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Stress Analysis and Care Prediction System for Online Workers

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Abstract: In recent years, the shift toward online work has increased significantly, especially after the COVID-19 pandemic. While working remotely provides flexibility, it has also led to higher stress levels due to continuous screen usage, workload pressure, and reduced social interaction. This paper presents a stress analysis and care prediction system designed for online workers. The system observes user behavior through facial expressions, typing patterns, and physiological signals to understand stress levels in real time. A combination of deep learning and machine learning techniques is used to improve the system's performance. The model is implemented using a Raspberry Pi setup, making it practical for real-world usage. Compared to traditional methods, this approach focuses on multiple inputs instead of relying on a single parameter, which helps in achieving better accuracy. The system also provides feedback to users so they can take necessary actions to manage their stress. Overall, this work aims to provide a simple and effective solution to support the well-being of people working in digital environments.

Index Terms*— Stress Detection, Machine Learning, Facial Recognition, Real-Time Monitoring, Raspberry Pi.*

I. INTRODUCTION

Nowadays, many people depend on online platforms for their work and studies. This change became more noticeable during the COVID-19 period, where working from home became common. Although this has many advantages, it also created new challenges such as long screen time, lack of physical activity, and reduced interaction with others.

These factors can slowly increase stress levels, which may affect both mental and physical health. If stress is not identified early, it can lead to problems like fatigue, anxiety, and reduced productivity. Therefore, it is important to monitor stress in a simple and effective way.

Many existing systems use sensors or single methods to detect stress, but they are not always practical for daily use. Some require special devices, while others do not provide accurate results in real-time conditions.

In this project, we propose a system that combines different types of data such as facial expressions, user behavior, and physiological signals to detect stress more effectively. By using both machine learning and deep learning techniques, the system can analyze the user's condition in real time.

The main idea of this work is to develop a system that is easy to use, non-intrusive, and capable of giving reliable results, helping users maintain a healthier lifestyle while working online.

II. LITERATURE REVIEW

Stress detection has become an important area of research due to the increasing use of digital devices and online working environments. Researchers have explored different approaches to identify stress levels using physiological, behavioral, and visual data.[1]

Physiological signal-based methods are widely used because they directly capture the body's internal responses. Parameters such as heart rate variability (HRV), electrodermal activity (EDA), and brain signals (EEG) are commonly analyzed. Several studies have shown that machine learning algorithms like Support Vector Machines (SVM), Random Forest, and Neural Networks can effectively classify stress levels based on these signals. However, these approaches often require wearable sensors or specialized equipment, which may not be suitable for continuous use in daily life.

With the advancement of computer vision, facial expression-based stress detection has gained significant attention. Deep learning models, especially Convolutional Neural Networks (CNNs), are used to analyze facial features and identify emotional states. These systems can detect signs of stress such as eye strain, facial tension, and changes in expressions. Although they provide good accuracy, their performance can be affected by lighting conditions, camera quality, and user movement.

Behavioral analysis is another non-intrusive approach that focuses on user interaction patterns. Researchers have studied typing speed, key press duration, mouse movement, and click pressure to understand stress levels. Changes in these patterns often indicate variations in mental state. Machine learning models such as K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) have been applied to classify stress based on behavioral features. However, these methods alone may not provide a complete understanding of stress, as they do not consider internal physiological changes.

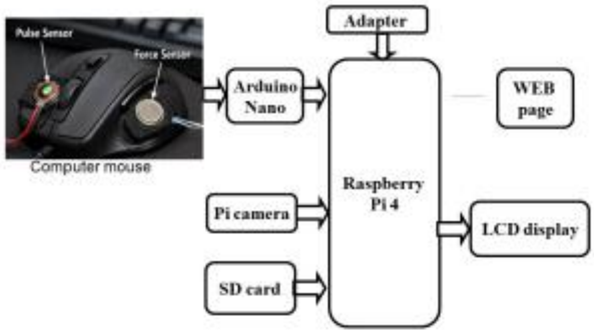

Fig. 1. Block Diagram

In recent years, multimodal stress detection systems have been proposed to overcome the limitations of individual methods. These systems combine multiple data sources such as physiological signals, facial expressions, and behavioral patterns to improve accuracy and reliability. Hybrid models that integrate deep learning for feature extraction and machine learning for classification have shown promising results.

