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Original Article

PulseIQ-Integrated Computational Intelligence for Implicit State Recognition

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Abstract *- In recent times, people are paying more attention to their health, but stress and sleep-related issues are still increasing due to busy schedules, academic pressure, and improper rest. To address this problem, the proposed system PulseIQ focuses on monitoring stress and sleep conditions using Heart Rate (HR) and Heart Rate Variability (HRV). The system is designed using a pulse rate sensor connected to a NodeMCU (ESP8266) module, which continuously collects real-time heart rate data. The collected data is transmitted to a Python-based system where it is stored and processed for further analysis. From this data, HRV features are extracted to understand the user's physiological conditions related to stress and sleep. Machine learning algorithms such as Decision Tree and Random Forest are applied to classify stress levels and estimate sleep states. The dataset used for training is updated regularly to improve the performance and accuracy of the model. A simple user interface is also developed, where users can enter their basic details like name, age, and gender. The system displays real-time predictions along with graphical representations, making it easy to understand the results. Overall, the proposed system provides an affordable and efficient solution for continuous health monitoring, helping users detect stress early and manage their sleep patterns effectively. This system can also be useful in future healthcare applications.*

Keywords *- Beats Per Minute (BPM) Analysis, Heart Rate Variability (HRV), Internet of Things (IoT), Machine Learning, NodeMCU ESP8266, Pulse Rate Sensor, Real-Time Monitoring, Sleep State Monitoring, Stress Level Monitoring.*

1. Introduction

In recent years, the development of wearable devices and Internet of Things (IoT) technology has created new opportunities in healthcare monitoring. Continuous tracking of health parameters has become essential to identify problems at an early stage and take necessary precautions. Among various physiological signals, Heart Rate (HR) and Heart Rate Variability (HRV) play an important role in understanding human health. HRV represents the variation in time intervals between consecutive heartbeats, and it gives useful insights into the functioning of the autonomic nervous system. Research indicates that HRV is strongly connected to stress levels and sleep quality. Generally, lower HRV values are associated with higher stress and poor sleep, whereas higher HRV values indicate a more relaxed and healthy condition. Because of this relationship, HRV can be effectively used to monitor stress and sleep patterns. Traditional methods for analysing stress and sleep often involve expensive medical equipment and regular hospital visits, which may not be convenient for everyone. To overcome these challenges, affordable sensors and microcontrollers can be used to build real-time monitoring systems. With the help of IoT technology, it becomes possible to collect and transfer health data continuously, making remote monitoring more accessible and efficient. In this project, a real-time stress and sleep monitoring system is developed using a pulse rate sensor and NodeMCU (ESP8266). The sensor continuously captures heart rate data from the user and sends it to a Python-based platform through serial communication. This data is stored and processed to extract HRV features, which are then used for analysis. To enhance prediction accuracy, machine learning techniques such as Decision Tree and Random Forest are implemented. These algorithms help in identifying patterns in the data and classifying the user's condition into different stress levels and sleep states. Compared to manual analysis, machine learning provides better accuracy and reliability. Additionally, the system includes a user-friendly interface where users can enter personal details like age and gender and view real-time results through graphs and predictions. This makes the system easy to use even for non-technical users. Overall, this project aims to provide a low-cost, efficient, and scalable solution for continuous health monitoring. It helps in early identification of stress and sleep-related issues, which can prevent serious health complications in the future. By combining IoT and machine learning, the system contributes to the advancement of smart healthcare solutions that can be used in everyday life.

2. Review of Literature

Significant research has been carried out in the field of stress and sleep monitoring using physiological signals, particularly Heart Rate (HR) and Heart Rate Variability (HRV). Existing approaches can be broadly classified into HRV-based stress detection, machine-learning-based classification, and sleep-monitoring systems.

2.1. HRV-Based Stress Detection

Heart Rate Variability (HRV) is widely recognised as an effective physiological marker for stress assessment. It reflects the balance between the sympathetic and parasympathetic nervous systems, which regulate the body's response to stress. Recent studies highlight that HRV, when combined with artificial intelligence techniques, provides a reliable and non-invasive method for detecting stress levels. [1] Rajendra Acharya. U, et al. "Heart rate variability: a review." Medical and biological engineering and computing 44.12 (2006): 1031-1051. [2] Shaffer, Fred, and Jay P. Ginsberg. "An overview of heart rate variability metrics and norms." Frontiers in public health 5 (2017): 290215. [3] Dalmeida, Kayisan & Masala, Giovanni, (2021) "HRV Features as Viable Physiological Markers for Stress Detection Using Wearable Devices". Sensors. 21. 2873. 10.3390/s21082873, demonstrated that HRV features derived from wearable devices can be effectively used to classify stress levels using machine learning models such as Random Forest and Decision Tree [3]. Their work confirmed that HRV-based features provide significant accuracy in stress prediction while enabling real-time monitoring. However, existing studies often rely on ECG-based systems, which increase cost and complexity. Moreover, variability in datasets and experimental conditions affects model generalisation and consistency [2].

