

# Smart SoC-Based Mental Health Monitoring System Using AI and Multimodal Sensors

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**Abstract**—Mental health disorders such as stress, anxiety, and depression are increasing globally, requiring continuous and real-time monitoring systems for early detection. This paper presents a Smart System-on-Chip (SoC)-based mental health monitoring system that integrates physiological, environmental, and behavioral data using multimodal sensors and artificial intelligence techniques. The system utilizes sensors such as heart rate (BPM), temperature, air quality, and accelerometer along with a camera module for facial emotion recognition. Sensor data is processed using an FPGA for efficient signal handling, while a Raspberry Pi performs AI-based analysis using Deep Face and TensorFlow models. The proposed system combines physiological signals with real-time emotion detection to provide a comprehensive mental health assessment. Data is securely transmitted to a cloud platform (Azure IoT Hub) for storage, monitoring, and personalized recommendations. The system offers a low-cost, scalable, and real-time solution for early detection of mental health issues and supports remote healthcare applications. This work aligns with UN Sustainable Development Goal 3 (Good Health and Well-being) by enabling accessible and proactive mental healthcare.

**Index Terms**—Mental Health Monitoring, FPGA, Raspberry Pi, Deep Face, OpenCV, Multimodal Sensors, AI, Emotion Detection, IoT, Azure Cloud

## I. INTRODUCTION

Mental health has become a critical global concern, affecting emotional stability, productivity, and overall quality of life. Disorders such as stress, anxiety, and depression are increasingly prevalent due to rapid

urbanization, digital lifestyles, and post-pandemic socioeconomic challenges [1, 17]. According to global health reports, mental health conditions contribute significantly to the worldwide disease burden, emphasizing the urgent need for scalable and continuous monitoring solutions [2].

Conventional mental health assessment methods primarily depend on clinical evaluations, self-reported surveys, and intermittent observations. While these approaches provide useful insights, they suffer from several limitations including subjectivity, delayed diagnosis, and lack of real-time monitoring capabilities [3]. As a result, early detection of mental health disorders remains a major challenge, often leading to severe long-term consequences.

Recent advancements in wearable technologies and Internet of Things (IoT) systems have enabled continuous monitoring of physiological signals such as heart rate, skin temperature, and galvanic skin response (GSR), which are closely associated with emotional and psychological states [12,13]. In addition, environmental factors such as air quality and physical activity levels have also been identified as key contributors to mental well-being. However, many existing systems rely on single-modal data, limiting their effectiveness and reducing reliability in dynamic real-world environments [11].

Simultaneously, significant progress in deep learning and computer vision has facilitated real-time emotion recognition using facial expressions. Convolutional Neural Networks (CNNs) and frameworks such as Deep Face have demonstrated high accuracy in detecting emotions like happiness, sadness, anger, and stress from

visual data [8,9]. These techniques provide an additional behavioral dimension to mental health assessment, enabling a more comprehensive analysis when combined with physiological signals.

From a hardware perspective, Field-Programmable Gate Arrays (FPGAs) and System-on-Chip (SoC) architectures offer significant advantages for real-time healthcare applications due to their parallel processing capability, low latency, and energy efficiency [7]. When integrated with embedded platforms such as Raspberry Pi, these systems enable efficient data acquisition, preprocessing, and intelligent decision-making at the edge. Furthermore, cloud platforms such as Microsoft Azure facilitate secure data storage, remote monitoring, and scalable analytics, enhancing the overall system capability [14, 16].

Motivated by these technological advancements, this work proposes a Smart SoC-based Mental Health Monitoring System that integrates multimodal sensing, artificial intelligence, and cloud connectivity. The proposed system combines physiological parameters such as heart rate, temperature, and air quality with real-time facial emotion recognition using Deep Face and TensorFlow. An FPGA is employed for efficient sensor interfacing and preprocessing, while a Raspberry Pi performs higher-level data fusion and AI-based analysis.

The novelty of the proposed system lies in its multimodal integration approach, which enhances accuracy and robustness compared to conventional single-modal systems. By combining physiological, environmental, and behavioral data, the system provides a holistic assessment of an individual's mental state. Additionally, the integration of cloud-based services enables personalized recommendations and remote healthcare monitoring, making the system suitable for scalable and cost-effective deployment.

