monitoring the electrocardiogram (ECG) and galvanic skin response (GSR). The dataset was categorized using the Multilayer Perceptron (MLP), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Deep Learning (DL) approaches. The best results were obtained by Decision Tree, which had 95% accuracy, 96% precision, 96% recall, and 96% F1-score. This illustrated the value of the recommended approach for real-time stress detection.

[2]A study conducted by A. Ghaderi and colleagues proposed a signal processing approach employing machine learning algorithms for the detection of stress through physiological signals. The research involved gathering biological data, including respiration, GSR Hand, GSR Foot, Heart Rate, and EMG, from various subjects engaged in driving activities. The collected data was segmented into different time intervals, and statistical features were derived from these segments. Stress levels were categorized into low, medium, and high, with the study revealing an accuracy of 98.41% for intervals of 100 seconds and 200 seconds, and 99% for intervals of 300 seconds. Notably, the respiration sensor emerged as the most crucial for stress detection. The findings suggested that gaining more insights into individuals' states in diverse situations could contribute to designing patterns for stress detection, ultimately assisting healthcare professionals in prescribing appropriate medications. In conclusion, the study highlighted the significance of respiratory sensors in effectively detecting stress levels.

[3] S. S. Thomas et al. suggested using an Arduino to measure heart rate and body temperature digitally. Based on the Arduino Mega microcontroller board the ATmega1280 included sixteen analog inputs, four UARTs, a crystal oscillator operating at 16 MHz, a USB port, a power jack, an ICSP header, and a reset button in addition to its 54 digital input/output pins. Systolic and diastolic heart rates were used to calculate the heart rate. 98.6°F (37°C) was the average normal temperature, yet "normal" varied from person to person. The project's goal was to create an embedded system that could take a patient's body temperature and heart rate, store the data for use by physicians, and show precise findings on an LCD monitor.

[5] D. McDuffy et al., was to employ physiological markers, namely heart rate variability (HRV), breathing rate (BR), and heart rate—that were captured remotely to identify cognitive stress using a digital camera three meters away. A person-independent classifier was created based on the physiological markers that were assessed, and it had an 85% accuracy rate in predicting cognitive stress. Though the results showed show significant differences in BR and HRV components between the rest and cognitive stress phases, heart rate alone was not a very strong predictor. The findings suggest that using a digital camera to measure cognitive stress non-contactly is feasible and may find use in the assessment of stress in the workplace and in educational settings.

[6] Using a dataset collected through an Android application named Emotion and Heart Rate Collection, N. T. Nguyen et al. suggested an emotion prediction system based solely on heart rate signals. The authors look at a variety of feature vectors, including maximum, mean, and median values; discrete wavelet transforms (DWT); and mel-frequency cepstral coefficients (MFCC). The tests look at a number of supervised learning models, such as k-nearest neighbor, decision trees, and support vector machines (SVM). According to the results, the SVM model that uses DWT features and 180-second time frames obtains the maximum accuracy of 79%. The project's objective is to enhance user experience through the use of widely available heart rate monitors and cellphones for emotion tracking.

[7] P. Bobade et al conducted a study that employed a diverse dataset collected from wearable motion and physiological sensors. The aim was to propose stress detection methods utilizing both machine learning and deep learning approaches. The dataset encompassed various bio-signals, including blood volume pulse, acceleration, ECG, respiration, electromyogram, and electrodermal activity. The study evaluated different classification models, including a basic feed-forward deep learning artificial neural network, K-Nearest Neighbour, Random Forest, Decision Tree, AdaBoost, and Kernel Support Vector Machine. Results indicated an accuracy of up to 84.32% and 95.21% using deep learning, and up to 81.65% and 93.20% using machine learning for three-class and binary classifications, respectively. This underscores the

effectiveness of both deep learning and machine learning methods in stress detection, showcasing promising accuracy rates in diverse classification scenarios.

[8] C. Vuppalapati et al introduced a novel approach to address mental stress identification through a combination of mobile development and machine learning. Their proposed system aimed to proactively detect and manage user stress levels by integrating Electroencephalogram (EEG) biosensors, various machine learning models (including Logistic Regression, Support Vector Machine, and Naive Bayes), and a mobile application. The article provided a comprehensive framework for machine learning centered on EEG data analysis, reviewing pertinent research in stress detection. The suggested approach demonstrated an accuracy of 83.43% in distinguishing between different stress levels and an impressive 96.4% accuracy in discerning stress from control levels. This innovative system showcases a promising avenue for effectively leveraging technology and machine learning in the identification and management of mental stress.