Some studies have also explored the use of embedded systems and edge devices for real-time stress monitoring. Platforms like Raspberry Pi and Arduino are used to develop portable and cost-effective solutions. These systems enable continuous monitoring without requiring high-end computational resources. However, integrating multiple data sources efficiently on such devices remains a challenge.[2]

In this work, a multimodal approach is adopted by combining physiological signals, behavioral data, and facial expression analysis. The proposed system uses a hybrid combination of machine learning and deep learning techniques to improve detection accuracy while maintaining real-time performance. Unlike many existing systems, this approach focuses on being non-intrusive, scalable, and practical for everyday use by online workers.

III. Methodology

The proposed system is developed to monitor the stress levels of online workers in real time. In this system, we use a combination of hardware components and intelligent algorithms to understand the user's mental state. Instead of relying on a single parameter, multiple inputs such as facial expressions, user behavior, and physiological signals are considered together.[3]

The overall setup is built using a Raspberry Pi, which acts as the central processing unit. It is connected to a Pi Camera for capturing facial expressions, along with sensors to collect heart rate and mouse interaction data. An Arduino Nano is used to handle sensor data collection and send it to the Raspberry Pi for further processing.

Initially, the system collects data from different sources while the user is working. The camera continuously captures images, and these frames are analyzed using a CNN model to detect facial expressions related to stress. At the same time, the pulse sensor measures heart rate, and the force sensor records mouse pressure to understand user behavior.

The collected data is then processed step by step. Facial data is handled using deep learning techniques, while sensor values are analyzed using simple threshold-based methods. These values are filtered and converted into meaningful information that reflects the user's condition.[4]

To further improve the system, temporal changes in user behavior are considered. Instead of looking at a single moment, the system observes how the data changes over time. This helps in identifying patterns related to stress more accurately.

Finally, all the processed outputs are combined to determine the overall stress level of the user. Based on the analysis, the system classifies the condition into low, medium, or high stress. The result is displayed on an LCD screen and can also be viewed through a web interface. This approach ensures real-time monitoring and provides useful feedback to the user.

A. Visual-Based Stress Detection Using CNN and Camera

The system utilizes a camera module connected to the Raspberry Pi to continuously capture video streams of the user during working sessions. These video frames are processed in real time to identify stress-related facial expressions and behaviors.

B. Dataset Preparation

A dataset is created by collecting video samples of users during work sessions and converting them into image frames. These images are categorized into different classes such as normal, stressed, fatigued, and other behavioral states. The images are preprocessed by resizing, normalization, and conversion into grayscale (if required) to improve feature extraction.

C. Training the CNN Model

In this work, a Convolutional Neural Network (CNN) is used to learn features from the collected facial image dataset. The model is designed with multiple layers that help in identifying important patterns from the input images.

During training, the network gradually learns to recognize different facial expressions related to stress. Functions like ReLU are used to introduce non-linearity, and the final output layer uses Softmax to classify the input into different categories. The model is trained over several iterations until a satisfactory level of accuracy is achieved.