2.2. Machine Learning Approaches for Stress Classification

Machine learning techniques have been extensively applied for stress detection using physiological data. Supervised learning algorithms, such as Decision Tree, Random Forest, and neural networks, are commonly used due to their ability to classify complex patterns in HRV data. [4] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors". Trans. Intell. Transport. Syst. 6, 2 (June 2005), 156–166. [5] Martin Gjoreski, Hristijan Gjoreski, Mitja Luštrek, and Matjaž Gams. 2016. "Continuous stress detection using a wrist device": In Association for Computing Machinery, New York, NY, USA, 1185–1193. Recent research indicates that machine learning models trained on HRV features can accurately distinguish between stressed and non-stressed states [4], [5]. However, challenges such as dataset dependency, feature selection, and real-time adaptability remain significant. Furthermore, studies on wearable-based stress detection highlight issues related to model generalisation across different datasets and environments. Variations in sensor types, stress conditions, and individual differences can impact prediction accuracy, emphasising the need for adaptive and real-time systems [5].

2.3. HRV-Based Sleep Monitoring Systems

HRV has also been widely used to analyse sleep quality and classify sleep stages. Compared with traditional methods such as Polysomnography (PSG), HRV-based approaches are cost-effective and non-invasive. Recent studies show that machine learning algorithms using HRV features can achieve high accuracy in sleep stage classification, making them suitable for real-time monitoring systems.[6] Kim, Kwang Bok, and Hyun Jae Baek. "Photoplethysmography in wearable devices: a comprehensive review of technological advances, current challenges, and future directions." [7] Penzel, Thomas et al. "Cardiovascular and respiratory dynamics during normal and pathological sleep." Chaos (Woodbury, N.Y.) vol. 17,1 (2007): 015116. Additionally, research demonstrates that sleep-phase HRV can be used to predict stress severity, highlighting the strong relationship between sleep patterns and stress levels. Despite these advancements, many systems still rely on large datasets and complex feature extraction methods, limiting their real-time applicability. HRV has been widely used in sleep monitoring systems to analyse sleep quality and to classify different sleep stages. During sleep, the balance between sympathetic and parasympathetic nervous activity changes, which is reflected in HRV patterns. For example, deep sleep is associated with higher parasympathetic activity and more stable HRV, while lighter sleep stages and REM sleep show more fluctuations.

2.4. Research Gaps Identified

From the reviewed literature, several research gaps are observed: Many systems depend on multiple physiological sensors, increasing hardware cost and complexity [2], [9]. Poor generalisation of machine learning models across different users [5]. Absence of user-friendly dashboards for real-time visualisation.[9] Patel, Shyamal et al. "A review of wearable sensors and systems with application in rehabilitation." Journal of Neuroengineering and Rehabilitation, Vol. 9, 21. 20 Apr. 2012, doi:10.1186/1743-0003-9-21. [10] Dotsinsky, Ivan. "Review of "Advanced Methods and Tools for ECG Data Analysis", by Gari D. Clifford, Francisco Azuaje and Patrick E. McSharry (Editors)." BioMedical Engineering Online vol. 6 18. 25 May. 2007. Existing studies on HRV-based stress and sleep monitoring have demonstrated promising results using machine learning techniques. However, most systems rely on offline datasets and complex medical-grade devices, limiting their applicability in real-time environments [1][3]. Additionally, many approaches focus primarily on model accuracy without providing an integrated system that includes data acquisition, processing, and visualisation [4]. Furthermore, challenges such as a lack of standardised datasets, high computational requirements, and poor generalisation across users remain unresolved [5], [7]. Therefore, there is a need for a cost-effective, real-time, and fully integrated system that utilises minimal hardware while maintaining reliable prediction accuracy.

3. Methodology

System methodology describes the design and implementation of the proposed Heart Rate and HRV-based Stress and Sleep Monitoring System. The system is designed as a modular, end-to-end pipeline that integrates IoT-based data acquisition, signal processing, machine learning, and data visualisation to enable real-time health monitoring.

