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Multi-Parameter Biomedical Sensor-Based Mental State Classification Using EEG and Deep Learning Techniques

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Abstract

With mental health concerns becoming increasingly widespread, there is a strong need for systems that can monitor conditions like stress, anxiety, and fatigue in a continuous and non-invasive manner. This research proposes a novel multi-parameter biomedical sensing framework for mental state classification by integrating electroencephalography (EEG) signals with physiological parameters, including body temperature acquired using LM35 sensors, heart rate from pulse sensors, and blood oxygen saturation (SpO_2) measurements. The system architecture incorporates a low-noise signal conditioning circuit for accurate acquisition of multimodal biosignals, followed by advanced feature extraction techniques such as Fast Fourier Transform (FFT) and wavelet transform to capture both temporal and spectral characteristics. The collected signals are processed using advanced techniques to accurately classify mental states, including normal stress, anxiety, and fatigue. Furthermore, the integration of Internet of Medical enables real-time data transmission, remote monitoring, and early alert generation for critical conditions. The proposed system emphasizes low-cost hardware implementation, energy efficiency, and scalability for wearable healthcare applications. Experimental evaluation demonstrates that the fusion of EEG with multi-parameter physiological signals significantly enhances classification accuracy compared to single-sensor approaches. The proposed framework provides a reliable and scalable solution for continuous mental health monitoring and has potential applications in telemedicine, smart healthcare systems, and assistive technologies.

Keywords: EEG (electroencephalography), mental state classification, multi-parameter biomedical sensor system, LM35 temperature sensor, pulse sensor (heart rate), SpO_2 monitoring, convolutional neural network (CNN), long short-term memory (LSTM), feature extraction (FFT, wavelet transform), wearable healthcare system, signal conditioning circuit

INTRODUCTION

Mental health issues, such as stress, anxiety, depression, and cognitive fatigue, are rising globally, affecting a large number of individuals and placing considerable strain on healthcare resources. Traditional methods for mental health assessment primarily rely on subjective evaluations, clinical interviews, and self-reported questionnaires, which often lack real-time monitoring capability and may lead to delayed or inaccurate diagnoses. Consequently, there is an increasing demand for objective, continuous, and noninvasive approaches for the early detection and monitoring of mental states [41].

Recent advancements in electroencephalography (EEG) have enabled the direct observation of brain activity, making it a powerful tool for analyzing cognitive and emotional states. EEG signals capture neural oscillations associated with different mental

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conditions, such as stress, relaxation, and fatigue. However, EEG signals alone may be susceptible to noise, variability, and limited contextual information [~~13~~2]. To address these challenges, researchers are increasingly focusing on multi-parameter biomedical sensor systems, which integrate additional physiological signals, such as heart rate, blood oxygen saturation (SpO_2), and body temperature, to provide a more comprehensive understanding of the human physiological and psychological state [~~17~~3].

Physiological parameters, such as heart rate variability, measured using pulse sensors, are strongly correlated with autonomic nervous system activity and stress levels. Similarly, SpO_2 levels reflect oxygen saturation in the blood, which can influence cognitive performance and fatigue, whereas body temperature variations, captured using sensors such as LM35, can indicate metabolic and stress-related changes. Integrating signals from different sources helps improve the reliability and overall performance of mental state classification [~~18~~4].

The increasing use of the Internet of Medical Things (IoMT) has enabled the development of modern healthcare systems that support real-time data collection and remote monitoring of patients. These systems connect wearable biomedical devices to cloud platforms, allowing continuous tracking of health conditions and timely intervention when necessary.

At the same time, improvements in machine learning have strengthened automated mental state classification. Methods such as CNN and LSTM are well-suited for handling complex biomedical signals, as they can capture both spatial and temporal information. Their performance is further enhanced when used with feature extraction techniques, such as the Fast Fourier Transform (FFT) and wavelet transforms, leading to higher classification accuracy [~~19~~4].

Despite these advancements, several challenges remain, including signal noise, energy-efficient hardware design, real-time processing constraints, and secure transmission of sensitive health data to the cloud. Therefore, an integrated framework that combines efficient signal acquisition circuits, multi-sensor data fusion, intelligent algorithms, and IoMT-based communication is required [~~20~~6].