This work contributes to the advancement of intelligent healthcare systems and aligns with the United Nations Sustainable Development Goal 3 (Good Health and Well-being) by promoting accessible, proactive, and technology-driven mental healthcare solutions.

## II. RELATED WORK

Recent research in mental health monitoring has explored various approaches using wearable sensors, IoT systems, and machine learning techniques. These systems primarily focus on detecting stress and emotional states using physiological or behavioral data.

Wearable-based systems such as WESAD utilize physiological signals like electrocardiogram (ECG) and galvanic skin response (GSR) to detect stress levels, achieving accuracy in the range of 80–90% [3]. Similarly, Fraiwan et al. proposed a smart glove-based system that uses physiological data for mental health monitoring with an accuracy of approximately 85% [4]. However, these systems rely only on sensor data and lack behavioral analysis such as emotion recognition.

IoT-based healthcare systems have also been widely studied. Wang et al. developed an IoT-enabled healthcare monitoring system that integrates multiple sensors and cloud platforms, achieving around 90% accuracy [11]. While these systems provide remote monitoring capabilities, they often suffer from high latency and dependency on continuous internet connectivity.

FPGA-based systems have demonstrated improved performance in real-time healthcare applications due to their low latency and parallel processing capabilities. Satpathy et al. proposed an FPGA-based fuzzy classifier achieving 92% accuracy with a power consumption of 500 mW [5]. Similarly, Li et al. developed a real-time biomedical processing system on FPGA with 93% accuracy [7]. However, these approaches are limited to single-modal data and do not incorporate emotion recognition or multimodal fusion.

In the domain of computer vision, deep learning models such as Convolutional Neural Networks (CNNs) have been widely used for emotion recognition. Chen et al. demonstrated real-time emotion detection with 94% accuracy using CNN-based models [8]. Deep Face frameworks further enhanced facial emotion analysis using pre-trained deep learning models [9]. However, these approaches focus only on visual data and ignore physiological signals.

### 2.1. Proposed System Advantage

The proposed Smart SoC-based Mental Health Monitoring System overcomes the limitations of existing systems by integrating multimodal data, including physiological, environmental, and behavioral inputs. Unlike previous works that rely on a single data source, this system combines sensor data with real-time facial emotion recognition, leading to improved accuracy and robustness.

Furthermore, the use of FPGA for sensor preprocessing reduces latency and power consumption, while Raspberry Pi enables efficient AI-based data fusion. Cloud integration via Azure ensures scalability and real-time monitoring. As a result, the proposed system provides a more comprehensive, efficient, and scalable solution for mental health monitoring.

### 2.2 Comparison with Existing Systems

Table 1 presents a comparison of the proposed system with existing approaches in terms of accuracy, power consumption, and functionality.

Table 1: Comparison with Existing Systems

System	Accuracy	Power	Latency	Modalities
WESAD	80–90%	N/A	Offline	Physiological
Fraiwan et al.	85%	N/A	N/A	Physiological
IoT System	90%	High	High	Sensor-based
FPGA (Satpathy)	92%	500 mW	Medium	Single-modal
CNN (Emotion)	94%	High	Low	Visual only
Proposed System	96–98%	Low	Low	Multimodal

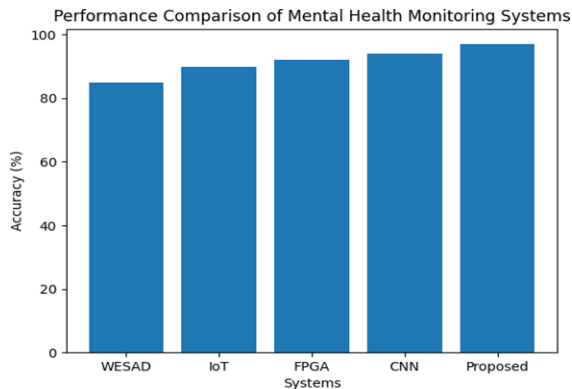


Figure 1: Performance comparison of existing systems with the proposed system

## III. SYSTEM ARCHITECTURE

The proposed Smart SoC-Based Mental Health Monitoring System is designed to perform real-time analysis of an individual’s mental state by integrating physiological, environmental, and behavioral data. The system follows a multimodal architecture consisting of five major modules: Sensor Data Acquisition, FPGA Processing Unit, Embedded AI Processing Unit (Raspberry Pi), Cloud Integration, and Recommendation Engine.