[9] M. Zubair et al, described the creation and application of a smart wearable band for stress detection in this paper. The band had a 3-axis accelerometer, a skin conductance sensor, bluetooth, and a microcontroller. It used skin conductance as a biomarker for stress. Through the sophisticated analysis of information from several sensors, such as skin conductance, the device was able to anticipate whether the user was under stress. Wireless transmission of the gathered data to the user's smartphone allowed for ongoing tracking of previous mental stress and allowed for prompt response. The band served as a low-cost, low-power remedy for prior stress-related health problems by improving users' comprehension of past stress patterns and providing trustworthy data for better past medical treatment.

[10] A. Simons et al, examined the impact of physiological sensor variance on machine learning algorithms for acute stress detection. Three support vector machine (SVM) models were trained using data from the RespiBAN and Empatica E4 sensors on skin temperature (TEMP) and electrodermal activity (EDA). On data captured by the same sensor that was used for training, SVM-R demonstrated 100% accuracy, SVM-E 99% accuracy, and SVM-RE 82% accuracy. The accuracy of SVM-R dropped to 64% when applied to Empatica E4 sensor data, highlighting the crucial consideration of sensor type and placement in the development of machine learning algorithms for stress detection based on physiological signals.

[11] P. S. Pandey et al, the study presented a Remote Stress Detector that combines internet of things (IoT) and machine learning (ML) to forecast and identify stress based on heart rate. The system made use of a server hosted on DigitalOcean, a pulse sensor, and a NodeMCU development board. Heart rate data was analyzed, and stress levels were predicted using machine learning (ML) algorithms such as Support Vector Machine (SVM) and Logistic Regression. The findings showed encouraging accuracy in stress detection, with 66% accuracy for Logistic Regression and 68% accuracy for SVM throughout testing. Future developments, according to the authors, could involve combining the system with health monitoring tools and looking at other physiological markers, such as galvanic skin reaction, to provide a more thorough evaluation of stress.

[12] A. Mustafa et al, suggested a system where three sensors were combined into a wearable device by the IoT stress detection and categorization system that was put into place: skin conductance, ECG, and skin temperature. Via the user's mobile device, real-time sensor data was sent to a cloud server, where AI algorithms evaluated the information to ascertain stress levels. The system classified binary stress states with a high accuracy of 97.6%. Based on information from cloud servers, alerts were sent to doctors in emergency situations so they could intervene.

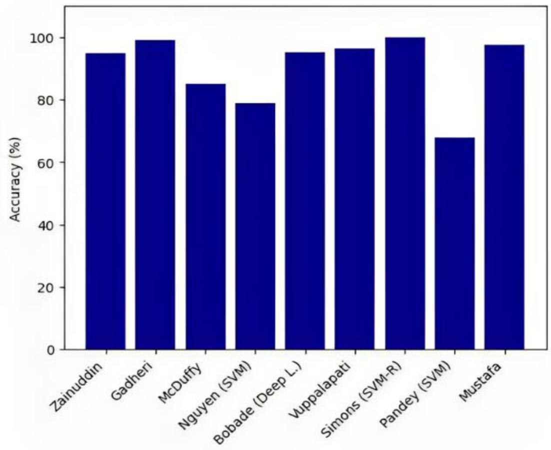

Fig 2.1: Comparison of accuracies achieved by different authors

The detection of stress is approached by taking into account several physiological characteristics at once. The heart rate, temperature and Galvanic Skin Response (GSR) values are included in the dataset that was gathered for this investigation. The goal is to acquire a more thorough knowledge of the physiological changes linked to stress by combining these various indicators. This multi-parameter method takes into account the intricate interactions between various physiological reactions under various circumstances in an effort to improve the precision and resilience of stress detection models.