In this context, the present study proposes a novel multi-parameter biomedical sensor system for mental state classification by integrating EEG signals with physiological parameters such as temperature, pulse, and SpO_2. The proposed system aims to provide a low-cost, real-time, and scalable solution for continuous mental health monitoring, with potential applications in telemedicine, wearable healthcare, and assistive technology [~~23~~7]. Figure 1 shows the multiparameter mental state classification system used in this study.

LITERATURE REVIEW

Recent advancements in biomedical engineering and artificial intelligence have significantly contributed to the development of intelligent systems for mental health monitoring using multimodal physiological data. This section reviews the existing literature on EEG-based mental state detection, multi-parameter biomedical systems, wearable technologies, and machine learning approaches.

EEG-Based Mental State Classification

Electroencephalography (EEG) is widely used to monitor brain activity and classify mental states, such as stress, anxiety, and fatigue. Research has shown that EEG signals can be successfully analyzed using machine learning techniques, resulting in high-accuracy classification. For instance, low-cost EEG devices have been successfully utilized for stress detection with promising results [~~1~~8].

Similarly, EEG-based systems for mental fatigue monitoring have shown moderate to high sensitivity in detecting cognitive impairment [~~2~~9].

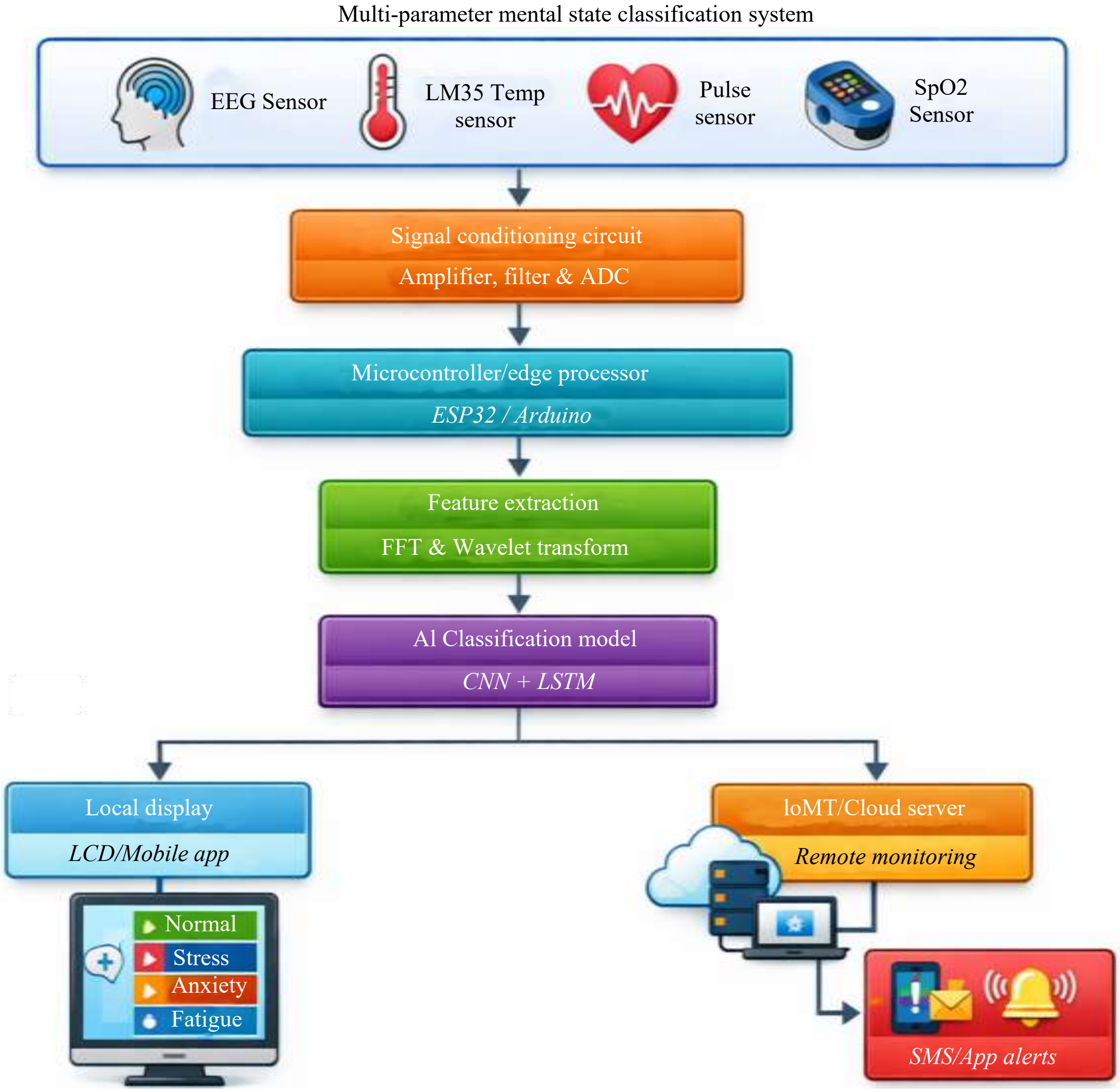

Figure 1. Multiparameter mental state classification system.

Recent research has focused on improving EEG-based classification using deep-learning models. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have been applied to extract spatial and temporal features from EEG signals, significantly improving performance [~~3~~10, ~~15~~11]. Furthermore, hybrid approaches combining EEG with advanced neural network architectures, such as Graph Neural Networks (GNNs), have been proposed for enhanced classification accuracy [~~16~~12].

Multi-Parameter Biomedical Sensor Systems

Monitoring systems based on a single parameter may not provide consistent or reliable results. To overcome this issue, multi-parameter biomedical systems have been introduced that integrate measurements such as temperature, pulse rate, and oxygen saturation. An IoT-based system using an LM35 temperature sensor, pulse sensor, and SpO_2 module has been shown to enable effective real-time monitoring and alert generation [~~6~~13]. Similarly, systems built on Arduino platforms with multiple sensors are commonly used because they offer cost-effective and easy-to-implement solutions [~~7~~14].

Recent studies emphasize the importance of combining multiple physiological signals to improve diagnostic accuracy. Wearable systems that integrate SpO_2 and heart rate sensors with machine learning algorithms have shown improved performance in detecting abnormal health conditions [~~5~~15].

