ISSN 2355-3286

Unlocking Wellness: Pioneering IoT Wearable Sensor with The Smart Ring for Body Fatigue Monitoring

Dewi Indriati Hadi Putri[1], Elysa Nensy Irawan[2], Liptia Venica[3], Hafiyyan Putra Pratama[4]
[1,2,3] Department of Mechatronics and Artificial Intelligence, Universitas Pendidikan Indonesia, Bandung, Indonesia
[1]dewiindri@upi.edu , [2]elysanensy@upi.edu , [3]liptiavenica@upi.edu
[4]Department of Telecommunication System, Universitas Pendidikan Indonesia, Bandung, Indonesia
[4]hafiyyan@upi.edu

Accepted on May 20, 2025
Approved on December 12, 2025

***Abstract*— This study present the development and implementation of an IoT-Based wearable device, namely a Smart Ring, designed to monitor body fatigue levels in real time. Physical fatigue caused by prolonged or intense activities has been reported as a contributing factor to serious health conditions such as cardiovascular disorders, asthma, and stroke. Existing wearable devices, including smartwatches and commercial smart rings, mainly provide raw physiological information without fatigue classification or early warning mechanisms. The proposed Smart Ring integrates a MAX30100 sensor to measure heart rate, blood oxygen saturation (SpO_2), and body temperature. A fuzzy logic algorithm is employed to classify fatigue levels into rest, normal, and risk categories. The system is connected to an Android application via IoT, enabling real-time monitoring, alerts, and GPS-based location reporting. Quantitative validation was conducted by comparing Smart Ring measurements with standard medical devices. The results show average deviations of ±5 bpm for heart rate, ±1.5% for SpO_2, and ±1.3 °C for body temperature, which fall within acceptable limits for non-invasive wearable monitoring. These findings demonstrate that the Smart Ring provides reliable fatigue detection while offering an affordable and practical solution for personal health monitoring in the Society 5.0 era.**

Index Terms*—, IoT, wearable sensor, smart ring, body fatigue monitoring, fuzzy logic

I. Introduction

Fatigue can occur in anyone as a result of energy-draining physical activities. Several studies have indicated that fatigue can trigger more serious illnesses such as heart attacks, strokes, arthritis, asthma, and others [1][2][3]. Heart attacks can be induced by stress, intense physical activity, or cold weather, all of which can cause blood vessels to contract or spasm. When blood vessels contract, the amount of blood entering the heart muscle can decrease, leading to a heart attack [4][5][6].

Research conducted by A. C. Perez-Moreno et al. (2014) found that 59% of 540 patients with heart failure experienced severe fatigue before the onset of a heart attack [7]. Based on this information, it is crucial for us, especially those with a history of serious illnesses, to monitor our fatigue levels during activities to minimize the risk of sudden attacks from dangerous conditions. Research on the classification of fatigue levels for both healthy individuals and those with diabetes has been conducted by L. Aljihmani et al. (2020) using wearable sensors and machine learning methods, achieving an accuracy of 96.1% [8]. There is currently various commercial smart ring product such as Oura Ring, GO2SLEEP Ring, and Motiv Ring, which are capable of monitoring heart rate, oxygen saturation, and sleep quality [9][10][11]. However, most of these devices do not integrate parameters such as body temperature and fatigue category analysis in one affordable and easy-to-use platform. In addition, clinical validation of body fatigue data based on physiological parameters is still very limited. Therefore, the development of this smart ring is aimed at addressing these limitations, especially on the aspect of parameter integration and the potential development of an IoT-based tool that can be used for early monitoring of fatigue risks that impact cardiovascular health.

Research on wearable sensor devices has been conducted by Niswar et al. (2019), who designed a system with two biomedical sensors: an airflow thermal sensor and a pulse oximeter sensor to measure patients' vital signs [12]. However, this research is not portable for daily use because one of the measured parameters is respiration, which requires the device to be attached to the nose.