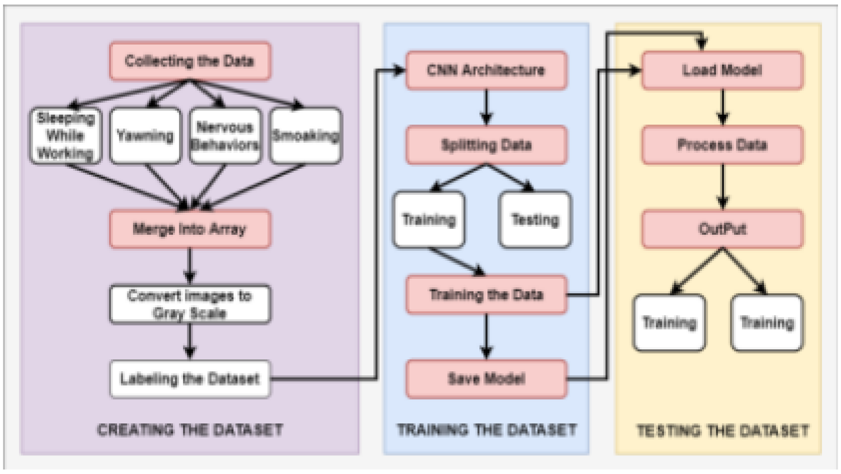

Fig. 2. Model developing flow

D. *Testing and Real-Time Detection*

After completing the training phase, the model is deployed on the Raspberry Pi for real-time usage. The camera continuously captures live video, and each frame is processed one by one. The trained model analyzes these frames to identify facial expressions and detect signs of stress. Features such as eye movement, facial tension, and slight behavioral changes are considered during this process. Based on these observations, the system classifies the user's current state in real time.

Fig. 7 CNN Training Accuracy and Loss Curves (50 Epochs)

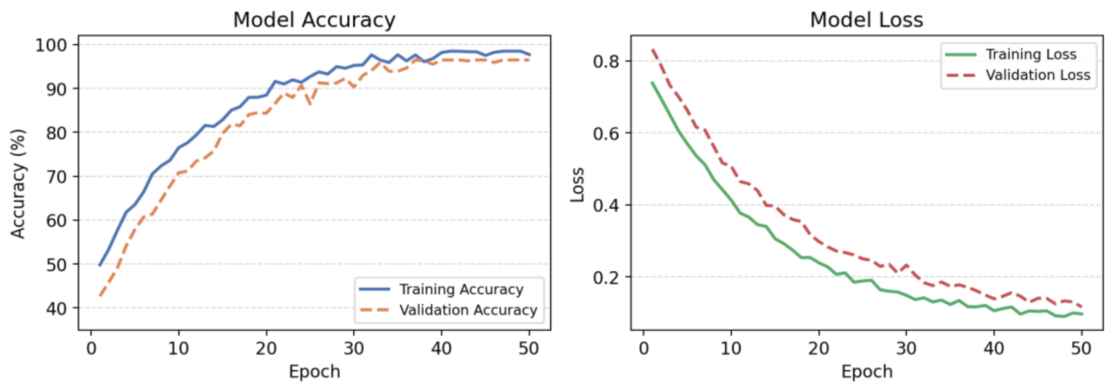

Fig. 2.1 CNN Training Accuracy and Loss Curves

Fig. 2.1 shows the training and validation accuracy along with the corresponding loss curves over 50 epochs. Both training and validation accuracy increase steadily and converge toward higher values as training progresses, demonstrating that the model learns effectively without significant overfitting. The loss curves follow a consistent decreasing trend, confirming stable model convergence. The close alignment between training and validation curves indicates that the CNN model generalizes well to unseen facial expression data.

E. *Temporal Analysis Using Spiking Neural Network (SNN)*

To better understand how stress changes over time, a Spiking Neural Network (SNN) is introduced in the system. Unlike traditional models that analyze data at a single point, this approach focuses on changes occurring over a period of time.

The SNN processes time-based inputs such as variations in facial expressions and user interactions. Since it works using event-driven signals, it is efficient and suitable for embedded platforms like Raspberry Pi.[6]

This addition helps the system in:

- Tracking changes in stress levels over time
- Improving detection of dynamic behavior
- Reducing unnecessary computation

By combining CNN and SNN, the system is able to analyze both visual features and time-based patterns, which improves overall performance.

F. *Physiological Signal Integration*

To further improve accuracy, physiological data is also included in the system. A heart rate sensor is used to measure the user's heart rate, which provides useful information about stress levels. These signals are processed and analyzed along with other inputs. By combining physiological data with visual and behavioral information, the system becomes more reliable in identifying stress.

