Advanced Approach for Real-Time Stress Monitoring and Emotion Analysis

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ABSTRACT

In recent days, mental health challenges like stress, anxiety, and emotional instability are raising common due to rapid-paced practices, workplace pressures, academic demands, and social factors. Previous detection and managing of these emotional variations are crucial to maintaining overall well-being. However, traditional methods of stress and emotion assessment—such as self-reporting and periodic psychological evaluations—are often subjective, non-continuous, and lack real-time responsiveness. This paper mainly aims on an advanced, real-time solution that integrates intelligent hardware with smart data analysis techniques to monitor and analyse human stress levels and emotional states. This method will not only ensure passive, continuously tracks and provides real-time monitoring but also it provides quick feedback and personalized suggestions by enabling active stress management. This system is designed to be flexible and adaptable in different domains including healthcare, education, workplaces, and personal wellness making it a significant tool for improving mind and emotional health in everyday life.

KEYWORDS

Mental Health Monitoring, Real Time Emotion Detection, Stress Management, Intelligent Hardware Integration, Smart Data Analysis, Non-Invasive Assessment

I. INTRODUCTION

This paper focuses on developing a integrated system which capable of monitoring stress levels in real time and also it analysing human emotions by combining physiological signals and behavioural signals. With a growing digital and high-pressure world, such systems give hopes in fields like mental health care,

workplace wellness, driver safety, and human-computer interaction. The system monitors real-time data from sensors, video/audio inputs and they will process this data using advanced algorithms, and this system also evaluates the emotional state or stress level of a person and give high accuracy.

Today's fast-paced and highly connected world, emotional well-being and mental health have become critical concerns. People face growing levels of stress due to academic, professional, and personal pressures. However, recognizing and addressing stress or emotional imbalance is often reactive and delayed. This paper aims to bridge that gap by introducing an advanced, real-time system capable of monitoring stress levels and analysing emotional states using IOT technology specially with camera lens.

The core idea behind this paper is to create a system that continuously collects physiological and behavioural data from users and processes it in real-time to determine their emotional condition and stress level. This allows for immediate feedback, proactive support, and even automated interventions in critical scenarios—such as alerting someone during emotional distress, or preventing accidents caused by stress-induced cognitive overload (e.g., in drivers or machinery operators).

1.1 PROBLEM STATEMENT

"Advanced Approach for Real-Time Stress Monitoring and Emotion Analysis"

- Because of lack of real-time monitoring systems, mental health issues such as stress and emotional imbalance often go undetected
- Already available stress and emotion detection techniques are typically manual, subjective, and not suitable for continuous assessment.
- The physiological signals (like heart rate) with behavioural cues (like facial expressions), there is limited integration of these and minimised accuracy.
- Non-invasive, automated, and intelligent solution are not present then it prevents timely feedback and early intervention.

II. LITERATURE REVIEW

Detecting objects with machines is seen as an important part of future human-computer interaction. Many studies have been done recently. They show that recognizing emotions automatically is hard but possible. Most efforts focus on analysing information. Only a few applications can respond to a user's emotions instantly. To address this gap, we introduce a framework termed Smart Sensor Integration (SSI), which significantly accelerates the development of multimodal online emotion recognition (OER) systems. Specifically, SSI supports the pattern recognition pipeline by providing customized tools for data segmentation, feature extraction, and pattern recognition, as well as tools for both offline (training phase) and online (real-time recognition) application. Furthermore, it is designed to accommodate input from various learning styles and to facilitate the integration of multimodal information. [1]

Stress is one of the crucial activate for many diseases. Improving stress balance is an important way to prevent problems. With wearable sensors, we can now track and analyse a person's behaviour all the time without them noticing. In this paper, we show a study where 21 teachers from a vocational school used wearable sensors. They could see their stress information related to their life events over four weeks using our software tool, without needing supervision. We aimed to see how actively users participated and if the system helped them coach themselves. Our results show that users looked closely at their high data during the study. A subsequent quality review was performed with 15 of 21 users indicated that 12 of 15 users were able to learn about their emphasis based on the information they obtained, but only 5 of them were able to come up with practical action for improving their optimal stress level on their own, while other users were of opinion that nothing can be done to reduce their stress, Although self-coaching has some potential, continued coaching support is nonetheless essential. [2]