In the era of Society 5.0, the development of the Internet of Things (IoT) is in full swing. One of the most popular IoT products is the smartwatch, which is highly favored by the public due to its minimalist design and advanced features for measuring vital signs such as heart rate, SpO2, and body temperature. However, the features provided by smartwatches only offer information about vital signs and do not help in minimizing the risk of fatigue.

In this research, a Smart Ring is introduced to address the shortcomings of smartwatches. The Smart Ring is capable of providing reminders when the user reaches the fatigue threshold during activities. Unlike existing wearable devices such as smartwatches and commercial smart rings that primarily provide raw physiological data, the proposed Smart Ring integrates multi-parameter sensing (heart rate, SpO_2, and body temperature) with fuzzy logic-based fatigue classification and real-time IoT notification. Furthermore, this study provides initial quantitative validation against medical reference devices, which is still limited in most commercial smart ring implementations. This combination of fatigue inference, affordability, and IoT-based alert functionality constitutes the main novelty of this research.

Additionally, as an IoT implementation, the Smart Ring comes with an Android application called the Smart Ring App. This app is connected to GPS. The Smart Ring is designed to be economical, making it accessible to people from various walks of life. By introducing the Smart Ring as an affordable healthcare device, it is hoped that the well-being of society in the era of Society 5.0 can be achieved, particularly in the field of health. The main problem to be solved in this research is how to design and develop a smart ring-based wearable device capable of monitoring physiological indicators of body fatigue in real-time, as well as how to conduct initial validation of the accuracy of its readings compared to standard medical devices.

II. Materials & Method

A. *Wearable Sensor for Fatigue Monitoring*

Based on their placement, sensors are classified into two types: wearable sensors and implantable sensors [13]. Wearable sensors are one of the rapidly developing technologies due to the significant benefits they offer, such as easy operation, quick response, portability, and small size, which make them highly desirable [14]. Wearable sensors are types of sensors that can be integrated into wearable objects or directly onto the body. They are generally used to help monitor or provide relevant information related to clinical conditions or overall health [15].

There are various types of wearable sensors commonly used to monitor the heart and blood vessels. These sensors can measure a range of physiological parameters, such as heart rate and blood oxygen levels. As shown in Table I, Multivariable (AMON), Photoplethysmography (PPG), and Electrocardiograph (ECG) sensors, when worn on the finger (ring sensor), can measure the most comprehensive set of physiological parameters, including blood pressure, blood oxygen saturation, body temperature, and heart rate rhythm [16], [17].

TABLE I. Types of Wearable Sensor

Location of Use	Types of Sensors	Marker
Wrist	Ultrasound	Blood Pressure
• **Wrist** • **Finger (Ring Sensor)**	Multivariable (AMON)	Blood Pressure Blood Oxygen Saturation Body Temperature Heart Rate Rhythm
	• Photoplethysmography (PPG) • Electrocardiography (ECG)	
	• Optical	Heart Rate
	• Radio-frequency Identification	Heart Rate and Body Temperature
Arm or Thigh	Microwave Reflectometric Cardiopulmonary	Heart Rate Variability as a Method for Evaluating Stress
Phone adapter	Single-channel ECG	Heart Rate
Seatbelt in a Car	Wire type Strain Gauge	Heart Rate and Respiration Rate

The Advanced Medical Monitor (AMON) is a device used to monitor patients with heart disease and respiratory disorders. It is worn on the patient's wrist and features an accelerometer that continuously measures the user's physical activity. AMON integrates various sensors to measure SpO2, blood pressure, body movement, body temperature, and pulse rate. Fig. 1 illustrates the AMON prototype and its role in physiological monitoring systems. The AMON device integrates multiple sensors, including SpO_2, body temperature, and heart rate, and has been widely referenced as an early model of wearable medical monitoring for high-risk patients [18].