3.1. Heart Rate and HRV Significance

Heart Rate (HR) refers to the number of Beats Per Minute (BPM) and is a primary indicator of cardiovascular activity. Heart Rate Variability (HRV) represents the variation in time intervals between successive heartbeats and reflects the functioning of the autonomic nervous system. HRV is widely used to evaluate physiological conditions such as stress and sleep states. A lower HRV is associated with higher stress levels, while a higher HRV indicates a relaxed state and better sleep quality. Since both HR and HRV can be measured non-invasively using a pulse sensor, they offer a reliable and cost-effective solution for continuous health monitoring, as shown in Figure 5.

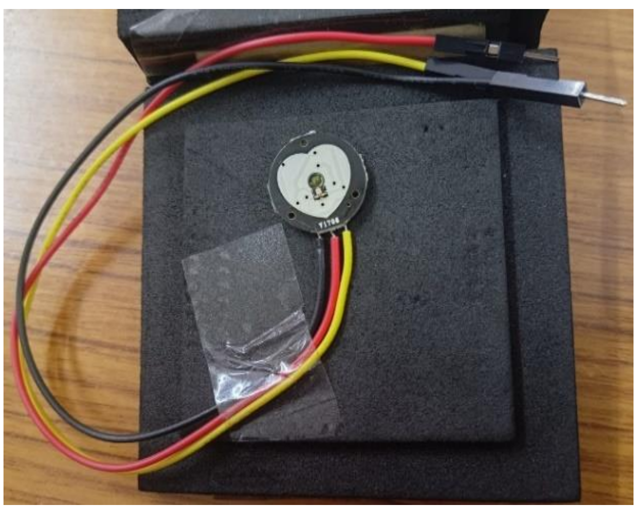


Fig. 1 The Pulse Sensor

3.2. System Architecture

The proposed system follows a five-stage modular pipeline:(1) Data Acquisition, (2) Data Transmission and Storage, (3) Feature Extraction (HRV Analysis), (4) Stress and Sleep Prediction, (5) User Interface and Visualisation. The system integrates hardware components such as a pulse sensor, as shown in Figure 1, and NodeMCU, as shown in Figure 2, with software components (Python, machine learning models, and dashboard) to enable real-time monitoring. The pulse sensor detects heartbeats by measuring changes in blood flow and provides real-time heart rate data, as shown in Figure 3.

It is simple, non-invasive, and suitable for continuous monitoring. It provides analogue output signals that are easy to read and process by microcontrollers such as the NodeMCU. It processes the sensor data and sends it to the system using serial communication, as shown in Figure 2.

Fig. 2 NodeMCU (Microcontroller)

3.3. Data Acquisition Module

The Data Acquisition Module uses a pulse-rate sensor connected to the NodeMCU (ESP8266) to capture real-time heart-rate data from the user. The sensor detects pulse signals and converts them into digital heart rate values. The NodeMCU reads the sensor output and continuously transmits the heart rate data through serial communication to a connected system. This enables real-time streaming of physiological data without requiring complex hardware, as shown in Figure 3.

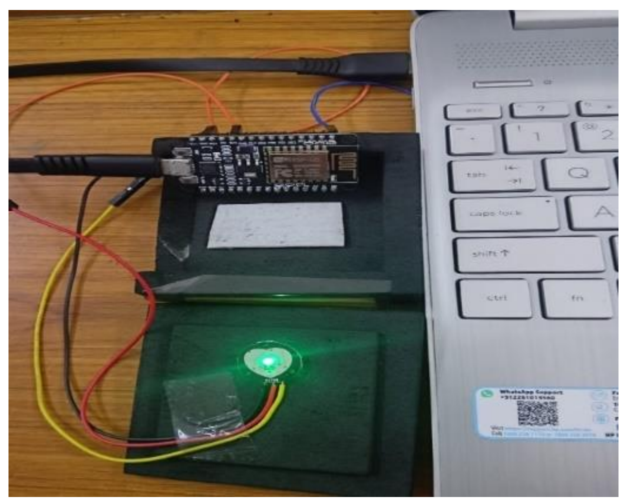


Fig. 3 Hardware setup showing components' connection to the PC using USB

3.4. Data Transmission and Storage

A Python-based system receives the transmitted heart rate data through a serial port. The data is processed and stored in a live dataset, typically in CSV format or a database. This module ensures (1) Continuous data logging, (2) Creation of a dynamic dataset for model training, and (3) Real-time availability of input data for prediction. The dataset is updated continuously, enabling both offline training and real-time inference as shown in Fig 8.