Continuous monitoring of stress is crucial for management. Heart Rate Variability (HRV) from heart rate signals is one technique for this purpose. The author addresses challenges of distinguishing stressed and non-stressed states using one minute of Inter Beat Interval (IBI) data. This technique captures short stress fluctuations and enables ongoing monitoring. The analysis uses time, frequency domain and nonlinear HRV features for accurate classification. The study presents a stress score to understand patterns and adjust levels. A system was developed as an Android application for real-time stress monitoring. [3]

Figure 1 shows flow diagram representing the steps taken to analyse heart rate variability for stress determination.

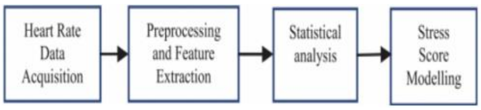

Figure 1 Flow diagram (Adapted from [3])

Figure 2 illustrates the dance of stress scores with RMSSD, as choreographed by the multinomial logistic regression model crafted from our ensemble of 41 subjects.

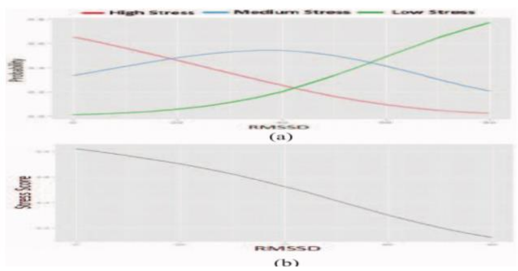

Figure 2 (A)probability of low, medium and high stress (b) stress score vs. RMSSD (Adapted from [3])

Recognizing the link between emotional states and physical health, affective computing is gaining traction as a field of interest. It is an active research area that has witnessed significant advancements in technology for analysing affective states in stress detection. The field's inception is attributed to Dr. Rosalind Picard of the Massachusetts Institute of Technology (MIT), who published a seminal article on affective computing in 1995. Today, it stands as a modern branch of computer science focused on human-computer interfaces. This branch encompasses two primary areas: 1) the detection and recognition of emotional information, and 2) the simulation of emotion in computational devices. The current survey emphasizes the detection and recognition of emotions in an affective manner. [4]

The main study of this paper is based on the driver's safety alert system, where in countries due to heavy traffic which is leading serious accidents on road. Measuring stress and fatigue emotional responses by means of a wireless wearable system would be useful for roadway tragedies. The focus of the study was to develop and verify an emotional response monitoring for drivers derived from earlobe signals, muscle, motion sensing of head movement. Here sensor are used and connected to microcontroller which are united with Bluetooth module which allows the transmission of those sensor readings to a mobile device, the mobile device application used to extract data from sensors and determine driver’s current status via machine (SVM) model using this model there high accuracy rate. In this study we can analysis that they use wearable system to driver’s safety and also for preventing the accident from emotional responses. [5]

As the counter reached the predefined threshold of C2 or C3 states (ten counters that equal 10 s consecutive increments), the warning module is triggered, involving audible sound, vibration, and visual text, as shown in Figure 3.

