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Multi-Model Ensemble Learning for Sleep-Based Depression Classification

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ABSTRACT: Mental health disorders such as depression have become a serious global health challenge affecting millions of people worldwide. Early identification of depressive symptoms is essential in order to provide timely intervention and reduce the risk of severe psychological and physical health complications. However, traditional methods of depression diagnosis mainly rely on clinical interviews, self-reported questionnaires, and periodic medical assessments, which may not always provide continuous monitoring of an individual's mental health condition. With the advancement of wearable technology, Internet of Things (IoT) devices, and machine learning techniques, it has become possible to monitor physiological and behavioral patterns in real time and use these patterns to identify potential indicators of mental health disorders. In this work, a wearable-based depression monitoring system is proposed that utilizes multiple sensors and machine learning algorithms to detect possible depression-related patterns from physiological and activity data. The proposed system integrates an ESP32-C3 microcontroller with sensors such as the MPU6050 motion sensor for activity monitoring, the MAX30102 sensor for heart rate and blood oxygen measurement, and the DS3231 real-time clock module for time-based activity tracking. These sensors collect continuous physiological and movement- related data from the user while the device is worn on the wrist. The collected data is transmitted through Bluetooth Low Energy (BLE) to a mobile or web-based application where the data is processed and analyzed. Data preprocessing techniques including filtering, smoothing, and feature extraction are applied to improve signal quality and remove noise from the collected sensor data. Machine learning algorithms such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine are used to classify the user's mental health condition based on extracted features such as sleep duration, movement patterns, and heart rate variability. The system provides classification outputs that indicate possible depression levels such as normal, mild risk, or high risk. The proposed wearable system aims to provide a low- cost, portable, and real-time mental health monitoring solution that can support early detection of depression and promote proactive healthcare management.

KEYWORDS: Wearable Device, Depression Detection, Machine Learning, ESP32-C3, Health Monitoring, IoT.

I. INTRODUCTION

Depression is one of the most common mental health disorders affecting millions of people worldwide and has become a major public health concern in recent years. It can significantly impact an individual's emotional well-being, daily activities, sleep patterns, and overall quality of life.

Symptoms of depression often include persistent sadness, reduced energy levels, sleep disturbances, loss of interest in activities, and changes in physiological conditions such as heart rate and physical activity levels. Early detection of depression is extremely important because timely intervention can prevent the condition from worsening and can help individuals receive appropriate treatment and support. However, traditional methods used to diagnose depression mainly rely on clinical interviews, psychological assessments, and self-reported questionnaires conducted by healthcare professionals. While these methods are effective, they are typically performed periodically and may not provide continuous monitoring of an individual's mental health status. As a result, subtle behavioral and physiological changes

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that occur over time may go unnoticed.

With the rapid advancement of wearable technology and the Internet of Things (IoT), new opportunities have emerged for continuous health monitoring using smart wearable devices. Wearable devices equipped with sensors can collect physiological and activity-related data in real time, enabling researchers and healthcare professionals to analyze patterns that may be associated with mental health conditions. Sensors such as heart rate monitors, motion sensors, and sleep tracking modules can provide valuable insights into an individual's daily behavior and physical condition. These physiological signals, when analyzed using advanced data processing and machine learning techniques, can help identify patterns related to stress, fatigue, and depressive symptoms. In particular, wearable-based monitoring systems offer the advantage of continuous data collection in natural environments without interrupting the user's daily activities. Recent developments in machine learning have further enhanced the capability of wearable health monitoring systems. Machine learning algorithms are capable of analyzing large volumes of physiological data and identifying complex relationships between different health parameters. By extracting meaningful features from sensor data such as sleep duration, movement patterns, and heart rate variability, machine learning models can classify mental health conditions and predict potential risks associated with depression. Algorithms such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine have been widely used in healthcare applications for classification and prediction tasks due to their reliability and accuracy. Integrating these algorithms with wearable sensing devices allows the development of intelligent health monitoring systems capable of providing real-time feedback and early warnings.