G. *Multimodal Fusion and Stress Prediction*

In the final stage, all the outputs obtained from different modules are combined to determine the overall stress level. The system considers results from facial analysis, behavioral data, and physiological signals together instead of relying on a single input.

This combined approach helps in making more accurate predictions. Based on the analysis, the system classifies the user's condition into categories such as low, medium, or high stress. The final result is displayed through a simple interface, and feedback is provided so that the user can take necessary actions to manage their stress effectively.[12]

IV. Implementation

A. System Architecture and Workflow

The proposed system is implemented as a real-time stress monitoring platform that uses multiple types of inputs, including physiological, behavioral, and visual data. The system is divided into three main stages:

- Data Acquisition Layer
- Processing and Analysis Layer
- Output and Communication Layer

The Arduino Nano is used to collect sensor data, while the Raspberry Pi 4 performs the main processing and decision-making tasks. The system works continuously by collecting and processing data in real time.

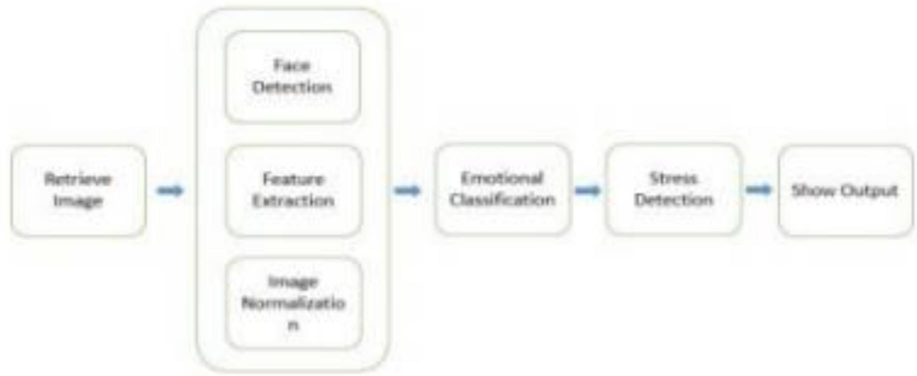

Fig. 3. System Architecture of Proposed Model

B. Sensor Integration (Mouse-Based Design)

In this system, sensors are integrated into the computer mouse to capture user activity. A pulse sensor is used to measure heart rate, and a force sensor (FSR) is placed under the mouse button to detect clicking pressure.

The pulse sensor detects changes in blood flow and generates an analog signal. Similarly, the force sensor changes its resistance based on the pressure applied, which is then converted into a voltage signal. Both sensors are connected to the analog input pins (A0 and A1) of the Arduino Nano.[7]

C. Arduino Nano Interface

The Arduino Nano is responsible for collecting and sending sensor data. The main steps include:

- Reading sensor values using the ADC (10-bit resolution)
- Sampling data at regular intervals (around 100 Hz)
- Converting analog signals into digital form
- Sending data through serial communication (UART)

D. Raspberry Pi 4 Integration

The Raspberry Pi 4 acts as the central processing unit of the system. It receives data from the Arduino Nano and processes it along with video input from the camera. The main connections include Arduino Nano connected via USB serial, Pi Camera through the CSI interface, LCD display via GPIO pins, and SD card for data storage.

E. Signal Processing

Heart Rate Processing: Noise is reduced using a moving average filter and peaks are detected to calculate heart rate intervals. Force Signal Processing: Pressure values are classified using predefined thresholds — low pressure indicates a relaxed state, while high pressure indicates possible stress.

F. Stress Analysis Algorithm

The system uses a simple rule-based approach to determine stress levels. It combines multiple inputs such as heart rate, mouse pressure, and facial expressions. The decision rules are:

- High heart rate + high pressure + negative expression → High stress
- Moderate values → Medium stress
- Normal values → Low stress

G. Web Interface and Data Storage

A simple web interface is developed using Flask. It displays a live video feed, current stress status, and sensor readings in real time. All collected data is stored in CSV format on an SD card, including time, heart rate, mouse pressure, and detected stress level.