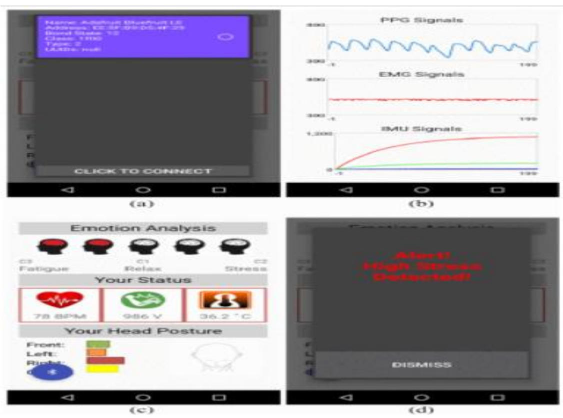

Figure 3 Screenshots of the proposed mobile application for a wearable emotional response evaluation system (Adapted from [5])

It is quite common that, during driving it often causes negative emotions like stress and anger that can harm cardiovascular health. It happens frequently and in traditional methods we use intrusive and infrequent subjective self-reports, which rely on honest feedback. This paper mainly shows result on how psychophysiological data is used to label driving data dynamically for better emotion detection. It uses two labelling methods one is self-report and one more is physiological report, these two were compared using Linear Discriminant Analysis and Support Vector Machines. These both methods resulted in similar accuracy. But physiological labelling is more objective, continuous and high fidelity. This helps drivers to reduce the burden and increases the real-time emotion detection. This method enhances driver safety and health monitoring. [6]

Physiological responses to mental and physical challenges can manifest as negative emotional stress. Prolonged exposure to stressful situations may have detrimental effects on individuals, potentially leading to depression and, in severe cases, suicide. Therefore, it is crucial to monitor and analyse stress in real time and address it appropriately. This paper introduces a novel framework for real-time stress detection. The framework identifies stress by recognizing three stress-related facial expressions: anger, fear, and sadness. When stress-related frames increase beyond a certain threshold, the framework indicates the need for rest or a break. Our experimental results demonstrate that the proposed methods enhance facial expression recognition performance and achieve high-performance stress detection. [7]

There are multiple measures of an individual's inclinations and personality that cannot be visually decoded. Technology can play a vital role in uncovering crucial information about an individual in various situations. By utilizing concepts such as Electrodermal Activity, rate detection, and Emotion and Sentiment Analysis, it is possible to identify an individual's stress and emotional state under diverse circumstances. This information facilitates a comprehensive assessment of an individual's attributes. These insights offer valuable analytical support in understanding how individuals behave in different situations, which can be beneficial for companies and government entities in applications such as recruitment, investigation, and lie detection processes, among others. This will enhance security and contribute to human well-being through the application of technology. [8]

This paper is pertinent to several significant fields of study, specifically sentiment analysis and human–robot interaction. Affective computing, a subset of sentiment analysis, examines text data to evaluate the emotions conveyed, based on the text's characteristics and prominent emotional indicators. Various methodologies and processes exist for detecting emotions in text data. Due to the inherent ambivalence and subjectivity in labelling emotions, it is possible to assign multiple emotions to a single sentence, thus presenting a multi-label challenge. Based on a survey of this issue, we conducted experiments utilizing the unconditional, Support Vector Machine, and Neural Network categories. The results obtained from these classifications were subsequently applied in human–robot experiments. [9]

The paper addresses the challenges of psychological stress detection in unmanned aerial vehicles (UAV's) operators, based on deep learning method. In increase in UAV's the communication between operators and systems became more stressful. For safety of UAV flights, stress detection became a key role. It leverages a multimodal emotion recognition system grounded in arousal valence space. The proposed multimodal vision modality uses CNN, LSTM with attention to process the cues, while using audio modality features like MFCC's. The multimodal-fusion approach uses a strategy referred to as “late-fusion” that involves the combination of unimodal model outputs as inputs of the decision engine. In the realm where human ingenuity meets the mechanical mind, we find ourselves navigating the intricate dance of operator-machine interactions. Here, our model is meticulously trained and evaluated on the one-minute Gradual Emotion Challenge dataset, a treasure trove of naturalistic behaviour that serves as our guiding star. [10]

Psychological stress detection through bio-signal analysis examines stress effects on the human body. When encountering threats, physiological processes prepare the body for adaptation. Key bio signals include physiological measures (EEG, ECG, EDA, EMG) and physical measures (respiratory rate, speech, skin temperature, pupil size, eye activity). Research aims to establish reliable bio signal indicators for stress responses, due to lacking guidelines on bio signal-stress behavior relationships. This paper examines stress effects through bio signals, focusing on feature efficiency and multimodal analysis methods. [11]

The proposed framework (as shown in Figure 4) demonstrates the internal layout of the student stress monitoring and alert generation system. It consists of three layers: the IoT layer, Fog layer, and Cloud layer.