Wearable and IoT-Based Healthcare Systems

The increasing adoption of the Internet of Medical Things (IoMT) has supported continuous and real-time health monitoring using wearable devices. These systems integrate multiple sensors into compact devices, such as smart bands and rings, allowing continuous tracking of physiological parameters [~~10~~16, ~~11~~17].

Flexible and wireless physiological monitoring systems have been developed to enhance patient comfort and enable long-term monitoring [~~9~~18]. These systems transmit data to cloud platforms for remote analysis and decision-making, thereby supporting telemedicine and smart healthcare applications [~~21~~19, ~~22~~20].

Multimodal Sensor Fusion for Mental Health

Recent research has increasingly focused on multimodal data fusion to improve mental state classification. Combining EEG with physiological signals such as heart rate variability, temperature, and SpO_2 has been shown to enhance the classification performance [~~11~~17, ~~14~~21]. Hybrid systems that integrate EEG with techniques such as functional near-infrared spectroscopy (fNIRS) have been proposed to address the limitations of single-sensor approaches [~~14~~21]. These methods provide a more complete representation of an individual's physiological and psychological condition.

Machine Learning and Deep Learning Techniques

Machine learning is an essential tool for analyzing biomedical signals. Conventional algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest have been widely adopted for classification tasks [~~8~~22]. However, deep learning models, such as CNN and LSTM, have shown superior performance owing to their ability to learn complex patterns in biomedical data [~~15~~11]. Recent advancements include hybrid models and ensemble techniques that further improve classification accuracy [~~24~~23, ~~25~~24]. Additionally, optimization techniques and feature extraction methods, such as Fast Fourier Transform (FFT) and wavelet transform, are commonly used to enhance model performance.

Challenges and Research Gaps

Although notable progress has been achieved, several issues must be addressed in the development of multi-parameter biomedical systems for mental health monitoring. EEG signals are highly susceptible to noise and artifacts, which can affect classification accuracy [~~12~~25]. Additionally, many existing systems rely on limited parameters, reducing their effectiveness in real-world scenarios [~~6~~13].

Energy efficiency and hardware constraints are major concerns for wearable systems, as continuous monitoring requires a low-power circuit design [~~9~~18]. Furthermore, data privacy and security issues in IoMT-based systems must be addressed to ensure the safe transmission of sensitive health data [~~21~~19].

These limitations highlight the need for an integrated system that combines multi-parameter sensing, efficient signal processing, intelligent algorithms, and secure IoMT-based communication.