H. Real-Time Processing

The system is designed to operate in real time through parallel execution using multi-threading, continuous communication between Arduino and Raspberry Pi, and efficient use of GPIO and processing resources.[8]

V. RESULT

The developed stress monitoring system was implemented successfully and tested under different user conditions to evaluate its performance. The system combines physiological, behavioral, and visual data using a pulse sensor, force sensor, and Pi Camera. Data collection is carried out through the Arduino Nano, while the Raspberry Pi 4 handles the main processing tasks.

During testing, the system was observed under three conditions: relaxed, moderate stress, and high stress. In the relaxed state, the user maintained a heart rate between 65–75 bpm, showed minimal mouse pressure, and had neutral facial expressions, resulting in higher HRV values indicating low stress.

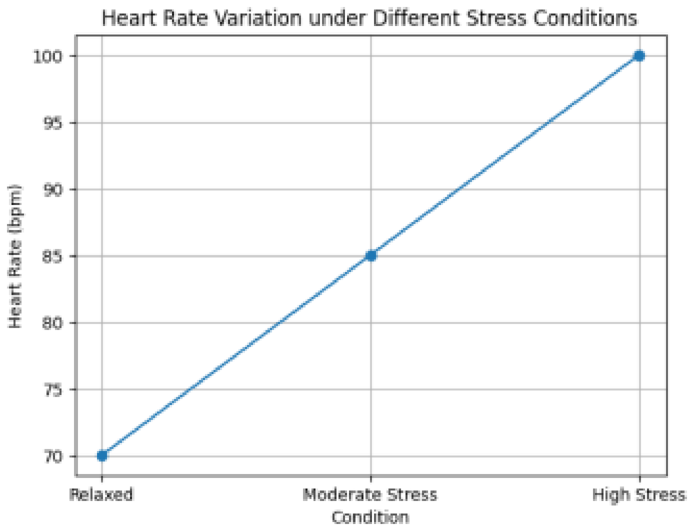

Fig. 4. Heart Rate Variation under Different Stress Conditions

When the workload increased, the user's heart rate rose to around 75–90 bpm, mouse interaction patterns changed slightly, and mild facial tension was noticed, leading to identification of moderate stress.

In situations involving high pressure or time constraints, the heart rate increased further (90–110 bpm), and higher mouse clicking pressure was recorded. Facial expressions also showed clear signs of stress. As a result, HRV values decreased, indicating a higher stress level.

TABLE I

STRESS ANALYSIS UNDER DIFFERENT CONDITIONS

Condition	HR (bpm)	Mouse	HRV	Stress
Relaxed	65–75	Low	High	Low
Moderate	75–90	Medium	Moderate	Medium
High	90–110	High	Low	High