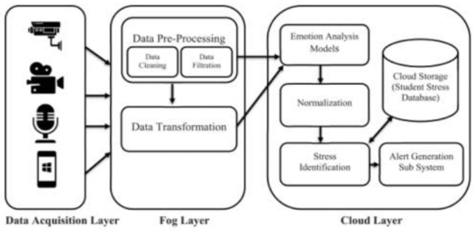

Figure 4 The layered architecture of the proposed system (Adapted from [11])

The paper mainly proposed the method to increase the spectral efficiency in energy-harvesting IoT networks by integrating Opportunistic Non-Orthogonal Multiple Access (NOMA) with Deep Reinforcement learning (DRL). It introduces how secondary user (SU) shares spectrum with primary users (PU) using the method NOMA during uplink transmissions, by avoiding the interferences, and also it optimizes the process using the method Deep Deterministic Policy Gradient (DDPG) algorithm. This provides the combined approach of convex optimization with DDPG that allows SU to make intelligent transmission decisions based on dynamic network conditions. Simulation results in spectrum management in energy-constrained IoT environments. The model significantly outperforms the traditional schemes regarding to the spectral efficiency. [12]

This paper presents a non-invasive stress detection method that uses camera to extract face related and emotion related features. Because of that, there's a growing need for stress detection methods that are non-invasive, do not require physical contact, and are easy to use. We introduce a method that uses features related to the face and emotions, all captured through a regular camera. The face-related features include things like facial expressions action units and face embeddings, while the emotion-related features include feelings such as valence, arousal, and emotion labels. By combining these features, we were able to achieve perfect accuracy 1.000 in detecting stress, 0.891 accuracy in recognizing tasks, and 0.883 in classifying stress levels, based on sample sizes of 111, 316, and 319 respectively. So, there must despite the promising results of the proposed stress detection method. First, the system's performance is sensitive to lighting conditions and camera quality. This approach offers a comfortable and practical alternative to sensor-based systems, making suitable for daily or real time applications. [13]

It includes feature extraction from input facial image sequence, feature fusion, segmentation and filtering, calculating mean and standard deviation per segment and feeding features into ML-based classifier. Prediction consists of stress state classification, task recognition and stress level classification as shown in figure 5.

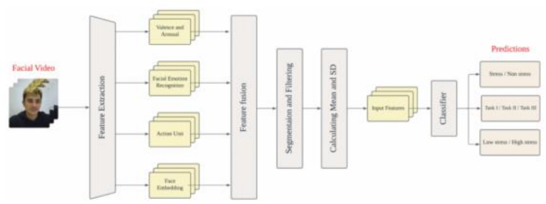

Figure 5 An overview of our proposed method. (Adapted from [13])

Action Units (AUs) are introduced as the set of standard movements of facial muscle by the FACS, which quantitatively evaluates facial expressions. To explain a specific emotion Combination of Aus can be used. Few of the examples are, the combination of AU06 (raising cheek) and AU12 (pulling lip corner) are associated with happiness. 41 AUs were estimated as the confidence score (probability of occurrence) represented by continuous values between 0 and 1 in face torch as shown in figure 6.