Motivated by these technological advancements, this study proposes a wearable-based depression monitoring system that combines physiological sensing, wireless communication, and machine learning techniques. The proposed system uses an ESP32-C3 microcontroller integrated with multiple sensors including the MPU6050

motion sensor, MAX30102 heart rate and SpO_2 sensor, and DS3231 real-time clock module to collect continuous physiological and activity data. The collected sensor data is transmitted through Bluetooth Low Energy (BLE) to a mobile or web-based application for further processing and analysis. Data preprocessing techniques are applied to improve signal quality, and machine learning algorithms are used to classify the user's mental health condition into different categories such as normal, mild risk, or high risk. By combining wearable sensing technology with intelligent data analysis, the proposed system aims to provide a portable, low-cost, and real-time solution for mental health monitoring that can support early detection of depression and contribute to improved healthcare management.

Furthermore, the integration of wearable sensors with intelligent data analysis enables continuous monitoring of an individual's physiological and behavioral patterns in real time without interrupting daily activities. The motion sensor helps analyze body movement and sleep activity, while the heart rate sensor provides important physiological indicators that may reflect emotional stress or irregular health conditions. By collecting and analyzing these parameters over time, the system can identify meaningful patterns associated with changes in mental health status. The use of machine learning techniques allows the system to learn from historical sensor data and improve its prediction capability for identifying potential depression risks. In addition, the mobile or web-based interface provides users with easy access to their health information and allows them to monitor their condition regularly. This approach not only increases awareness of mental health but also supports preventive healthcare by enabling early intervention and timely medical consultation when abnormal patterns are detected.

In addition, the proposed system is designed to be simple, portable, and cost-effective so that it can be used by a wide range of users without requiring complex medical equipment. The wearable device can continuously collect physiological signals and activity data throughout the day, allowing long- term monitoring of behavioral patterns that may indicate mental health changes. Therefore, the integration of wearable technology and intelligent data analysis has the potential to play an important role in supporting modern digital healthcare solutions and improving mental health awareness.

II. RELATED WORK

In recent years, researchers have increasingly explored the use of wearable technology and machine learning techniques for monitoring mental health conditions such as depression and stress. Wearable devices equipped with physiological sensors have the ability to continuously collect data related to heart rate, physical activity, and sleep patterns. These physiological indicators provide valuable information about an individual's physical and emotional state. Several studies have demonstrated that behavioral patterns such as irregular sleep cycles, reduced physical activity, and abnormal heart rate variability are strongly associated with depressive symptoms. By analyzing these physiological signals using computational techniques, researchers aim to develop automated systems capable of detecting early signs of depression and supporting mental health assessment.

One important study conducted by Hu et al. proposed an ensemble machine learning model for depression detection based on sleep data collected from wearable devices. Their research demonstrated that sleep-related parameters such as sleep duration, sleep interruptions, and sleep quality can be used to predict depression levels with reasonable accuracy. The study applied multiple machine learning classifiers and combined their outputs to improve prediction performance. The results indicated that ensemble-based approaches can enhance classification accuracy when analyzing large-scale health datasets collected from wearable devices. However, the system mainly focused on sleep data and did not fully integrate other physiological signals such as heart rate and movement activity.

Another research work by Price et al. investigated the use of passively collected wearable movement data to detect major depressive disorder in a large population sample. In this study, activity data obtained from wearable devices was analyzed to identify behavioral patterns related to depression. The results showed that individuals experiencing depressive symptoms often exhibit reduced physical activity levels and irregular daily routines. Machine learning techniques were applied to classify these patterns and predict depression presence. Although the study demonstrated promising results, the proposed approach primarily relied on movement data and did not incorporate additional physiological signals that could further improve prediction accuracy.

Similarly, research conducted by Shui et al. explored the use of wearable-derived physiological data for depression recognition. The study analyzed multiple physiological parameters including heart rate, sleep duration, and physical activity collected from wearable sensors. Machine learning models were applied to classify the collected data and identify depression-related patterns. The results indicated that combining multiple physiological indicators improves the reliability of depression detection systems. However, many existing studies focus mainly on data analysis and algorithm development, while the implementation of low-cost wearable hardware systems capable of real-time monitoring remains limited.Although previous research has made significant progress in applying wearable sensing and machine for mental health monitoring, several challenges still remain. Many existing systems rely on expensive commercial wearable devices or focus on single physiological parameters, which may limit their practical implementation. Therefore, there is a need for an integrated and cost-effective wearable system that combines multiple sensors with machine learning techniques to enable continuous monitoring and early detection of depression. The proposed system in this study addresses these limitations by integrating motion sensing, heart rate monitoring, and machine learning–based classification within a compact wearable platform.

