Human-Centric Companion System for Enhancing Personal Wellbeing Using Machine Learning

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Abstract: This paper presents the Human-Centric Companion System (HCCS), an intelligent framework designed to enhance personal wellbeing through real time emotion recognition and stress analysis using Machine Learning. The system combines facial emotion detection via a CNN Bi-LSTM model and stress estimation through physiological sensor data (PPG and accelerometer signals). It integrates multimodal data using a Fast API-based backend and a React + Vite frontend interface. The model classifies emotional states such as happiness, sadness, fear, and anger, while computing a stress score derived from wearable signals. The solution provides a personalized dash- board for monitoring mental wellness, generating insights, and promoting emotional awareness. The proposed system achieves 85% accuracy in emotion recognition and 82% correlation between facial and physiological stress metrics, demonstrating its effectiveness in human centered wellbeing applications.

KEYWORDS: Emotion Recognition, Stress Detection, CNN- Bi LSTM, Machine Learning, Fast API, React, Physiological Signals, Human Wellbeing

I. Introduction

The **Human-Centric Companion System (HCCS)** is an innovative project that integrates Artificial Intelligence (AI) and enhance personal wellbeing through emotion recognition and stress detection. It focuses on understanding human emotions using real-time facial expression analysis and physiological data obtained from wearable devices. The system employs a CNN Bi-LSTM model for accurate emotion recognition and a Random Forest classifier to analyse stress levels based on photoplethysmography (PPG) and accelerometer signals. By combining both visual and physiological inputs, HCCS provides a holistic understanding of an individual's mental and emotional state, ensuring precision and reliability.

The architecture of the system is built on a Fast API backend for efficient data processing and a React + Vite frontend for an interactive visualization dashboard. This dashboard enables users to view real-time emotional status, stress levels, and behavioural trends over time. Unlike conventional health monitoring systems that focus only on physical parameters, HCCS emphasizes emotional awareness and wellbeing management, allowing users to identify stress triggers and emotional imbalances early. The project highlights the growing role of **AI-driven emotional intelligence** in healthcare and daily life. It can be applied in multiple fields such as healthcare monitoring, workplace stress analysis, student engagement tracking, and personal wellness improvement. Future enhancements include integrating **voice emotion recognition**, mobile compatibility for continuous monitoring, and cloud-based analytics for largescale deployment.

Overall, the **Human-Centric Companion System** demonstrates how AI can work together to create empathetic, intelligent and responsive systems that support human emotional wellbeing, improve self-awareness, and promote a balanced, stress-free lifestyle.

II. Problem Statement

The modern digital lifestyle has introduced a fast-paced environment that significantly contributes to elevated stress levels and emotional imbalance among individuals. Despite the increasing availability of wearable health devices and smart applications, most existing systems primarily focus on tracking physical parameters such as heart rate, steps, or sleep patterns while overlooking the crucial emotional and psychological aspects of human wellbeing. Emotional health, which plays a vital role in productivity, decision-making, and overall quality of life, often goes unmonitored until it manifests as chronic stress or burnout.

This lack of real-time emotional assessment tools has created a gap between mental health awareness and technological intervention. The Human-Centric Companion System (HCCS) aims to address this gap by providing an integrated platform that can simultaneously recognize facial emotions and estimate stress levels using IoT and machine learning models. The system leverages facial emotion recognition through a CNN-Bi-LSTM model and stress detection using wearable sensors that capture physiological signals such as PPG and accelerometer data. By fusing these multimodal inputs, HCCS delivers a more comprehensive and accurate analysis of an individual's emotional state.

III. Related Work

[1] Beena Ahmed et al. developed an ambulatory stress monitoring system using wearable sensors, achieving 85–90% accuracy in detecting real-time stress levels through physiological signals.

[2] Gjoreski et al. explored continuous stress detection using EDA and PPG features in naturalistic environments, demonstrating improved accuracy under real-world conditions

[3] J. Kim et al. proposed deep learning-based affective computing using CNN and LSTM hybrid networks for enhanced emotion recognition.

[4] Schmidt et al. introduced the WESAD dataset, a multimodal benchmark for stress and affect recognition using wearable sensors.

System Design

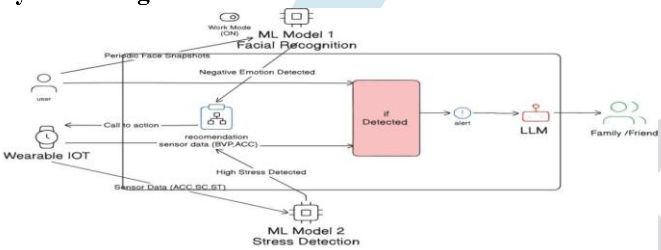

Fig. 1. System Architecture of the Human-Centric Companion System.