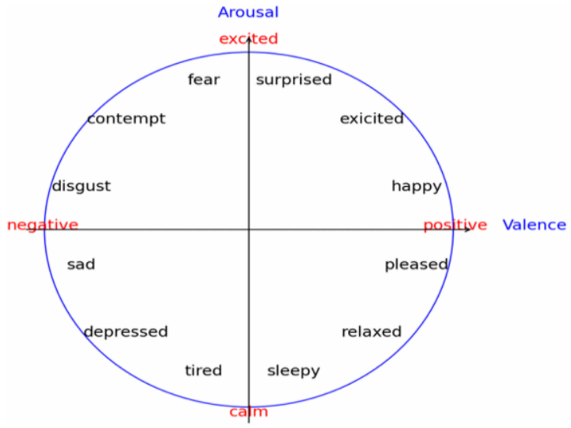

Figure 6 Valence and Arousal space model and corresponding emotions distributed in the model space (Adapted from [13])

In recent years stress during and after the pandemic have seen a significant invisible, made emotion a hot topic. It is more affected by and became more worse by the current economic inflation and increasing cost of living. By the growing stress person's well-being and development of business and nation is analysed. Using single model to identify the stress give less accurate results, delays may occur, and it can also mislead the findings, if the input is not properly detected and separated. Therefore, this paper use 15 facial expression methods and 17 voice approaches. There will be advantages and dis advantages for each method again, but it gives the result at certain accuracy level. [14]

In figure 7 it explains how the emotions are detected by both the facial expression and the trained voice samples. It results in showing the accurate output.

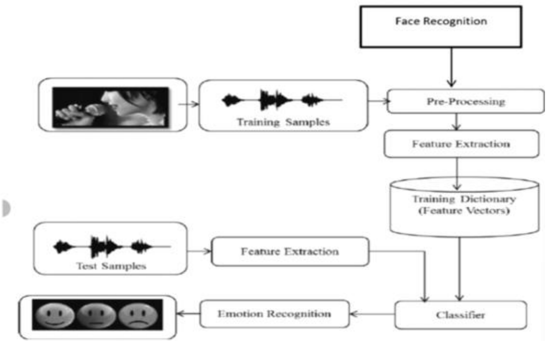

Figure 7 Architectural diagram of the proposed work (Adapted from [14])

Stress affects mental and emotional well-being significantly, for making precise, reliable evaluation for meaning full and accurate outcomes. This study combines predefined set of questions with camera tracking to monitor and evaluate stress in real time. This system will also detect the facial expressions and self-recorder data to enable a complete and understand the insight of individual stress. Machine learning algorithms such as Random Forest, k-Nearest Neighbours (KNN), Support Vector Machines (SVM), and Naive Bayes these are used in this to categorize stress levels. 632% accuracy is achieved by analysing Facial expression alone. By combining both data sources we get overall optimistic assessment precision. This mixed strategy illustrates potential for personalized stress management. [15]

Nowadays the most common health issue emerged in research is stress and mental well-being. It is proved that Chronic stress affects the people's physical and mental well-being. This paper introduces the integrated model of ML and CNN that predicts the stress from the detection of facial emotion. It collects the random forest and adaptive boosting required to evaluate the real time emotional states of the students and it also keep the track on the previous mental health issues. The model is designed on these bases. It mainly targets university students for categorizing their academic stress levels either as low, medium or high by detection of their behaviour and by collecting their facial emotional data. The CNN model that collects the facial expressions and categorise the emotions like happiness, sadness and it provides real time insight to stress level monitoring. This results in how ML and CNN based facial emotion detection can monitor and improve student health by managing their stress levels. It also works at an early stage. [16]

Real-time stress detection using facial emotion recognition by deep learning-based system. Traditional methods often be reliable on physiological sensors which are accurate, interrupts your normal routine(intrusive) and are not suitable for daily use. Unlike the approach for this method uses Convolutional Neural Network (CNN) trained on the FER-2013 dataset which classifies seven core facial emotions such as anger, disgust, fear, happiness, sadness, surprise, and neutral. Stress levels (i.e, low, moderate, high) are connected to these emotions, which enables dynamic stress assessment based on facial expressions. The system provided includes a real-time visual feedback interface, enhancing user experience and making it applicable in various real time scenarios such as workplace monitoring, mental health care, and personal well-being tracking. By having Experimental evaluations and demonstrate high accuracy in recognizing emotions and predict the reliable stress-level. Its Ambient, seamless, user-friendly design supports integration into everyday technologies like wearables and smartphones, offering a scalable and adoptable solution to the growing issue of stress in modern life. [17]