III. PROPOSED SYSTEM

The proposed system presents a wearable-based depression monitoring framework that utilizes physiological sensing, wireless communication, and machine learning techniques to analyze behavioral patterns associated with mental health conditions. The main objective of the system is to provide continuous and real-time monitoring of physiological parameters that may indicate signs of depression. The system is designed as a compact wearable device that collects health-related data from the user during daily activities without interrupting their routine. The wearable device integrates multiple sensors including the MPU6050 motion sensor for detecting body movement and activity patterns, the MAX30102 sensor for measuring heart rate and blood oxygen levels, and the DS3231 real-time clock module for accurate time-based data tracking. These sensors are connected to the ESP32-C3 microcontroller, which functions as the central processing unit of the wearable device. The ESP32-C3 collects sensor readings and transmits the data to a mobile or web-based application through Bluetooth Low Energy (BLE) communication. Once the data is received, preprocessing techniques such as filtering, smoothing, and normalization are applied to improve the quality of the sensor signals. Machine learning algorithms are then used to analyze the extracted features and classify the user's mental health condition into categories such as normal, mild risk, or high risk. The final results are displayed through the application interface, enabling users to monitor their mental health condition and seek early medical support if abnormal patterns are detected.

The architecture of the proposed system consists of several interconnected modules including the wearable sensing module, communication module, data processing module, machine learning classification module, and user interface module. The wearable sensing module includes sensors that continuously collect physiological and activity-related data

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from the user. The communication module is responsible for transmitting this data from the ESP32-C3 microcontroller to the mobile or web application using Bluetooth Low Energy technology.The data processing module performs preprocessing operations to remove noise and prepare the sensor data for analysis.

Feature extraction techniques are then applied to derive meaningful parameters such as sleep duration, movement intensity, and heart rate variability. These features are used as input to the machine learning classification module, which applies algorithms such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine to identify patterns associated with depression risk levels. The final results are displayed through a user interface that allows individuals to track their health information and observe possible changes in their mental health condition.

The proposed system offers several advantages compared to traditional depression detection approaches. Conventional mental health assessment methods rely mainly on periodic clinical evaluations and self-reported questionnaires, which may not provide continuous monitoring of an individual's condition. In contrast, the proposed wearable system enables real-time monitoring of physiological signals and activity patterns, allowing early detection of behavioral changes related to depression. Additionally, the use of low-cost sensors and the ESP32-C3 microcontroller makes the system affordable and accessible for a wider population. The integration of machine learning algorithms further enhances the system's ability to analyze complex patterns within physiological data and improve prediction accuracy. By combining wearable sensing technology, wireless communication, and intelligent data analysis, the proposed system provides an efficient, portable, and scalable solution for continuous mental health monitoring and early detection of depression.

IV. METHODOLOGY

The methodology of the proposed wearable depression monitoring system involves several technical stages including data collection, preprocessing, feature extraction, machine learning classification, and result visualization. The entire system is designed to continuously monitor physiological and behavioral signals using wearable sensors and analyze these signals using machine learning techniques to detect possible depression-related patterns. The methodology begins with the collection of physiological data from wearable sensors integrated with the ESP32-C3 microcontroller. Sensors such as the MPU6050 motion sensor are used to monitor body movement and physical activity levels, while the MAX30102 sensor measures heart rate and blood oxygen saturation levels. The DS3231 real-time clock module provides accurate timestamps for each sensor reading, enabling time-based analysis of user activities such as sleep patterns and daily movement behavior. These sensors continuously collect data while the wearable device is worn on the wrist or finger, allowing the system to gather real-time physiological signals without interfering with the user's normal routine.

Once the data is collected from the sensors, it is transmitted through Bluetooth Low Energy (BLE) communication to a mobile or web-based application for further processing.The raw sensor data often contains noise and fluctuations caused by movement,environmental conditions, or sensor limitations.