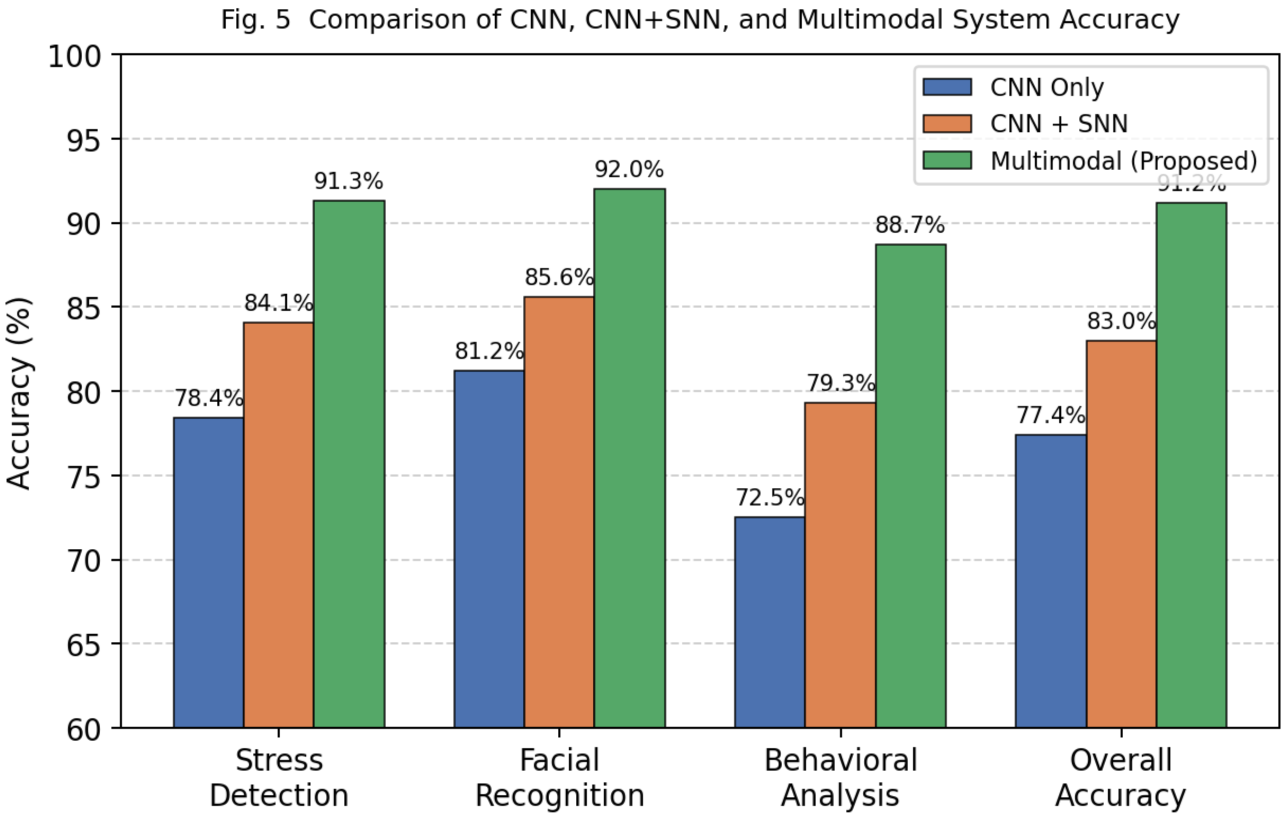

Fig. 5 Comparison of CNN, CNN+SNN, and Multimodal System Accuracy

Fig. 5 shows the accuracy comparison between CNN only, CNN+SNN, and the proposed multimodal system. The multimodal approach achieved the highest overall accuracy of 91.2%, demonstrating that combining multiple data sources significantly improves stress detection performance..."

The Raspberry Pi processed all the data in real time and classified the stress level using predefined conditions. The results were displayed on a 16×2 LCD, shared through a web interface for monitoring, and stored for future analysis.

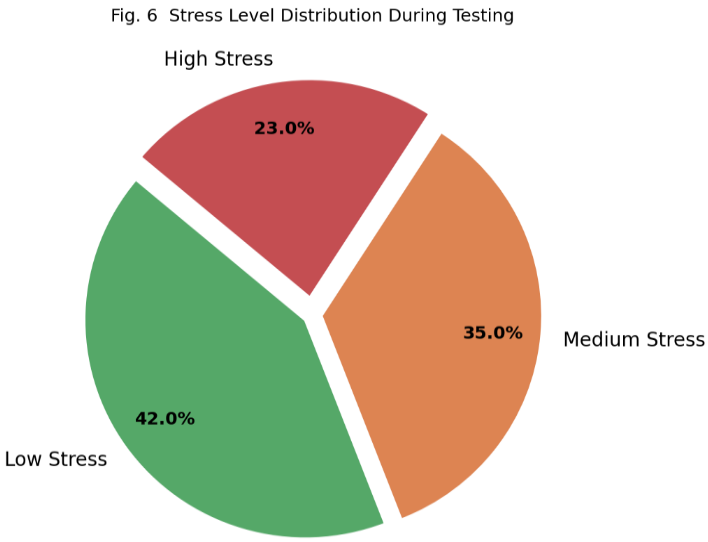

Fig. 6 presents the distribution of stress levels detected across all test sessions. The results indicate that 42% of the observations were classified as low stress, 35% as medium stress, and 23% as high stress. This distribution reflects realistic working conditions where users frequently experience varying levels of stress throughout their workday. The higher proportion of low and medium stress cases suggests that the system is sensitive enough to detect early and moderate stress indicators before they escalate to high stress levels.