2.1

SURVEY OF EXISTING LITERATURE

Sl.no	Title	Author	Key Features	Technology Used	Advantages	Drawback
1	A Smart sensor integration: A framework for multimodal emotion recognition in real-time	J. Wagner et. al	Multimodal sensor fusion	Multimodal sensing	High accuracy via diverse inputs	High system complexity
2	Personalized Stress Management: Enabling Stress Monitoringwith LifelogExplorer	Kocielnik, R. et. al	Personalized feedback	Lifelogging	Customized stress relief insights	Privacy concerns
3	Continuous monitoring of stress on smartphone using heart rate variability	S. Mayya et. al	Uses HRV to detect stress	Smartphone sensors	Non-invasive continuous monitoring	Movement affects accuracy
4	A Survey of Affective Computing for Stress Detection: Evaluating technologies in stress detection for better health	S. Greene et. al	Comparative tech analysis	Biosignals, ML	Broad overview for researchers	Lacks implementation
5	Wearable Mobile-Based Emotional Response-Monitoring System for Drivers	B. G. Lee et. al	Wearable for drivers	Wearables, mobile app	Improves road safety	Context-specific
6	Detecting Negative Emotions During Real-Life Driving via Dynamically Labelled Physiological Data	C. Dobbins and S. Fairclough	Real-world physiological data	Dynamic labeling	Labeling challenges	Adaptive to real scenarios
7	Detecting Negative Emotional Stress Based on Facial Expression in Real Time	J. Zhang et. al	Real-time facial detection	Computer vision	Immediate visual feedback	Occlusion issues
8	Stress and Emotion Analysis using IoT and Deep Learning	A. N. Parab et. al	IoT integrated deep learning	IoT, CNN, LSTM	Automation in detection	Network dependency
9	Emotion analysis in human–robot interaction	Martin Sarnovsky et. al	HRI emotion study	Facial & speech sensing	Useful in robotic assistants	Not generalizable
10	A Multimodal Non-Intrusive Stress Monitoring From the Pleasure-Arousal Emotional Dimensions	M. Dahmane et. al	Pleasure-arousal model	Multimodal emotion model	Comfortable & less invasive	Ambiguity in arousal

11	A Facial and Vocal Expression Based Comprehensive Framework for Real-Time Student Stress Monitoring in an IoT-Fog-Cloud Environment	M. Singh et al	IoT + fog + cloud model	Facial & vocal + IoT	Efficient multi-layer processing	Latency issues
12	Review on Psychological Stress Detection Using Biosignals	G. Giannakakis et. al	Biosignal review	EEG, ECG, GSR	Useful reference for developers	No new models
13	Camera-Based Stress Detection Using Face-Related and Emotion-Related Features	R. Ogasawara et. al	Face & emotion detection	Computer vision	Camera-only stress monitoring	Lighting issues
14	Emotional Evaluation of Facial Tension Using LSTM for Psychological Assessments	M. Sreekrishna et. al	Facial tension + LSTM	Deep learning	Effective temporal modeling	Needs lots of data
15	A Multimodal Approach for Stress Detection through Questionnaire and Emotion Analysis.	J. Sharma et. al	Subjective + AI methods	Surveys + AI	Holistic stress profiling	Response subjectivity
16	Mental Stress Prediction Using Machine Learning and Facial Emotion Recognition	C. Swedheetha et. al	ML + facial detection	ML, facial features	Automation + precision	Bias in dataset
17	A ML-Driven Real-Time Emotion and Stress Level Monitoring	B. Parate et. al	End-to-end monitoring	ML pipeline	Live feedback system	Real-time tuning