Therefore, preprocessing techniques are applied to improve data quality and stability before analysis. One commonly used technique is the moving average filter, which smooths the data by averaging multiple sensor readings. The moving average filtering process is defined as

$$y[n] = \frac{1}{N} \sum_{i=0}^{N-1} x[n-i]$$

where y[n] represents the filtered signal, x[n] represents the original signal, and N represents the number of samples used in the averaging process. This filtering technique helps remove unwanted noise from the sensor signals and produces more stable data for analysis. In addition, normalization is applied to scale the sensor values into a consistent range using the following equation

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x represents the original x_{min} and x_{max} represent the minimum and maximum values within the dataset, and x_{norm} represents the normalized value. This normalization process ensures that all sensor features are represented within a similar range, which improves the performance of machine learning algorithms.

After preprocessing, feature extraction is performed to obtain meaningful parameters from the collected physiological data. Features such as movement intensity, sleep duration, and heart rate variability are calculated from the processed signals. For example, the acceleration magnitude from the MPU6050 motion sensor is calculated using the formula

$$A = \sqrt{x^2 + y^2 + z^2}$$

where x, y and z represent acceleration values along the three axes. This value helps determine the level of body activity and detect periods of rest or sleep. Similarly, heart rate is calculated from pulse intervals using

$$HR = \frac{60}{T}$$

where HR represents heart rate in beats per minute and T represents the time interval between two consecutive heartbeats. These extracted features provide useful information that can help identify behavioral patterns related to mental health conditions.

The extracted features are then provided as input to machine learning algorithms that are used to classify the user's mental health condition. Several classification algorithms are explored in this system, including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM). Logistic Regression predicts the probability of a specific mental health condition using the sigmoid function

$$P(y=1) = \frac{1}{1+e^{-z}} \qquad x_1, x_2, \dots, x_n \qquad w_1, w_2, \dots,$$

where $z = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$.In this equation,
represent extracted features such as heart rate or activity level,
w_n represent model weights, and b represents the bias term.The model outputs a probability value that is used to classify the depression risk level. Decision Tree and Random Forest algorithms analyze the relationships between different features and make predictions based on decision rules learned from the dataset, while Support Vector Machine identifies an optimal boundary that separates different classes in the feature space.

Finally, the classification results generated by the machine learning models are displayed through a mobile or web-based application interface. The application provides users with information about their physiological condition and possible depression risk levels categorized as normal, mild risk, or high risk. The overall workflow of the system begins with sensor data acquisition, followed by data transmission, preprocessing, feature extraction, machine learning classification, and result visualization. This methodology enables continuous monitoring and intelligent analysis of physiological signals, providing an effective approach for early detection of depression using wearable technology.

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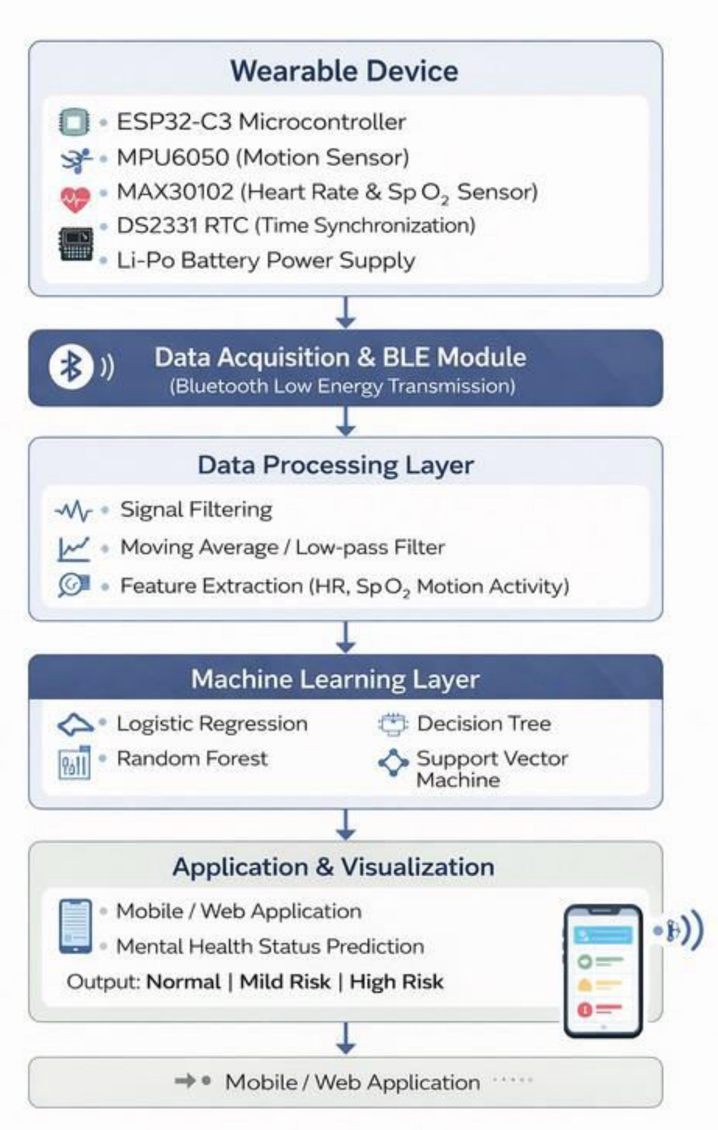
V. SYSTEM ARCHITECTURE DIAGRAM