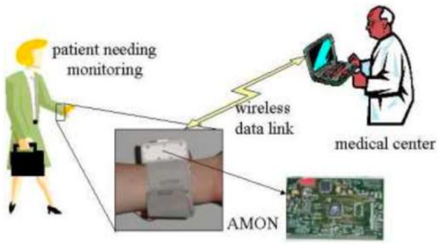


Fig. 1. *AMON* Prototype and Its Role in Monitoring Systems

The development of physiological monitoring systems continues to advance, aiming to produce simpler, more user-friendly, and cost-effective systems. One such development involves leveraging Photoplethysmography (PPG) sensors due to their ease of use and minimal impact on user mobility. PPG sensors are widely used in wearable technology because they can measure changes in blood vessel volume and estimate health metrics such as heart rate, respiration rate, blood pressure, body temperature, and blood oxygen saturation [19]. PPG sensors operate in either transmission or reflectance mode, as illustrated in Fig.2. In transmission mode, LED light is detected by a photodiode or photodetector positioned on the opposite side. In reflectance mode, the photodiode detects light reflected back from tissues, bones, and/or blood vessels

[20]. Transmission mode is commonly used in hospital settings, whereas reflectance mode is prevalent in wearable devices like smartwatches.

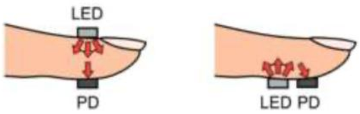


Fig. 2. Placement of LED and Photodetector in PPG Sensors: Transmission and Reflectance Modes[20]

By adapting the AMON prototype and utilizing a PPG sensor, a smart ring prototype has been designed. The PPG sensor used in this study is the MAX30100.

B. Fuzzy Logic for Classification of Fatigue Levels

Fuzzy logic was first introduced in 1965 by Lotfi A. Zadeh from the University of California through his publication titled "Fuzzy Sets." Boolean logic, which consists of binary membership values of 0 or 1, was deemed inadequate to represent human logic or thinking. Fuzzy logic was developed as an alternative to Boolean logic by allowing membership values to range between 0 and 1 [20]. In fuzzy logic, values between true/false, yes/no, high/low, far/near, and other similar dichotomies can be defined. These values can then be processed by computers to apply a form of reasoning in programming that more closely resembles human thought [21]. Generally, fuzzy logic is used to design intelligent systems capable of handling processes of human reasoning [22] [23]. It can also be utilized to determine the relationship between vital signs and physiological indicators, as shown in Table II.

TABLE II. RELATIONSHIP BETWEEN VITAL SIGNS AND PHYSIOLOGICAL INDICATORS. H=HIGH, L=LOW, N/A = NOT APPLICABLE, N=NORMAL[13]

Physiological Conditions	Heart Rate	Blood Pressure	Blood Oxygen Saturation	Body Temperature
Bradycardia	L	N/a	N/a	N/a
Tachycardia	H	N/a	N or l	N/a
Hypotension	N/a	L	N/a	N/a
Hypertension	N/a	H	N/a	N/a
Hypoxemia	N/a	N/a	Often l	N/a
Fever	H or n	N/a	N/a	H
Hypothermia	L	N or l	N/a	L
Normal Range	60-90 bpm	100-140/60-80 mm/hg	94-99%	36.5-37.5^{0}C

In Table II, the notation “N/a” (not applicable) indicates that the corresponding physiological parameter does not have a direct or clinically significant correlation with the specific condition. For example, blood oxygen saturation is not a defining marker for hypertension, hence it is marked as N/a.

The fuzzy logic model can be employed to interpret various physiological parameters by using information from collected vital signs, such as heart rate, blood pressure, blood oxygen saturation, and body temperature. An example of this implementation is illustrated in Table 2, demonstrating how vital signs can be mapped to detect a physiological condition using fuzzy logic [13]. his model can similarly be applied to detect fatigue in individuals based on specific fatigue parameters. Based on these vital signs, the fuzzy rules for this study can be categorized as shown in Table III.