Following are different parameters and their use in stress detection:

A. Galvanic Skin Response (GSR)

A major area of emphasis for comprehending stress is the Galvanic Skin Response (GSR). Changes in skin conductivity are reflected in GSR and are linked to the sympathetic nervous system's activity under stressful situations. The goal of the research is to clarify how changes in skin conductance can serve as an indicator of stress levels by examining the physiological underpinnings of GSR. Furthermore, the research investigates the independent significance of GSR as a characteristic in stress detection models, evaluating its capacity to differentiate between states that are stressed and those that are not.

B. Body Temperature

One important factor in the identification of stress is body temperature. The study explores how stress affects peripheral blood flow and, in turn, skin temperature by delving into the thermal dynamics of stress. The research attempts to assess the usefulness of temperature for stress classification by examining aspects connected to temperature. This investigation sheds light on the physiological modifications brought on by stress that result in changes in body temperature.

C. Heart Rate

Another critical component of stress detection is the cardiovascular response, namely variations in heart rate. The goal of the research is to clarify the complex relationship between stress and heart rate by comprehending the cardiovascular response to stress and how the autonomic nervous system modulates it. Heart rate variability is investigated as a component in stress detection. It is variance in the time intervals between successive heartbeats. This study adds to our understanding of the complex ways in which the cardiovascular system reacts to stress.

***D.** Combination of all these parameters for Effective Stress Detection*

For developing comprehensive and efficient stress detection model, the research investigates the amalgamation of characteristics derived from GSR, temperature, and heart rate. The information obtained from these factors is integrated using feature fusion techniques. The objective is to utilize the complimentary nature of these physiological indicators for improving sensitivity and specificity of stress detection. To build a complete stress detection system, the study evaluates several models that combine data from several factors at once. Ensemble methods and fusion procedures are used in this process.

III. PROPOSED SYSTEM FOR REAL TIME STRESS DETECTION SYSTEM

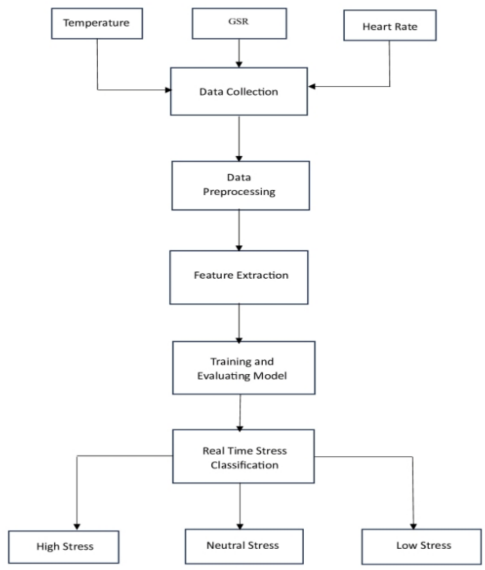

Fig 1.3: Flowchart for proposed system

IV. METHODOLOGY

A. Data Collection

The data collecting stage makes use of a publicly accessible supervised learning dataset and is designed to facilitate multi-parameter stress categorization. This dataset includes body was carefully chosen for its diversity. The model's adaptability to a wide range of stressful situations and demographic changes is ensured by the emphasis on diversity, which improves the model's practicality.

B. Data preprocessing

Preprocessing, which begins with the dataset's raw values, is essential for enhancing data that includes parameters like heart rate, temperature, and GSR prior to model training. Because these characteristics are so varied, efficient preprocessing becomes even more important. In order to avoid biases in the model, it entails managing missing values, lowering noise, normalizing or standardizing numerical features like heart rate and temperature, encoding categorical factors like stress levels, and making sure the dataset is balanced. The complex interactions between these parameters require careful preprocessing, which enhances the machine learning model's overall resilience and precision in stress detection.

1. Feature Extraction

The interpretation of several characteristics, such as temperature, heart rate, and GSR, depends heavily on the feature extraction process. To comprehend the distribution and variability of each parameter, it is transformed into a statistical metric, like the mean or standard deviation. Additionally, temporal data is gathered, including fluctuation in heart rate and temperature patterns. Cross-parameter relationships are quantified by correlation coefficients, which offer a thorough comprehension of stress levels. Similar to spectral power, frequency domain characteristics offer details on autonomic nervous system activity linked to stress. By using these extracted features, model training is able to identify intricate stress patterns and increase accuracy in stress detection scenarios that occur in everyday life.