2.2 COMPREHENSIVE LITERATURE GRID

Paper No./ TOPIC	**Multimodal Emotion Detection**	**Mobile-Based Emotion Detection**	**HRV Sensors**	**Facial Expression / Camera**	**Speech or Vocal Input**	**IoT and Deep Learning**	**Real-Time Feedback**	**Emotion & Stress Joint Detection**	**Machine Learning Use**
(Wagner)	✓								
(Kocielnik)									
(Mayya)			✓						
(Greene)									✓
(Lee)		✓							
(Dobbins)			✓						
(Zhang)	✓			✓			✓		
(Parab)						✓			

(Sarnovsky)					✓				
(Dahmane)	✓				✓	✓	✓		
(Singh)									✓
(Giannakakis)									✓
(Ogasawara)				✓					✓
(Sreekrishna)									✓
(Sharma)				✓					✓
(Swedheetha)						✓	✓	✓	✓
(Parate)									

2.3 OVERVIEW

The major paper presented in this overview focuses on a multimodal, real-time and non-disturbing system for detecting stress and emotional states using a combination of functional signals (HRV, GSR), facial expressions, and voice analysis, with data processed via machine learning (ML) techniques on an embedded IoT platform. A survey of literature reviewed spans a range of approaches from early sensor-based multimodal systems (e.g., Wagner et al., 2009) to modern AI-driven and deep learning models (e.g., Ogasawara et al., 2024; Swedheetha et al., 2025). Most existing works either specialize in single-modality stress detection (e.g., HRV via smartphones, facial analysis via camera) or are limited to specific applications such as driving safety or robotic interaction. For instance, camera-based models (like R. Ogasawara, 2024) offer comfort but lack sensor fusion, while HRV-based apps (Mayya et al., 2015) offer portability but are sensitive to movement and lack emotional context. On the other hand, several works (e.g., Parab et al., 2020; Dahmane et al., 2022) explore multimodal stress estimation, yet these often remain theoretical or laboratory-bound, lacking real-world deployment mechanisms or embedded integration. Notably, some recent systems propose cloud-fog-IoT architectures (e.g., Singh et al., 2022), but these introduce latency and dependency on internet infrastructure.

2.4 GAP ANALYSIS

The gap between the major paper and prior research lies in the paper's holistic integration of hardware (wearable sensors, camera, microphone), real-time data addition on embedded platforms (e.g., ESP32/Raspberry Pi), and multimodal combination using deep learning (CNN, LSTM) to enable on-device, continuous monitoring—something that many reviewed papers have not completely implemented. Moreover, most previous systems focus on backward-looking analysis or theoretical modelling, whereas the proposed system offers real-time feedback, personalized stress management creating a customized plan for managing stress that's tailored to your individual needs, and cross-domain adaptability (education, healthcare, workplace), thereby closing the loop between detection and intervention. The paper also addresses users should be able to understand and navigate the product without confusion, non-invasiveness, and low-latency processing needs that are often observed in prior academic solutions. Hence, the proposed solution advances current research by bridging the gap between research prototypes and movable, real-time emotion-aware systems.

III. PROPOSED METHODOLOGY

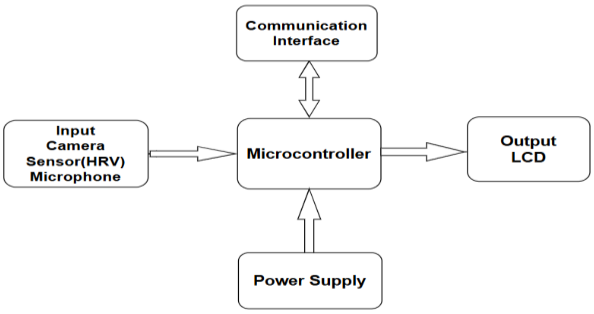

Figure 8 Block diagram for Proposed solution

Block diagram of a microcontroller-based system, likely used for monitoring or interfacing with human inputs (e.g., for health or communication purposes). The explanation of each block in the diagram:

1. Input (Camera, Sensor (HRV), Microphone)

- Camera: Captures visual information, possibly used for image processing, face detection, or behavioural analysis.
- Sensor (HRV - Heart Rate Variability): Measures physiological signals related to heart activity, it can be used for stress, health, or emotional state monitoring.
- Microphone: Captures audio input. This may be used for voice commands, sound monitoring, or communication.
- These components send raw data to the microcontroller for processing.