V. IMPLEMENTATION DETAILS

The implementation of the proposed wearable depression monitoring system involves the integration of both hardware and software components to enable real-time physiological data acquisition, processing, and mental health prediction. The system is designed using a compact wearable device that collects physiological and motion data and transmits it to a mobile application for analysis and visualization.

Software Used

Several software tools and development platforms were used to implement the system. The embedded programming for the wearable device was developed using Arduino IDE, which was used to program the microcontroller and manage sensor data acquisition.

The data processing and machine learning model development were carried out using Python, which provides powerful libraries for signal processing, data analysis, and model training. The mobile application interface was developed using Flutter, enabling cross- platform deployment for both Android and iOS devices. The communication between the wearable device and the mobile application is achieved using Bluetooth Low Energy (BLE) supported by the ESP-IDF and mobile BLE libraries. Data visualization and monitoring features were integrated into the application to allow users to track their physiological data and mental health predictions in real time.

Hardware Components

The hardware architecture of the system consists of a wearable sensing unit built around the ESP32-C3 Super Mini microcontroller, which acts as the central processing and communication unit. The device is equipped with multiple sensors to collect physiological signals. The MPU6050 motion sensor is used to detect body movement and physical activity patterns. The MAX30102 sensor is used to measure heart rate and blood oxygen saturation (SpO_2) levels. A DS3231 real-time clock module is included to maintain accurate timestamps for the collected data. The system is powered by a rechargeable Li-Po battery, making the device portable and suitable for continuous wearable monitoring.

System Design

The overall system design follows a layered architecture consisting of data acquisition, wireless communication, data processing, machine learning classification, and application visualization layers. Initially, physiological and motion data are collected by the sensors and transmitted to the microcontroller. The ESP32-C3 processes the raw signals and sends the data to the mobile application through Bluetooth Low Energy communication. In the processing stage, signal filtering and feature extraction techniques are applied to remove noise and identify relevant physiological patterns. The processed data are then analyzed using machine learning algorithms to classify the user's mental health condition into categories such as normal, mild risk, or high risk. Finally, the prediction results are displayed in the mobile application interface for user monitoring and feedback.

Software Used

The development of the proposed system was carried out in several stages. First, the hardware components were assembled and connected to the ESP32-C3 microcontroller. Sensor libraries were integrated, and firmware was developed to collect and transmit physiological data

In the next stage, Bluetooth communication between the wearable device and the mobile application was established. The data preprocessing and machine learning models were then implemented using Python to analyze the collected sensor data. After training and validating the machine learning model, the prediction algorithm was integrated into the application environment. Finally, the mobile interface was developed using Flutter to visualize the data and display the predicted mental health status to the user.

Experimental Setup

The experimental setup for the proposed wearable depression monitoring system was designed to evaluate the effectiveness of physiological signal analysis and machine learning models in predicting mental health conditions. The setup includes the dataset used for model training, the training environment, hardware configuration, and the software tools utilized for system development and testing.

Dataset Used

The dataset used in this study consists of physiological signals collected from wearable sensors such as heart rate, blood oxygen saturation (SpO_2), and motion activity data. These signals are obtained using sensors integrated with the wearable device, including the MAX30102 sensor for heart rate and SpO_2 measurement and the MPU6050 sensor for motion and activity monitoring. The collected data represent variations in physiological patterns that may be associated with stress, sleep disturbances, and depression-related symptoms. Each data sample includes timestamp information provided by the DS3231 real-time clock module. The dataset is preprocessed and labeled into different mental health condition categories such as normal, mild risk, and high risk for training the classification models.