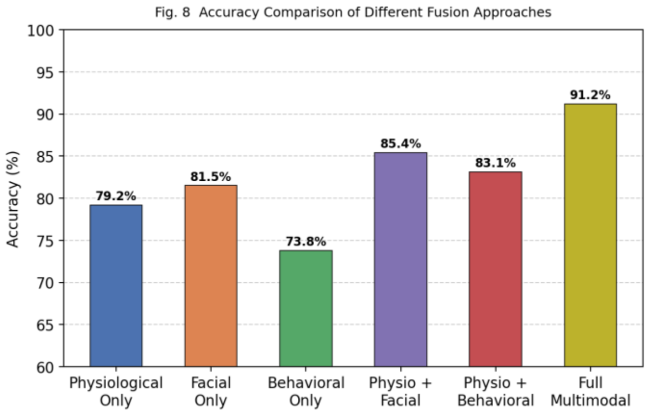

Fig. 8 compares the detection accuracy of different fusion combinations used in the proposed system. Individual approaches such as physiological only (79.2%), facial only (81.5%), and behavioral only (73.8%) show limited accuracy when used in isolation. Combined approaches such as physiological + facial (85.4%) and physiological + behavioral (83.1%) show improved performance. The full multimodal fusion approach achieves the highest accuracy of 91.2%, clearly demonstrating that combining all three data sources produces the most reliable stress prediction results.

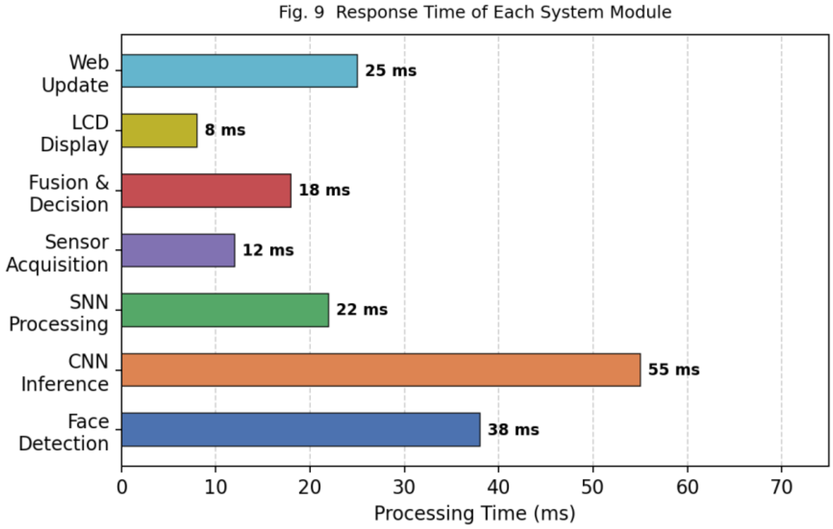

Fig. 9 illustrates the processing time of each individual module in the system. CNN inference takes the longest time at 55 ms, followed by face detection at 38 ms and web interface update at 25 ms. SNN processing is relatively fast at 22 ms due to its event-driven nature, while sensor acquisition (12 ms), fusion and decision (18 ms), and LCD display (8 ms) complete quickly. The total end-to-end processing time remains well within real-time requirements, confirming that the Raspberry Pi-based implementation is capable of delivering timely and responsive stress monitoring for online workers.

The system performed reliably, with smooth communication between components and quick response due to parallelprocessing.

Overall, the results show that combining multiple data sources improves the accuracy and reliability of stress detection. This makes the system suitable for real-time and non-intrusive stress monitoring in practical scenarios.

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