3.5. Feature Extraction (HRV Analysis)

From the collected heart rate data, Heart Rate Variability (HRV) is computed as the standard deviation of recent heart rate values over a short time window. This approach captures short-term variations in heart rate and reflects changes in the user's physiological condition. The calculated HRV, along with heart rate, is used as input for the machine learning model to predict stress levels and sleep states. In this system, HRV is derived from variations in recent heart rate readings, making it suitable for real-time analysis. Both HR and HRV features play a crucial role in accurate prediction.

3.6. Stress and Sleep Prediction Model

Machine learning algorithms are used to classify stress levels and sleep states based on HR and HRV features. The system employs Decision Tree and Random Forest models. These models are trained using a dataset containing HR, HRV features, and corresponding labels. During real-time operation, the trained model takes live input data and predicts: Stress levels (Low, Moderate, High) and Sleep states (Awake, REM state, Light Sleep, Deep Sleep). Continuous updates to the dataset help improve model performance over time, as shown in Figure 6. Machine learning models like Decision Tree and Random Forest are used to classify stress levels. The model is trained using heart rate and HRV data along with labelled stress levels. During real-time use, the system predicts stress levels and estimates sleep states based on live input data.

3.7. User Interface and Visualisation

A user-friendly dashboard is developed using a Python framework such as Streamlit. The interface allows users to interact with the system and view results in real time. The dashboard provides: Input fields for name, age, gender, and date and time, as shown in Figure 4. Real-time heart rate display using gauge visualisation and HRV metrics, as shown in Figure 5. Stress and sleep predictions, along with a health interpretation column, are shown in Figure 6. Graphical representation of heart rate and HRV trends, as shown in Figure 7. Storage and display of patient data and predicted results, as shown in Fig 8. Calculation of average heart rate, along with minimum and maximum values across timestamps, as shown in Figure 9.

3.8. System Workflow

The overall workflow of the system is as follows:
1. The pulse sensor captures heart rate signals
2. NodeMCU transmits the data to the Python environment
3. Data is stored in a live dataset
4. HRV features are extracted from the data
5. Machine learning models predict stress and sleep states
6. Results are displayed on the dashboard with graphs

4. Results and Discussion

The results and discussion involve the performance evaluation of the suggested stress and sleep monitoring system. The evaluation is carried out based on the accuracy, response time, and overall effectiveness of the system.

4.1. Model Performance

The machine learning models were trained using heart rate and computed HRV features. Among the models used, Random Forest showed better performance due to its ability to handle non-linear data and reduce overfitting, as shown in Table 1.

Table 1. Performance of the models

Model	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	85	0.84	0.83	0.83
Random Forest	90	0.89	0.88	0.88

It should be noted that the values provided in the table above are experimental and approximated. It is observed from the results that the Random Forest model achieved higher accuracy than the Decision Tree model.

4.2. System Performance

The system was tested for real-time data processing and prediction. The response time and system behaviour were analysed under normal conditions, as shown in Table 2.

Table 2. Performance of the system

Parameter	Observed Value
Data Acquisition Rate	Continuous
Prediction Time	<2 Seconds
HRV Computation Time	<1 Second
Dashboard Response Time	<2 Seconds
System Accuracy	Up to 90%

The system successfully performs real-time monitoring with minimal delays. The prediction time and dashboard response time are within acceptable limits, ensuring a smooth user interaction experience.