2.Training and Evaluating the model

Using the pre-processed and feature-extracted dataset, the stress detection model is trained and evaluated in this phase. Through the use of machine learning algorithms such as Support Vector Machine, the model is trained to discover patterns that correspond to different stress levels. To facilitate generalization and optimization, the dataset is divided into training and validation sets. The model's performance is evaluated by the performance metrics such as accuracy, recall, precision and F1 score. Insights are gained by using methods including cross-validation, confusion matrices, and ROC curves, which direct ongoing improvement to increase the model's dependability under stressful situations.

3. Support Vector Machine (SVM)

Numerous research studies show the effectiveness and accuracy of SVM in stress detection, especially when combined with a linear kernel. The SVM model, which was trained on pre-processed and feature-extracted data, is excellent at classifying physiological values in real time, such as temperature, heart rate, and GSR, into three different stress states: neutral, high, and low. Utilizing decision boundaries acquired during training, SVM shows itself to be a dependable and

4.Real Time Stress Detection

The trained and assessed model is operationalized for real-world application during the stress detection in real-time phase. Real-time physiological readings from an individual are obtained by deploying the NodeMCU board, which is equipped with sensors including temperature, GSR, and heart rate. After acquired, these readings are easily sent using Tera Term software to the model for categorization. By integrating the NodeMCU with various sensors, it is possible to acquire data continuously and guarantee that the system will react dynamically to the user's physiological status. After getting the real-time data, the stress detection model uses the patterns it has learnt to categorize the incoming signals into three predetermined groups: low, high, and neutral stress states. Based on the integrated physiological indicators, this real-time categorization capability enables quick and precise evaluation of an individual's stress levels. The seamless integration of NodeMCU data collecting and model classification results in a simplified and efficient real-time stress detection system that can be used for a variety of purposes, including stress management and health monitoring.

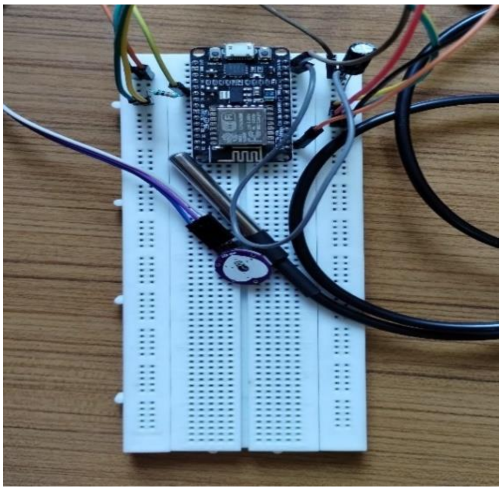

Fig 1.3: Prototype of proposed system

V. CONCLUSION AND FUTURE SCOPE

In continuously emerging society, where the effects of stress on people's mental and physical well-being are becoming more widely acknowledged, stress detection has become a crucial concern. A great deal of scientific effort has been devoted to this problem, indicating the increasing recognition of the significance of early stress detection. This survey study highlights the importance of stress detection in modern culture by combining findings from numerous studies. This study shows a full convergence of hardware and software for real-time stress detection by utilizing modern machine learning algorithms to explore several physiological characteristics like heart rate, temperature, and GSR. By using NodeMCU with smart algorithms, we can quickly and accurately assess stress levels, which can improve people's overall well-being

Prospective directions for further research are opened by the convergence of hardware and software in real-time stress sensing. The usefulness of the integrated system can be improved for a wider range of demographic groups with additional optimization and refinement. Expanding the range and precision of stress detection could be achieved by investigating other physiological metrics or integrating wearable technology. To further strengthen the system's resilience, research on customized stress thresholds and dynamic model adaptation to individual differences should be done. The general acceptance and accessibility of real-time stress detection could be facilitated by its integration into commonplace devices or applications as technology progresses. Furthermore, for the responsible development and use of such technologies in the future, it will be imperative to investigate the ethical implications and guarantee user privacy in stress detection systems. This work establishes a framework for future research and development in the ever-evolving field of stress detection, opening doors for developments that may have a positive effect on people's mental health and general well-being in the digital age.

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