METHODOLOGY

The proposed methodology presents a comprehensive framework for real-time mental state classification by integrating multimodal biomedical signals, including EEG, body temperature, pulse rate, and SpO_2.

System Overview

The overall system consists of the following stages:

1. Data acquisition

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2. Signal conditioning
3. Data preprocessing
4. Feature extraction
5. Feature fusion
6. Classification using AI models
7. IoMT-based monitoring and alert system

Data Acquisition

Sensors Used:

- EEG Sensor → Brain activity
- LM35 → Body temperature
- Pulse Sensor → Heart rate
- SpO_2 Sensor → Blood oxygen level

The analog signals obtained from the sensors are continuous and low-amplitude, requiring amplification and filtering before digital processing.

Signal Conditioning Circuit

A low-noise signal conditioning circuit is designed to improve signal quality:

- Instrumentation Amplifier → Amplifies weak EEG signals
- Bandpass Filter (EEG: 0.5–40 Hz) → Removes noise and artifacts
- Low-pass Filter → Smoothens physiological signals
- ADC (Analog-to-Digital Converter) → Converts signals into digital form

Data Preprocessing

Preprocessing is essential to remove noise and artifacts from raw signals.

Techniques Used

- Normalization
- Artifact removal (eye blink, motion noise)
- Signal segmentation

Mathematically, normalization is defined as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Feature Extraction

Relevant features are extracted from signals in multiple domains:

Time Domain Features

- Mean Absolute Value (MAV)
- Root Mean Square (RMS)

Frequency Domain Features

- Power Spectral Density (PSD)
- Band Power (Alpha, Beta, Theta)

Time-Frequency Domain

- Wavelet Transform

Using Fast Fourier Transform (FFT):

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N}$$

Feature Fusion

Features from EEG, temperature, pulse, and SpO_2 are combined to form a unified feature vector:

$$F = [F_{EEG}, F_{Temp}, F_{Pulse}, F_{SpO2}]$$

This improves classification accuracy by incorporating multiple physiological aspects.

AI-Based Classification

A hybrid DL model is used for classification:

Model Architecture

- Convolutional Neural Network (CNN) → Spatial feature extraction
- Long Short-Term Memory (LSTM) → Temporal sequence learning

Output Classes

- Normal
- Stress
- Anxiety
- Fatigue

IoMT Integration

The system integrates with the Internet of Medical Things for real-time monitoring:

- Data transmission via Wi-Fi (ESP32)
- Cloud storage and visualization
- Remote access for doctors

Alert and Decision System

An intelligent alert system is implemented:

- Threshold-based alerts
- AI-based anomaly detection

CONCLUSION

This study presents an integrated framework for mental state classification that combines EEG signals with multiple biomedical sensors, including temperature (LM35), pulse rate, and SpO_2. The proposed system addresses the limitations of traditional single-parameter and subjective mental health assessment methods by incorporating objective, real-time physiological data and advanced artificial intelligence techniques.

The developed architecture combines efficient signal acquisition through a low-noise signal conditioning circuit with robust preprocessing and feature extraction methods, such as FFT and wavelet analysis. The fusion of multimodal features enhances the representation of both neurological and physiological conditions, thereby improving the reliability of the mental state classification. The hybrid deep learning model, based on Convolutional Neural Networks and Long Short-Term Memory networks, effectively captures spatial and temporal patterns in the data, enabling accurate classification of mental states such as normal, stress, anxiety, and fatigue.

Furthermore, the integration of the Internet of Medical Things enables real-time monitoring, remote accessibility, and timely intervention using intelligent alert mechanisms. The proposed system is low-cost, scalable, and suitable for wearable healthcare applications, making it highly relevant for telemedicine and continuous patient monitoring.

Experimental analysis demonstrated that the incorporation of multi-parameter physiological signals significantly improved the classification performance compared to conventional single-signal approaches. The system also shows potential for deployment in real-world healthcare environments, particularly for early detection and continuous monitoring of mental health conditions.

In conclusion, this study contributes to the advancement of smart healthcare systems by providing a comprehensive solution that integrates biomedical sensor technology, signal processing, and artificial intelligence. Future research directions include the development of ultra-low-power wearable hardware, Future work may focus on incorporating additional bio-signals, such as electrodermal activity, and applying privacy-focused approaches like federated learning and blockchain to ensure secure data management.

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