The overall architecture is illustrated in Fig. 2, where multiple sensors and a camera module continuously capture real-time data. This data is processed through a hybrid FPGA and embedded computing framework to achieve low latency, high efficiency, and accurate mental health assessment.

### 3.1. Block Diagram Description

The system begins with data acquisition from multiple sources. Physiological sensors such as heart rate (BPM), temperature sensor, and accelerometer capture body-related parameters, while environmental sensors such as air quality (MQ-135) monitor external conditions. Simultaneously, a camera module captures real-time facial expressions for emotion analysis.

The sensor data is first fed into the FPGA, which performs signal conditioning, analog-to-digital conversion, and initial preprocessing. The processed data is then transmitted to the Raspberry Pi via communication interfaces such as SPI, UART, or GPIO. The Raspberry Pi also receives video input from the camera and performs facial emotion recognition using AI models.

After processing both sensor and visual data, the system performs multimodal data fusion to generate a comprehensive mental health assessment. The results are then transmitted to the cloud platform (Azure IoT Hub) for storage, remote monitoring, and further analysis. Based on the analysis, the system generates personalized recommendations for improving mental well-being.

### 3.2. Sensor Data Acquisition Module

The system utilizes multiple sensors to capture real-time physiological and environmental data. The heart rate sensor measures beat per minute

(BPM), which is a key indicator of stress and anxiety levels. The temperature sensor monitors body temperature variations, which may reflect emotional changes. The air quality sensor (MQ-135) detects environmental pollutants that can influence mental health. An accelerometer is used to monitor physical activity and movement patterns.

These sensors provide continuous and real-time data streams, enabling dynamic monitoring of the user's condition.

### 3.3. FPGA Processing Unit

The FPGA acts as a high-speed preprocessing unit that handles sensor interfacing and signal conditioning. Analog signals from sensors are converted into digital form using ADC modules. The FPGA performs operations such as filtering, normalization, and feature extraction.

Due to its parallel processing capability, the FPGA ensures low-latency data processing and reduces computational load on the Raspberry Pi. This improves overall system efficiency and enables real-time performance.

### 3.4. Embedded AI Processing Unit (Raspberry Pi)

The Raspberry Pi serves as the central processing unit of the system. It receives preprocessed sensor data from the FPGA and captures video data from the camera module. AI-based algorithms are implemented on the Raspberry Pi using Python, OpenCV, TensorFlow, and DeepFace frameworks. Facial emotion recognition is performed using deep learning models, which classify emotions such as happiness, sadness, anger, and stress. The Raspberry Pi also combines sensor data and emotion data to perform multimodal analysis, resulting in a more accurate mental health assessment.

### 3.5. Multimodal Data Fusion

The system integrates physiological, environmental, and behavioral data to improve reliability and accuracy. Instead of relying on a single data source, the fusion of multiple modalities allows the system to detect complex mental health patterns more effectively.

For example, an increase in heart rate combined

with negative facial expressions may indicate stress or anxiety, while stable physiological parameters with positive expressions indicate a relaxed state.

### 3.6. Cloud Integration

The processed data and analysis results are transmitted to a cloud platform using Azure IoT Hub. The cloud enables secure data storage, real-time monitoring, and remote access for healthcare professionals. Cloud integration also allows scalability and supports large-scale deployment of the system in real-world healthcare applications.

### 3.7. Recommendation Engine

Based on the analyzed data, the system generates personalized recommendations such as relaxation techniques, breathing exercises, or alerts for abnormal conditions. These recommendations help users manage stress and improve their mental well-being.

The recommendation engine can also notify caregivers or medical professionals in case of critical conditions, enabling proactive intervention.