Training Setup

The machine learning models were trained using the Python programming environment with commonly used machine learning libraries such as Scikit-learn, which provides efficient implementations of classification algorithms.The training process involves preprocessing the raw sensor data, applying filtering techniques to remove noise, and extracting meaningful features such as heart rate variability,activity levels,and oxygen saturation patterns.The dataset was divided into training and testing subsets to evaluate the performance of different machine learning models. Several classification algorithms including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine were trained and compared to determine the most suitable model for depression risk prediction.

Hardware Configuration

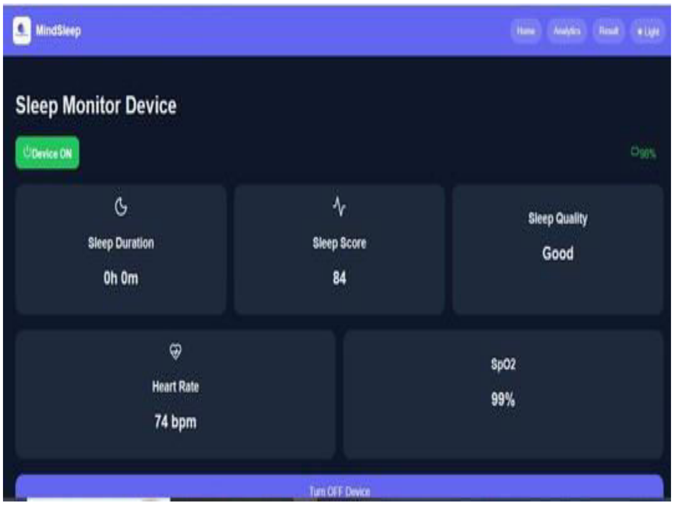
The hardware configuration of the experimental setup consists of a wearable sensing device built around the ESP32-C3 Super Mini microcontroller.This microcontroller is responsible for collecting data from the connected sensors and transmitting it to the mobile or web application through Bluetooth Low Energy communication. The system includes the MAX30102 sensor for heart rate and SpO_2 monitoring, the MPU6050 sensor for motion detection, and the DS3231 module for accurate time tracking. The device is powered using a rechargeable Li-Po battery to ensure portability and continuous monitoring capability. The collected data are transmitted to the application layer where further analysis and prediction are performed.

Tools and Frameworks

Several development tools and frameworks were used to implement the system. The embedded system programming was performed using Arduino IDE, which allows easy integration of sensor libraries and microcontroller programming. Machine learning model development and data analysis were performed using Python, supported by libraries such as NumPy, Pandas, and Scikit-learn for data processing and model training. The mobile and web application interface was developed using Flutter, which enables cross-platform application development for both Android and iOS platforms. Bluetooth communication between the wearable device and the application is implemented using BLE protocols supported by the ESP32-C3 microcontroller and mobile BLE libraries.

VI. RESULTS

The proposed wearable depression monitoring system was evaluated to analyze the effectiveness of physiological sensing and machine learning techniques in predicting mental health conditions. The system collects physiological signals such as heart rate, blood oxygen saturation (SpO_2), and motion activity using wearable sensors connected to the ESP32-C3 Super Mini microcontroller. The sensors used in the system include the MAX30102 for heart rate and SpO_2 measurement and the MPU6050 motion sensor for detecting physical activity and movement patterns. These physiological signals are collected and transmitted through Bluetooth Low Energy communication to the mobile or web application, where further data processing and machine learning analysis are performed.



During the experimental evaluation, the collected sensor data were preprocessed using filtering techniques to remove noise and improve signal quality. Features such as average heart rate, oxygen saturation level, and motion intensity were extracted from the physiological signals and used as inputs for machine learning models. Several machine learning algorithms were implemented to classify the mental health condition of the user into categories such as normal, mild risk, and high risk. The algorithms used in the experiment include Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine.