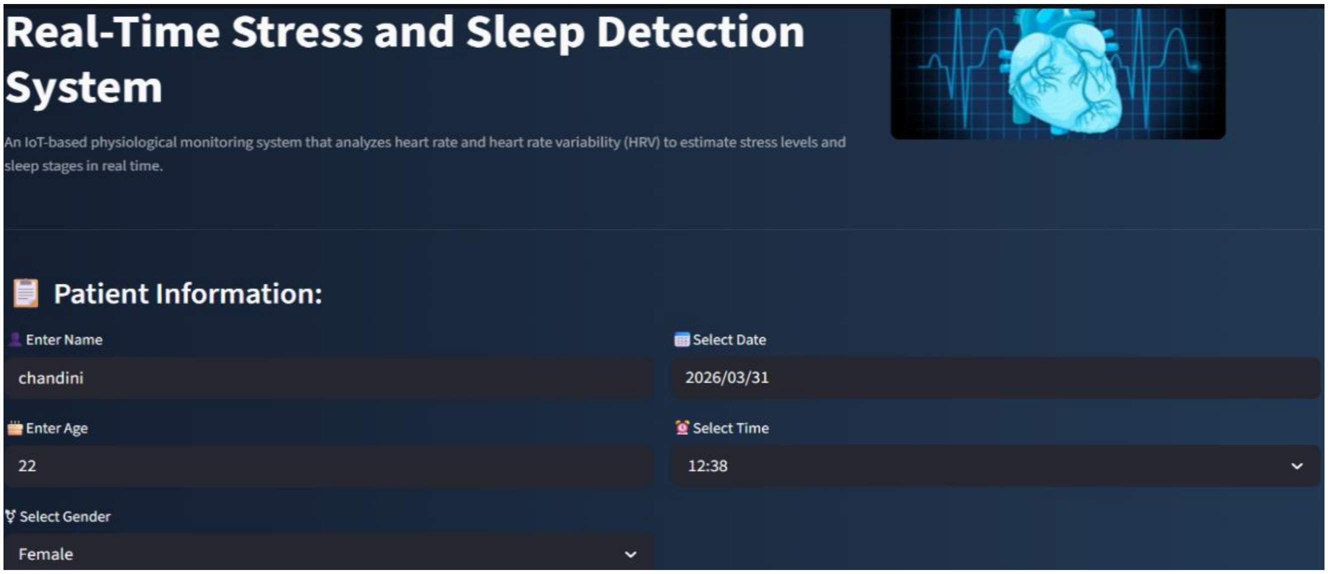


Fig. 4 Dashboard interface showing patient information input fields

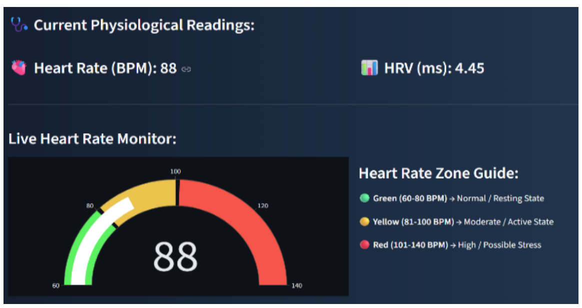


Fig. 5 Displaying heart rate & HRV with gauge visualisation

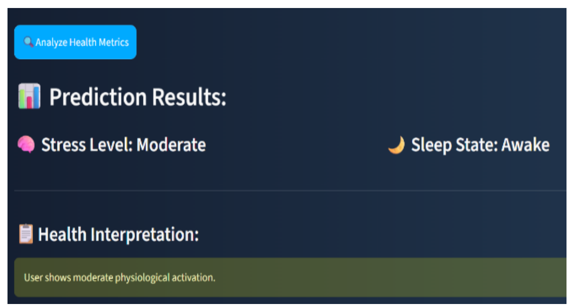


Fig. 6 Prediction results displaying stress level and sleep state

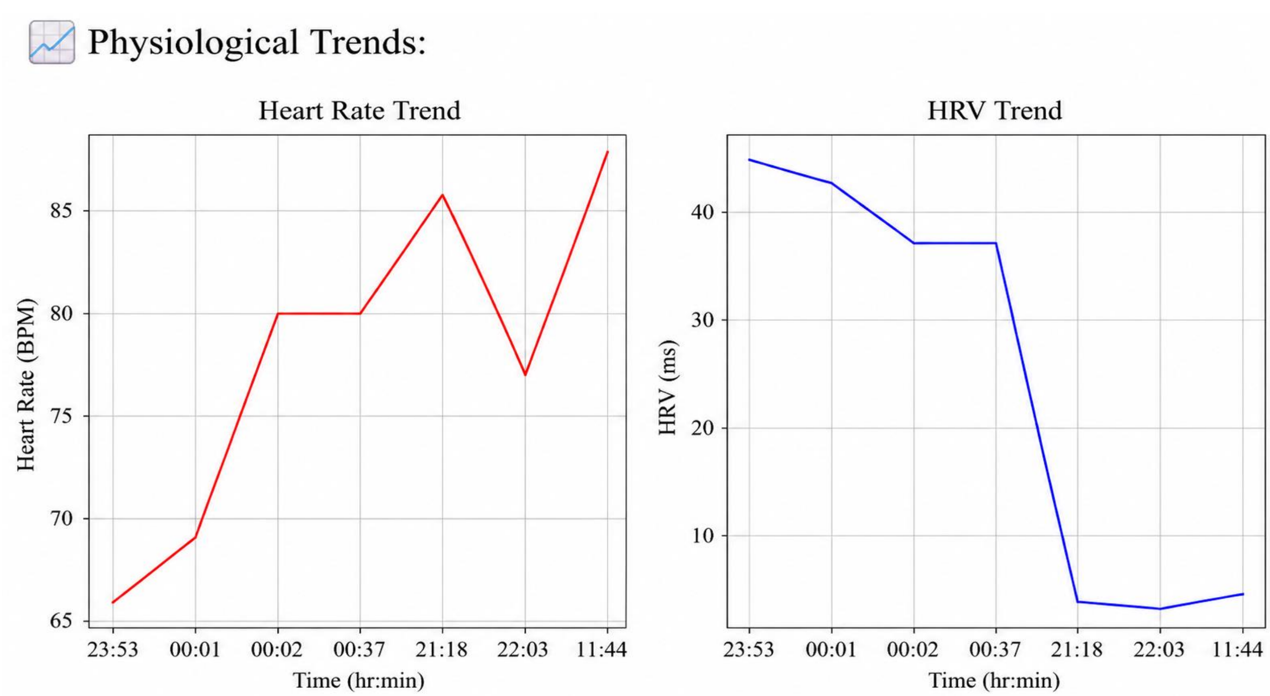
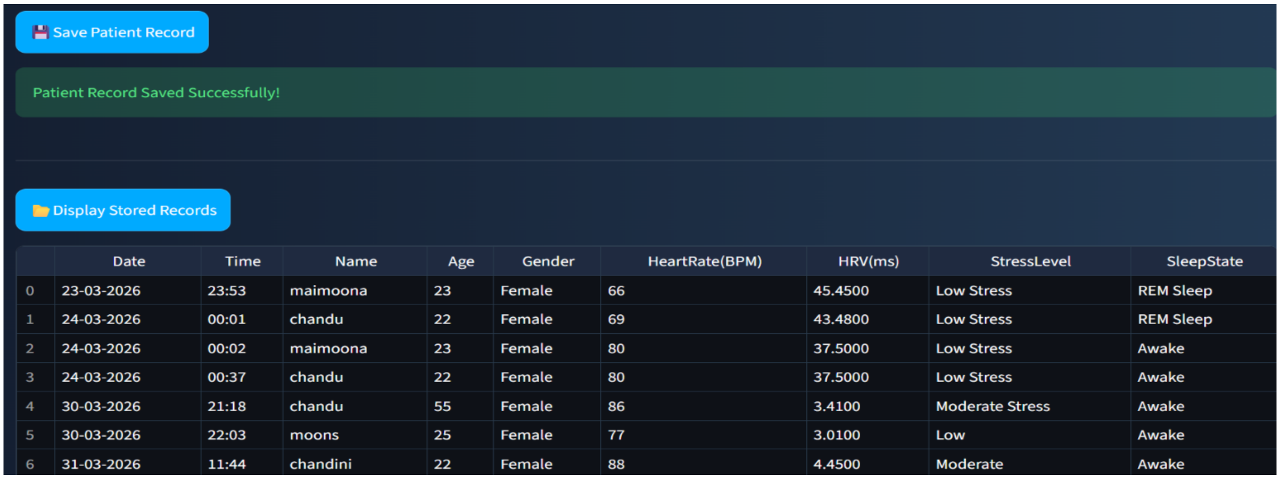


Fig. 7 Physiological trends showing variation of heart rate and HRV over time



	Date	Time	Name	Age	Gender	HeartRate(BPM)	HRV(ms)	StressLevel	SleepState
0	23-03-2026	23:53	maimoona	23	Female	66	45.4500	Low Stress	REM Sleep
1	24-03-2026	00:01	chandu	22	Female	69	43.4800	Low Stress	REM Sleep
2	24-03-2026	00:02	maimoona	23	Female	80	37.5000	Low Stress	Awake
3	24-03-2026	00:37	chandu	22	Female	80	37.5000	Low Stress	Awake
4	30-03-2026	21:18	chandu	55	Female	86	3.4100	Moderate Stress	Awake
5	30-03-2026	22:03	moons	25	Female	77	3.0100	Low	Awake
6	31-03-2026	11:44	chandini	22	Female	88	4.4500	Moderate	Awake

Fig. 8 Stored patient records displaying heart rate, HRV, stress level, and sleep state