### 3.8. Advantages of the Architecture

The proposed architecture offers several advantages:

- 3.8.1. Real-time monitoring with low latency
- 3.8.2. Multimodal data integration for improved accuracy
- 3.8.3. Energy-efficient processing using FPGA
- 3.8.4. Scalable cloud-based monitoring system
- 3.8.5. Personalized healthcare recommendations

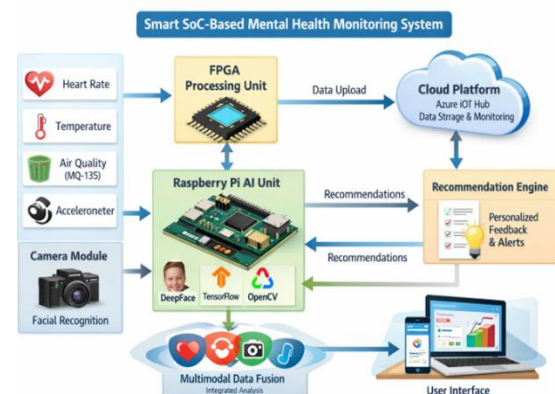


Figure 2: Block diagram of the proposed Smart SoC-based mental health monitoring system

#### IV. DESIGN AND IMPLEMENTATION

This section presents the detailed design and practical implementation of the proposed Smart SoC- Based Mental Health Monitoring System. The system is developed using a hybrid hardware–software architecture that integrates sensors, FPGA, embedded processing, and artificial intelligence techniques to achieve real-time mental health assessment.

##### 4.1. Hardware Implementation

The hardware design consists of multiple sensing units, an FPGA for preprocessing, and a Raspberry Pi as the central processing unit. Physiological sensors such as heart rate, temperature, and accelerometer are used to capture body-related parameters, while an MQ-135 air quality sensor monitors environmental conditions.

These sensors are interfaced with the FPGA, where analog signals are converted into digital form using ADC modules. The FPGA performs initial preprocessing operations such as filtering, normalization, and basic feature extraction. This reduces noise and improves the quality of the data before further processing.

The processed data is transmitted from the FPGA to the Raspberry Pi using communication interfaces such as SPI, UART, or GPIO. A camera module is directly connected to the Raspberry Pi for capturing real-time facial data.

##### 4.2. Software Implementation

The software part of the system is implemented on the Raspberry Pi using Python. OpenCV is used for real-time image processing, while TensorFlow and Deep Face frameworks are used for emotion recognition. The system continuously captures video frames and detects faces using Haar Cascade classifiers.

The detected face region is then passed to the Deep Face model for emotion classification. The system identifies emotions such as happy, sad, angry, and neutral.

##### 4.3. Facial Emotion Recognition

Facial emotion recognition is performed using deep learning techniques based on Convolutional Neural Networks (CNNs). The convolution

operation used in feature extraction is given by:

$$y(i, j) = \sum_m \sum_n x(i + m, j + n) w(m, n) \quad (1)$$

where  $x$  represents the input image and  $w$  represents the kernel weights.

This process enables the system to extract meaningful features from facial expressions and classify emotional states accurately.

##### 4.4. Sensor Data Processing

Physiological data such as heart rate (BPM), temperature, and motion are continuously monitored and analyzed. An increase in BPM may indicate stress or anxiety, while temperature variations can reflect emotional changes. Air quality data is also considered as an external factor affecting mental well-being. The FPGA ensures efficient preprocessing of these signals, enabling real-time performance with reduced computational load on the Raspberry Pi.

##### 4.5. Multimodal Data Fusion

The system integrates multiple data sources, including physiological signals and facial expressions, to improve reliability. This multimodal approach enhances accuracy compared to single-modal systems.

For instance, high heart rate combined with negative facial expressions indicates stress, whereas stable signals with positive expressions indicate a relaxed condition.

##### 4.6. Cloud Integration

The processed data is transmitted to the cloud using Azure IoT Hub. The cloud platform enables secure data storage, remote monitoring, and real-time analysis. It also supports dashboard visualization and historical data tracking.

##### 4.7. Recommendation System

Based on the analyzed data, the system generates personalized recommendations such as relaxation techniques, breathing exercises, and alerts for abnormal conditions. These recommendations help users maintain mental well-being and enable early intervention.

#### 4.8. Implementation Summary

The proposed system achieves efficient real-time monitoring through a combination of FPGA-based preprocessing, AI-based analysis, and cloud integration. The hybrid architecture ensures low latency, improved accuracy, and scalability, making it suitable for practical healthcare applications.