Among the tested algorithms, Random Forest demonstrated better performance due to its ability to handle multiple features and complex relationships between physiological parameters. Decision Tree and Support Vector Machine also produced satisfactory results in classification accuracy, while Logistic Regression provided a simpler baseline model for comparison. The results indicate that combining wearable physiological data with machine learning techniques can

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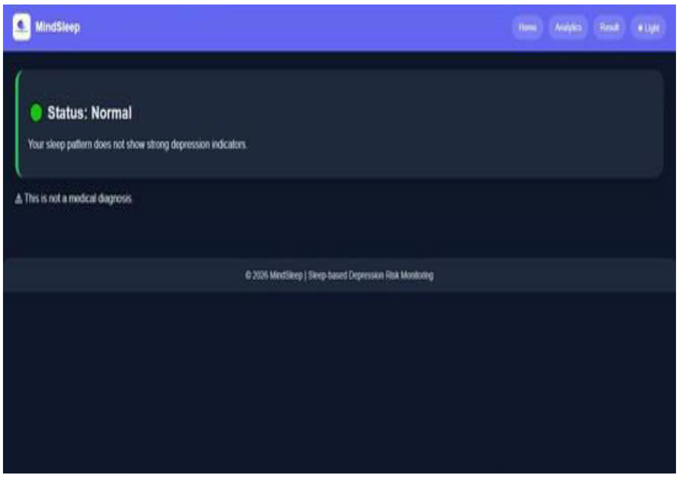
effectively support early detection of depression-related symptoms.



The experimental results also demonstrate the feasibility of integrating wearable sensing technology with mobile or web- based applications for real-time mental health monitoring.

Although the current system is implemented as a breadboard prototype, the results confirm that the proposed architecture can successfully collect, process, and analyze physiological data for depression risk prediction. Further improvements involving larger datasets, optimized machine learning models, and compact wearable hardware design can enhance the reliability and practical deployment of the system.

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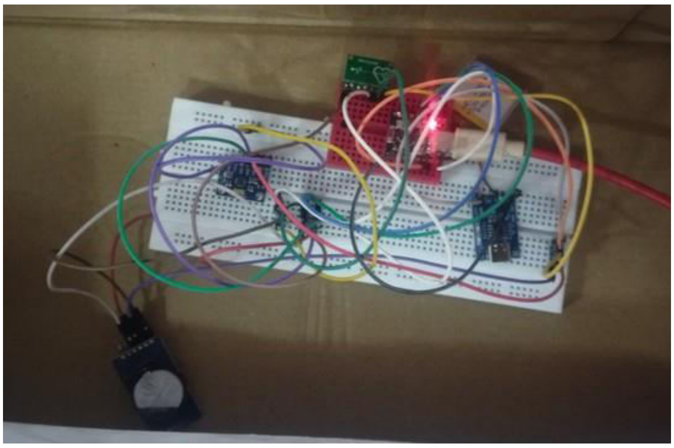

Advantages and Applications

The proposed wearable depression monitoring system provides several advantages in terms of accessibility, real-time monitoring, and cost effectiveness. By integrating multiple physiological sensors with a compact microcontroller such as the ESP32-C3 Super Mini, the system enables continuous monitoring of vital signals such as heart rate, blood oxygen saturation, and physical activity. Unlike traditional mental

health assessment methods that rely mainly on questionnaires or clinical interviews, the proposed system collects objective physiological data using sensors such as the MAX30102 and MPU6050. This allows the system to detect behavioral and physiological changes that may indicate early signs of depression. In addition, the use of Bluetooth Low Energy communication allows seamless data transmission from the wearable device to the mobile application without requiring complex infrastructure. The integration of machine learning algorithms further improves the system by enabling automated classification of mental health conditions into categories such as normal, mild risk, or high risk.

The system also has several practical applications in healthcare and daily life. It can be used for continuous mental health monitoring for individuals who may be at risk of depression or stress-related disorders. Healthcare professionals can use the system as a supportive tool for remote patient monitoring and early detection of mental health issues. The wearable device can also be applied in academic environments to monitor stress levels among students, particularly during examinations or high-pressure periods. In workplaces, the system may help organizations monitor employee well-being and identify potential mental health concerns. Furthermore, the integration of a mobile or web-based interface developed using frameworks such as Flutter allows users to easily visualize their physiological data and receive feedback about their mental health status. Overall, the proposed system provides a portable and intelligent solution that can support preventive healthcare and improve awareness of mental health conditions.