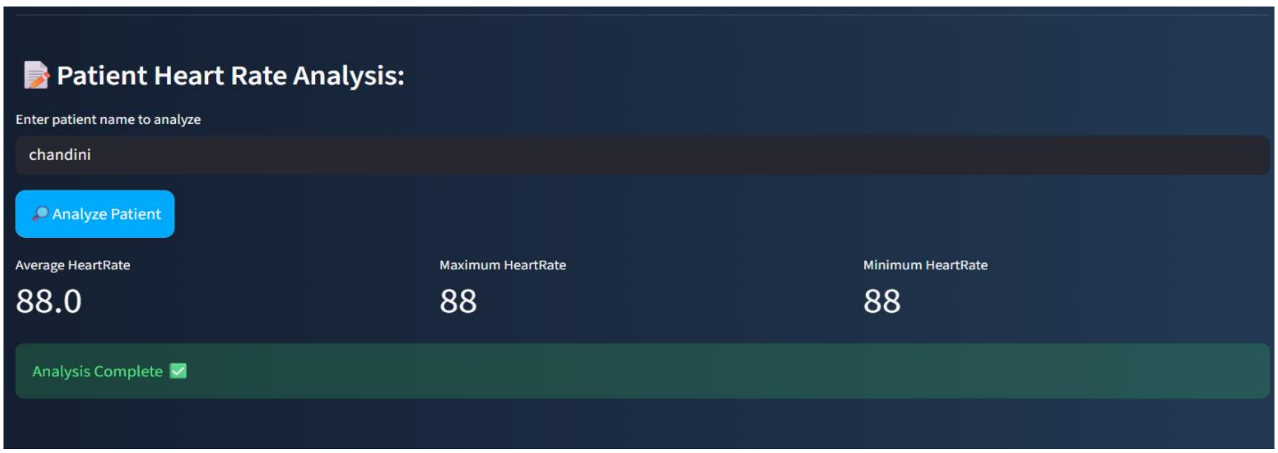


Fig. 9 Patient heart rate analysis displaying average, minimum, and maximum values

5. Overall Discussion

From the experiments carried out, it is evident that the proposed approach is effective in monitoring stress levels and sleep states using heart rates and HRV values. The application of machine learning techniques enhances the prediction accuracy of the system. Also, the dashboard provides a user-friendly presentation of the findings obtained. The proposed system is more affordable, portable, and fit for real-time purposes than other existing approaches. The main limitation of the system is its effectiveness, which is dependent on the amount and quality of the data used.

6. Conclusion and Future Scope

6.1. Conclusion

The design and development of a Real-Time Stress and Sleep Monitoring System using Heart Rate (HR) and Heart Rate Variability (HRV). The proposed system comprises a pulse rate sensor along with NodeMCU for continuous data collection and the utilization of a Python-based framework for data processing, storage, and analysis. HRV indicators are derived from the acquired data set and used as input features for machine learning algorithms such as Decision Tree and Random Forest. The proposed system is capable of executing real-time monitoring and classification of stress states and sleep quality with acceptable accuracy levels. Implementation of a user-friendly dashboard allows for visualization of heart rate patterns, HRV indicators, and prediction outcomes, thus ensuring an interactive and user-friendly experience. The application of inexpensive hardware and open-source software solutions ensures the practicality and accessibility of the proposed system for real-world health monitoring purposes. Overall, the developed system represents a cost-efficient, scalable, and effective approach to continuous health monitoring, which contributes to early detection of stress conditions and improving sleep quality.

6.2. Future Scope

Although the proposed system is able to perform efficiently, there are certain areas where further improvement can take place to improve the system's functionality and applicability:

- Model Accuracy Improvements: The use of advanced machine learning and deep learning algorithms can further increase the accuracy of predictions. This includes the implementation of neural networks or LSTM models.