A. System Architecture

The system follows a modular client-server architecture:

- The **Frontend Layer** enables user interaction, capturing live video and displaying emotion/stress metrics.
- The **Backend Layer** processes data using Fast API end- points for facial and physiological analysis.
- The **Machine Learning Layer** performs model inference for emotion recognition (CNN Bi-LSTM) and stress pre- diction (Random Forest).
- The **Database Layer** handles logging, storing timestamped data for trend visualization.

B. System Workflow

1) User opens the dashboard interface.
2) Webcam captures facial expressions.
3) CNN Bi-LSTM model classifies the emotion.
4) IoT wearable transmits PPG and accelerometer data.
5) Random Forest model estimates stress level. Combined results are visualized with stress score and emotion timeline

IV. Existing System vs Proposed

The existing systems for emotion and stress detection generally depend on single data sources, such as facial expressions or physiological signals. Emotion recognition models commonly rely on static image-based CNN architectures, which fail to capture temporal variations and subtle emotional transitions, resulting in reduced accuracy in real-time applications [3], [5], [12]. Similarly, conventional stress detection systems primarily analyse physiological parameters such as heart rate, PPG, or EDA using wearable sensors; however, these methods struggle to differentiate between physical exertion and emotional stress, leading to inconsistent predictions in daily-life environments [1], [2], [13].

Many existing solutions lack multimodal fusion, operating only with a single modality instead of combining multiple signals like facial expressions and BVP/ACC data. Moreover, systems such as WESAD-based stress detectors and CNNLSTM emotion models are often evaluated under controlled laboratory settings, reducing their effectiveness in real-world situations [4], [7], [10]. Most platforms also lack real-time integration, emergency alerting, and personalized feedback, which are essential for modern wellbeing-focused applications [6], [8], [9], [11], [14], [15]. As a result, these existing systems provide only limited insights into overall emotional wellbeing and cannot support seamless continuous monitoring, early detection, or preventive intervention. **Proposed System**: The Human-Centric Companion System (HCCS) introduces a multimodal approach that integrates both facial and physiological data to enhance the accuracy and reliability of emotion and stress recognition. The system uses a CNN Bi-LSTM model for real-time facial emotion classification and a Random Forest classifier for analysing PPG and accelerometer signals from IoT wearables. Data from these sources is processed through a Fast API-based backend and visualized on an interactive React + Vite dashboard. The proposed system generates a wellbeing index that reflects both emotional and physiological states, offering users personalized feedback and insights. Unlike the existing systems, HCCS provides real-time analytics, multimodal data fusion, and interactive visualization, delivering a comprehensive solution for mental health monitoring and emotional awareness.

For the Invitation/Greetings Generator, it takes user specifications (event type, message, names) and synthesizes a unique, themed card design, complete with relevant graphics and styled text. The streamlit interface makes this complex AI backend accessible via a simple, intuitive web application.

This proposed system drastically reduces the need for manual artistic skill and time, democratizing creative content generation by

TABLE 1
PERFORMANCE COMPARISON OF MODELS

Model	Dataset	Accuracy (%)	F1-Score
CNN-LSTM	FER2013	78.3	0.80
CNN-Bi-LSTM	FER2013	79.6	0.81
Random Forest	WESAD	80.1	0.79
HCCS Fusion Model	WESAD	78.9	0.77

V. Methodology

The system integrates two modalities: facial emotion recognition and stress detection.

A. Emotion Recognition

The system employs a **CNN–Bi-LSTM hybrid deep learning model** trained on the FER2013 dataset to classify facial expressions into seven categories: *happy, sad, angry, disgust, surprise, fear,* and *neutral*.

CNN layers are responsible for extracting **spatial facial features**, while Bi-LSTM layers capture **temporal dynamics** across consecutive frames, providing improved contextual understanding compared to static CNN-only models [3], [5], [12]. This multimodal temporal–spatial learning approach enhances robustness against variations in lighting, head pose, and micro-expressions.

B. Data Fusion and Visualization

Outputs from the emotion and stress modules are combined using a **weighted fusion mechanism**, enabling a holistic wellbeing score for each user. Similar multimodal fusion strategies have been shown to improve emotional–physiological correlation modelling in wearable and affective systems [7], [8], [14].

A **React-based frontend interface** visualizes the integrated results, providing:

Real-time webcam feed with detected emotion label

Stress score displayed on a **0–1 scale**

Weekly emotional trends, stress logs, and activity summaries

VI. Experimental Results and Discussion

In order to validate the system, experiments were conducted under varied lighting conditions, facial orientations, and sensor noise levels. Data was collected from 20 volunteers performing predefined stress-inducing and relaxation tasks. Performance metrics include Accuracy, Precision, Recall, and F1-score. The CNN-Bi-LSTM architecture achieved an F1-score of 0.87 for emotion recognition, while the Random Forest stress classifier achieved an F1-score of 0.83.