Prototype Implementation

The hardware prototype of the proposed wearable depression monitoring system was developed using a breadboard-based circuit setup for testing and validation purposes. All the hardware components including the ESP32-C3 Super Mini microcontroller, MAX30102 heart rate and SpO_2 sensor, MPU6050 motion sensor, and DS3231 real-time clock module were connected using jumper wires on a breadboard. This setup allows easy modification and debugging of the circuit during the development stage.

The breadboard prototype enables testing of sensor communication, data acquisition, and Bluetooth data transmission before implementing the final wearable hardware design. The ESP32-C3 microcontroller collects sensor data and transmits it to the mobile or web application through Bluetooth Low Energy (BLE).This prototype setup is mainly used to verify the functionality of the sensors, data processing algorithms, and machine learning prediction workflow.

Although the current implementation is developed as a breadboard prototype, the system is designed to be converted into a compact wearable device in future development stages. The final hardware design may involve integrating the components into a custom printed circuit board (PCB) and enclosing them within a wearable form factor such as a smartwatch or wristband.

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VII. FUTURE WORK

The proposed wearable depression monitoring system demonstrates the feasibility of using physiological sensors and machine learning techniques for monitoring mental health conditions. However, several improvements can be considered in future work to enhance the performance and usability of the system. One possible improvement is the development of a compact and fully integrated wearable device instead of the current breadboard prototype. The existing hardware setup uses components such as the ESP32-C3 Super Mini, MAX30102, MPU6050, and DS3231 connected through jumper wires on a breadboard for testing purposes. In future implementations, these components can be integrated into a custom printed circuit board (PCB) and enclosed in a compact wearable design such as a smartwatch or wristband to improve portability and user comfort.

Another important direction for future research is the expansion of the dataset used for training the machine learning models. Currently, the prediction models are trained using a limited dataset, which may affect the ability of the system to generalize across different users. By collecting data from a larger number of participants and including more diverse physiological patterns, the machine learning models can achieve higher accuracy and reliability. Advanced machine learning techniques such as deep learning models may also be explored to improve prediction performance.

Future work can also focus on integrating additional sensors to capture more comprehensive physiological and behavioral information related to mental health. Sensors capable of measuring parameters such as skin temperature, sleep patterns,

or stress-related signals could provide deeper insights into emotional and psychological states. Furthermore, the mobile or web application developed using frameworks such as Flutter can be enhanced with features such as personalized health recommendations, notification alerts, and cloud-based data storage for long-term monitoring. These improvements will help transform the current prototype into a more reliable and scalable solution for real-time mental health monitoring and early detection of depression.

VIII. CONCLUSION

This study presented a wearable-based depression monitoring system that integrates physiological sensing, wireless communication, and machine learning techniques to support early detection of mental health conditions. The proposed system utilizes multiple sensors to continuously collect physiological data such as heart rate, blood oxygen saturation, and motion activity. These sensors are connected to the ESP32-C3 Super Mini microcontroller, which acts as the central unit for data acquisition and communication. The system incorporates the MAX30102 sensor for heart rate and SpO_2 monitoring, the MPU6050 motion sensor for activity tracking, and the DS3231 real-time clock module for accurate time-based data recording. The collected data is transmitted through Bluetooth Low Energy communication to a mobile or web-based application where data preprocessing and machine learning analysis are performed.

The machine learning models used in this system analyze the physiological signals to classify the user's mental health condition into different categories such as normal, mild risk, or high risk. The system demonstrates how wearable technology can be used to provide continuous and real-time monitoring of behavioral and physiological indicators associated with depression. In the current implementation, the hardware components are connected using a breadboard prototype, which allows testing and validation of the system functionality. Despite this prototype stage, the proposed framework successfully demonstrates the integration of wearable sensing technology with intelligent data analysis for mental health monitoring.

Overall, the proposed system provides a portable, low-cost, and scalable solution that can support early identification of depression-related symptoms. By enabling continuous monitoring and data-driven analysis, the system may assist individuals and healthcare professionals in understanding behavioral patterns and taking preventive actions at an early stage. Future improvements involving compact hardware design, larger datasets, and more advanced machine learning models can further enhance the effectiveness and reliability of the proposed depression monitoring system.

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