2. Microcontroller

- Acts as the CPU of the system.
- It processes data taken from input devices and makes decisions based on programmed logic.
- It controls communication with external devices and handles output display.
- This is the core unit that manages the entire system.

3. Output (LCD)

- The LCD (Liquid Crystal Display) shows the processed output.
- It could display text, numerical data (like HRV), or graphical information to the user.
- Serves as the user interface for visual feedback.

4. Communication Interface

- Allows the microcontroller to communicate with external systems (e.g., PC, smartphone, or cloud).
- Could be wired (e.g., USB, UART) or wireless (e.g., Bluetooth, Wi-Fi).
- Facilitates data transmission, remote control, or logging.

5. Power Supply

- Provides necessary electrical energy for the microcontroller and all connected peripherals.
- May include voltage regulators, batteries, or USB power sources.
- Ensures the system runs safely and reliably.

We are going to design a real-time system to detect emotional and stress states that is represented by the figure 1 above that represents the model with combined data from multiple sensors (heart rate, facial expressions) and a camera. For data acquisition and communication, we are implementing IoT-based sensor modules and a central embedded platform (e.g., Raspberry Pi or ESP32). To analyse multimodal data and classify stress levels and emotions with high accuracy, we use machine learning algorithms. Real-time alerts, data logging, and personalized feedback to support proactive stress management features are added. The system is adaptable for use in fields like personal monitoring, healthcare, corporate wellness and education, also it ensures the system is non-invasive and portable.

IV. EXPECTED OUTCOME

After collecting real-time data from hardware sensors such as heart rate monitors, and cameras, the system processes and analyses the information using advanced machine learning algorithms.

- **Quantitative Stress Level Indicator**: A continuous numerical value or categorized labels (e.g., low, medium, high) representing the user's current stress intensity based on physiological data patterns like heart rate variability and skin conductance.
- **Emotion Classification**: Identification of the user's emotional state (such as happiness, sadness, anger, fear, or calm) derived from combined analysis of facial expressions, voice tone (if used), EEG brainwave patterns, and physiological signals.
- **Real-Time Visualization**: A dynamic dashboard or mobile interface displaying live graphs of sensor data, stress levels, and detected emotions, providing immediate feedback to the user or caregiver.
- **Personalized Feedback**: Based on the detected patterns, the system may offer suggestions such as breathing exercises, mindfulness prompts, or rest reminders to help manage stress effectively.

The final expected outcome is continuous monitoring of user stress levels and also detect multiple emotional states like anxiety, excitement, angry by face and vocal recognition using cameras and sensors. Finally the output that means the stress level user is displayed in percentage in LCD display.

V. CONCLUSION

The detailed and thorough examination of existing literature highlights there are significant advancements in this field that is stress and emotion detection using various technologies such as physiological signal monitoring, computer vision, AI, body sensors, camera and machine learning. However, these works either use one type of input or sources, focus on specific situations, application-specific use cases, or lack real-time and embedded implementation. The proposed major paper effectively addresses these gaps by integrating multiple safe, comfortable and easy to use sensors (HRV, GSR, camera, microphone) with an embedded IoT platform, enabling real-time, multimodal stress and emotion analysis. This positions the paper as a practical and scalable solution suitable for diverse real-world applications, bridging the divide between academic research and functional deployment this means transforming the research into actionable solutions.

Declarations

Ethical Approval: Not applicable

Competing Interests: The authors declare no competing interests.

Author's contribution:

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings.

Funding Statement: Not applicable

Availability of data and materials: Not applicable

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