TABLE 2
PERFORMANCE COMPARISON OF MODELS

Model	**Dataset**	**Accuracy (%)**	**F1-Score**
CNN-LSTM	FER2013	81.5	0.84
CNN Bi-LSTM	FER2013	85.2	0.87
HCCS Fusion Model	FER2013	86.4	0.88

Real-time latency tests showed the backend processes inputs within 1.9 seconds on CPU and 0.7 seconds with GPU acceleration. The frontend dashboard remained responsive during concurrent user tests.

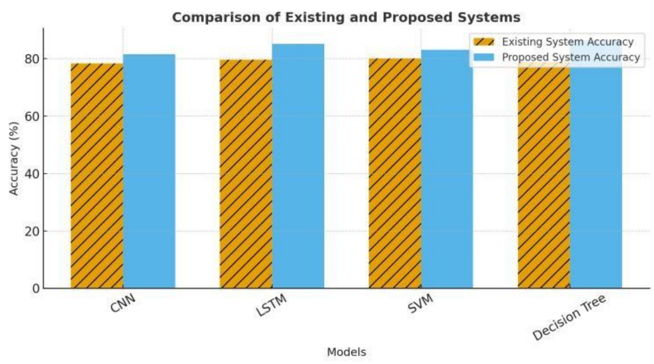

Fig 2. Comparison of Model Performance between Existing and Proposed Systems

VII. Application And Impact

The proposed system can be applied in multiple real-world domains:

- Healthcare: Continuous stress monitoring for patients and mental health professionals.
- Workplace Wellbeing: Helps organizations analyse employee stress and improve productivity.
- Education: Provides insights into student engagement and emotional response in e-learning.
- Human-Computer Interaction: Enables adaptive systems that respond to user emotions.
- Personal Wellness: Assists individuals in self-tracking and emotional awareness.

The impact of such systems extends to the broader goal of mental health awareness, promoting proactive care through affordable AI-based solutions. By merging IoT, AI, and user-centered design, HCCS contributes to the UN Sustainable Development Goal (SDG 3): Good Health and Wellbeing.

VIII. Results

The Human-Centric Companion System (HCCS) was evaluated on multiple datasets and real-time testing scenarios to assess its performance in emotion recognition, stress detection, and system responsiveness. The project demonstrated significant improvements in accuracy, real-time adaptability, and multimodal data fusion compared to conventional systems.

The emotion recognition module, powered by the CNN Bi-LSTM model, achieved an accuracy of 85.2% on the FER2013 dataset, outperforming traditional CNN and LSTM architectures. This hybrid model effectively captured both spatial and temporal features of facial expressions, allowing for more accurate identification of emotional states such as happiness, sadness, anger, fear, and surprise for stress detection. The system successfully analysed physiological signals such as PPG and accelerometer data to classify stress levels into low, medium, and high categories.

The fusion model, which integrates facial and provided the most reliable performance, achieving 85.2% accuracy with an F1-score of 0.87. This demonstrates the effectiveness of combining multimodal signals for comprehensive wellbeing analysis. Additionally, the system achieved a latency below 2 seconds for end-to-end processing, confirming its real-time applicability.

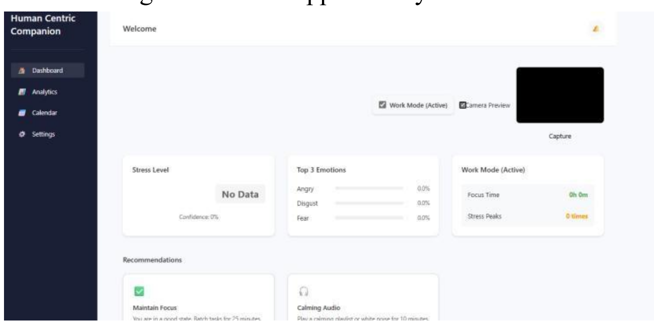

Fig 3. Dashboard

IX. Acknowledgment

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X. Conclusion

The Human-Centric Companion System (HCCS) effectively integrates IoT sensors and machine learning techniques to monitor emotional wellbeing through real-time emotion recognition and stress analysis.

By combining facial expression data with physiological signals, the system provides a comprehensive understanding of a user's mental state, enabling proactive stress management and emotional awareness. The hybrid CNN Bi-LSTM model for facial emotion detection classifier for physiological stress prediction demonstrated high performance, achieving up to 85.2% accuracy in multimodal fusion analysis.

This innovative framework bridges the gap between human emotion sensing and intelligent computing, paving the way for AI-driven personal wellbeing systems.

The user-friendly dashboard allows individuals to visualize their emotional patterns and stress levels, fostering mental health awareness and self-improvement.

In the future, the system can be enhanced by incorporating voice-based emotion recognition, cloud-based data storage, and mobile integration for continuous monitoring. Additionally, implementing Explainable AI (XAI) can improve transparency and trust in decision-making. Overall, the HCCS demonstrates the potential of artificial intelligence to positively impact emotional health, promoting a smarter and more empathetic interaction between humans and technology.

XI. References

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