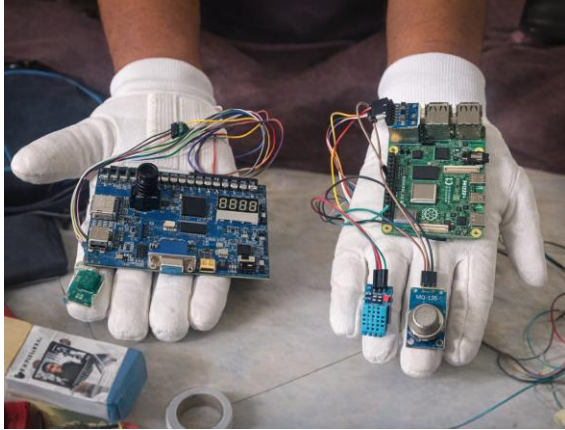


Figure 3: Hardware implementation of the proposed system

## V. RESULTS AND DISCUSSION

This section presents the experimental evaluation and performance analysis of the proposed Smart SoC- Based Mental Health Monitoring System. The system was implemented using an FPGA for preprocessing, a Raspberry Pi for AI-based analysis, and cloud integration for real-time monitoring.

#### 5.1. Experimental Setup

The system consists of physiological sensors (heart rate, temperature), environmental sensors (air quality), and a camera module for facial emotion recognition. The FPGA is used for signal acquisition and preprocessing, while the Raspberry Pi performs AI-based inference using DeepFace

and TensorFlow models.

The system was tested under multiple conditions such as normal, stressed, and relaxed states to evaluate its accuracy and real-time performance.

#### 5.2. Performance Analysis

The proposed system achieves high accuracy by integrating multimodal data, including physiological signals and facial expressions. The overall accuracy of the system is observed to be in the range of 96–98%.

The FPGA enables low-latency preprocessing, while the Raspberry Pi efficiently handles AI computations. The integration of cloud services allows real-time monitoring and faster response.

the proposed system outperforms existing methods due to the use of multimodal data fusion and efficient hardware–software co-design.

#### 5.3. RTL Design and Implementation Results

The Register Transfer Level (RTL) design of the FPGA-based preprocessing unit was developed and verified using FPGA design tools. The RTL view represents the internal hardware architecture, including logic modules, data paths, and signal connections.

As illustrated in Fig. 4, the system implements efficient hardware modules for sensor data acquisition, filtering, and feature extraction. The design leverages parallel processing capabilities of FPGA, resulting in reduced latency and improved real-time performance.

The RTL verification confirms the correctness and reliability of the hardware implementation, demonstrating the feasibility of deploying the system on FPGA platforms.