- Integration of Additional Sensors: Sensors like SpO_2, temperature, or respiratory sensors can be used in addition to the current sensor to have better health care management.
- Development of Mobile Application: Developing a mobile application for Android and iOS platforms can improve accessibility and user convenience.
- Addition of Personalised Health Insights: Implementing personalised recommendations based on user data can improve the system's effectiveness.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] U. Rajendra Acharya et al., "Heart Rate Variability: A Review," *Medical and Biological Engineering and Computing*, vol. 44, no. 12, pp. 1031-1051, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[2] Fred Shaffer, and Jay P. Ginsberg, "An Overview of Heart Rate Variability Metrics and Norms," *Frontiers in Public Health*, vol. 5, pp. 1-17, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] Kayisan M. Dalmeida, and Giovanni L. Masala, "HRV Features as Viable Physiological Markers for Stress Detection Using Wearable Devices," *Sensors*, vol. 21, pp. 1-18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] J.A. Healey, and R.W. Picard, "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 156-166, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[5] Martin Gjoreski et al., "Continuous Stress Detection Using a Wrist Device: In Laboratory and Real Life," *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, pp. 1185-1193, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kwang Bok Kim, and Hyun Jae Baek, "Photoplethysmography in Wearable Devices: A Comprehensive Review of Technological Advances, Current Challenges, and Future Directions," *Electronics*, vol. 12, no. 13, pp. 1-24, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Thomas Penzel et al., "Cardiovascular and Respiratory Dynamics during Normal and Pathological Sleep," *Chaos*, vol. 17, no. 1, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[8] Akane Sano, and Rosalind W. Picard, "Stress Recognition using Wearable Sensors and Mobile Phones," *Humaine Association Conference on Affective Computing and Intelligent Interaction*, pp. 671-676, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[9] Shyamal Patel et al. "A Review of Wearable Sensors and Systems with Application in Rehabilitation," *Journal of Neuroengineering and Rehabilitation*, vol. 9, pp. 1-17, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[10] Ivan Dotsinsky, ""Review of "Advanced Methods and Tools for ECG Data Analysis," by Gari D. Clifford, Francisco Azuaje and Patrick E. McSharry (Editors)."" *BioMedical Engineering OnLine*, vol. 6, pp. 1-3, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[11] Prosanta Gope, and Tzonelih Hwang "BSN-Care: A Secure IoT-based Modern Healthcare System Using Body Sensor Network," *IEEE Sensors Journal*, vol. 16, no. 5, pp. 1368-1376, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[12] Jonghwa Kim, and Elisabeth André, "Emotion Recognition Based on Physiological Changes in Music Listening," *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 30, vol. 12, pp. 2067-2083, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[13] Eman M.G. Younis et al., "Machine Learning for Human Emotion Recognition: A Comprehensive Review," *Neural Computing and Applications*, vol. 36, no. 16, pp. 8901-8947, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Mustafa Radha et al., "Sleep Stage Classification from Heart-Rate Variability using Long Short-Term Memory Neural Networks," *Scientific Reports*, vol. 9, pp. 1-11, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] V. Subha Ramya, and J. Bethanney Janney, "Stress Detection Using Physiological Signals and Machine Learning," *Twelfth International Conference on Bio Signals, Images, and Instrumentation*, pp. 1-5, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[16] Karen Hovsepian et al., "cStress: Towards a Gold Standard for Continuous Stress Assessment in the Mobile Environment," *Proceedings of the ACM International Conference on Ubiquitous Computing*, vol. 2015, pp. 493-504, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[17] Muhammad Zubair, and Changwoo Yoon, "Multilevel Mental Stress Detection Using Ultra-Short Pulse Rate Variability Series," *Biomedical Signal Processing and Control*, vol. 57, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[18] Rossana Castaldo et al., "Heart Rate Variability Analysis and Performance during a Repeated Mental Workload Task," *European Medical and Biological Engineering Conference*, pp. 69-72, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[19] Nandita Sharma, and Tom Gedeon, "Objective Measures, Sensors and Computational Techniques for Stress Recognition and Classification: A Survey," *Computer Methods and Programs in Biomedicine*, vol. 108, no. 3, pp. 1287-1301, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[20] Mohammed Faraz Uddin et al., "Real Time Heart Rate Monitoring System," *International Journal of Information Technology and Computer Engineering*, vol. 13, pp. 271-279, 2025. [CrossRef] [Publisher Link]

[21] G. Giannakakis et al., “Stress and Anxiety Detection Using Facial Cues from Videos,” *Biomedical Signal Processing and Control*, vol. 31, pp. 89-101, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[22] Alexandros Zenonos et al., “HealthyOffice: Mood Recognition at Work Using Smartphones and Wearable Sensors,” *IEEE International Conference on Pervasive Computing and Communication Workshops*, pp. 1-6, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[23] Najat Boufa et al., “IoT-Based Patient Health Monitoring System Using NodeMCU,” *Surman Journal of Science and Technology*, vol. 7, pp. 129-144, 2025. [Google Scholar] [Publisher Link]

[24] R. Rajani, and C.H. Vasavi, “ML-Based Stress Detection via Heart Rate Variability,” *International Journal of Engineering and Techniques*, vol. 10, no. 3, pp. 239-250, 2024. [Publisher Link]

[25] Moein Razavi et al., “Machine Learning, Deep Learning, and Data Preprocessing Techniques for Detecting, Predicting, and Monitoring Stress and Stress-Related Mental Disorders: Scoping Review,” *JMIR Mental Health*, vol. 11, 2024. [CrossRef] [Google Scholar] [Publisher Link]