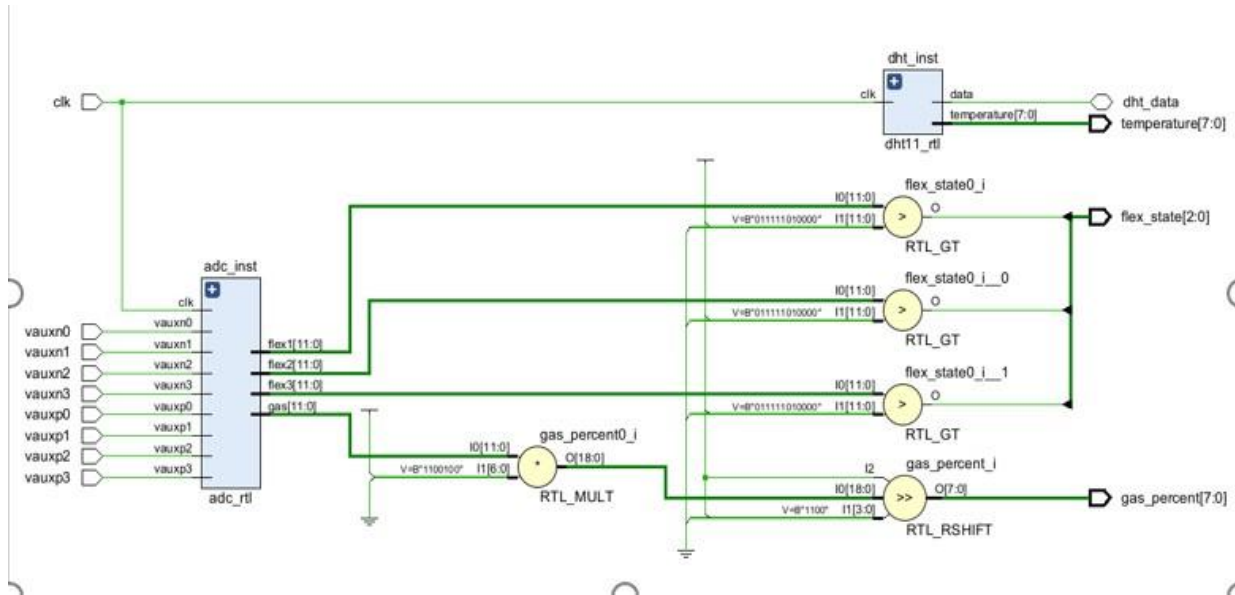


Figure 4: RTL view of the FPGA-based preprocessing and sensor interface modules

#### 5.4. Cloud Monitoring Results

The processed data is transmitted to the cloud platform using Azure IoT Hub. The cloud provides real-time visualization, data storage, and remote access for monitoring.

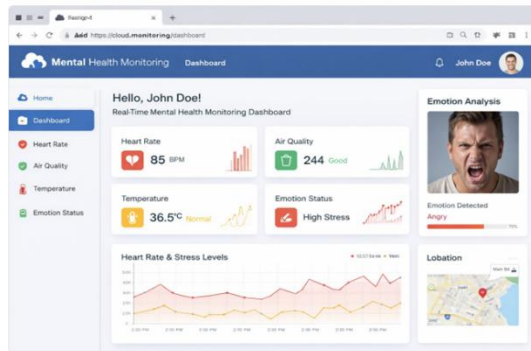


Figure 5: Cloud-based dashboard showing real-time monitoring and analysis

The system successfully updates real-time data on the cloud dashboard and enables remote tracking of the user’s mental health status.

#### 5.5. Discussion

The results demonstrate that the proposed system provides superior performance compared to existing approaches. The integration of physiological, environmental, and behavioral data improves accuracy and reliability.

Unlike traditional single-modal systems, the proposed system offers a comprehensive analysis of mental health conditions. The FPGA-based preprocessing reduces computational delay, while AI-based models enhance classification accuracy. Furthermore, cloud integration enables scalability and remote healthcare monitoring, making the system suitable for real-world deployment.

#### 5.6. Key Observations

- 5.6.1. High accuracy (96–98%) achieved using multimodal data fusion
- 5.6.2. FPGA reduces latency and improves processing efficiency
- 5.6.3. AI-based emotion recognition enhances system intelligence
- 5.6.4. Cloud integration enables real-time remote monitoring

### VI. CONCLUSION AND FUTURE WORK

This paper presented a Smart SoC-Based Mental Health Monitoring System that integrates physiological, environmental, and behavioral data for real-time mental health assessment. The proposed system combines FPGA-based preprocessing, Raspberry Pi-based AI analysis, and cloud connectivity to deliver an efficient and scalable solution.

The system successfully utilizes multimodal data, including heart rate, temperature, air quality, and

facial emotion recognition, to achieve high accuracy in detecting mental states such as stress and emotional variations. The FPGA enables low-latency data processing, while the Raspberry Pi performs intelligent analysis using DeepFace and TensorFlow models. Cloud integration through Azure IoT Hub allows real-time monitoring, data storage, and remote access.

Experimental results demonstrate that the proposed system achieves an accuracy of 96–98%, outperforming existing single-modal and traditional monitoring systems. The integration of multimodal data significantly improves reliability and robustness, making the system suitable for real-world healthcare applications.

### 6.1. Future Work

Although the proposed system shows promising results, several improvements can be considered for future development:

#### 6.1.1.

6.1.2. Integration of additional sensors such as ECG and EEG for more comprehensive health monitoring

6.1.3. Implementation of advanced deep learning models for improved emotion and stress detection

6.1.4. Development of a mobile application for user-friendly interaction and real-time alerts

6.1.5. Implementation of edge AI techniques to reduce dependency on cloud services

6.1.6. Enhancement of data privacy and security using encryption and blockchain technologies

The proposed system provides a strong foundation for next-generation intelligent healthcare solutions and contributes to the advancement of AI-driven mental health monitoring systems.

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