TABLE III. FUZZY RULES

Input	Age (years)	Young	1-30
		Middle	20-60
		Old	50-100
	Body Temperature (^{0}C)	Low	0-36.5
		Normal	35-39
		High	37.5-50
	Heart Rate (bpm)	Slow	0-70
		Normal	60-90
		Fast	80-200
	Oxygen (%)	Low	0-92
		Normal	90-98
		High	96-100
Output	Category	Rest	0-50
		Normal	25-75
		Risk of Fatigue	50-100

Based on the fuzzy rules, the output from the system will help users determine the threshold for bodily fatigue. When this threshold is reached, a reminder will be triggered along with a slight vibration from the ring. In the event of a significant drop in condition or if the user faints, the system will automatically send an alert message to the emergency contact number listed in the Smart Ring App.

C. System Design

The Smart Ring is physically designed to be as minimalistic as possible to avoid interfering with the user during activities and resembles a typical ring worn on the finger. The Smart Ring consists of three main components: the electronic hardware, the software, and the communication system using IoT. The system designed for the Smart Ring prototype is illustrated in Fig.3.

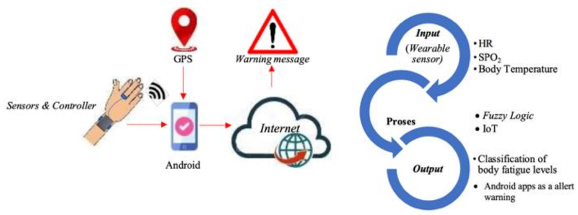


Fig. 3. Architecture Smart Ring

Data can be processed through the IoT-based monitoring system application. As shown in Fig.3, sensor data is collected by the Android software paired with the Smart Ring. The Android device can transmit data and GPS information over the internet to a server with a database [24]. If the data indicates fatigue, as recognized by the fuzzy algorithm, the Android application will trigger an alert to notify the user. Fig. 4 shows the operational flow of the Smart Ring system, starting from data acquisition, fuzzy logic-based fatigue classification, and ending with alert generation and IoT-based data transmission.

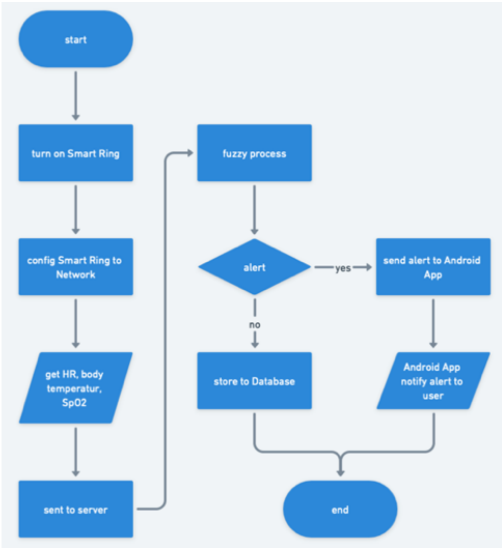


Fig. 4. Flowchart for The Smart Ring System

In this study, the Android application is designed to display fatigue data generated by the MAX30100 sensor, provide user location information to facilitate identification, and issue notifications about fatigue risk conditions. The application is developed using the Blynk server, which is connected to the NodeMCU controller.

III. Result and Analysis

This section will describe the results of the hardware design, including the smart ring box design and wiring diagram, the implementation of fuzzy logic, and the integration of sensor data with the Android application (Blynk).

A. Hardware Implementation

The smart ring prototype has a control box part which consists of several components, namely the Max30100 sensor to obtain heart rate (HR), SPO2 oxygen saturation, body temperature (0C), Oled as a display, NodeMCU as a microcontroller and battery as shown in Fig. 5.

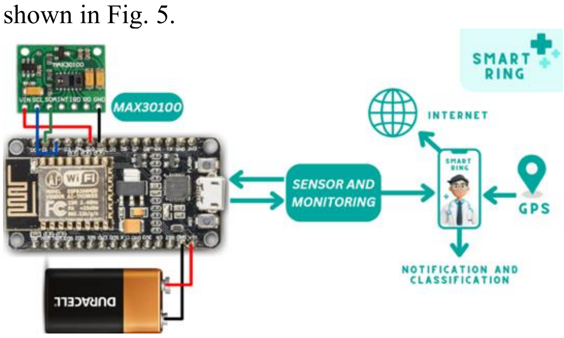
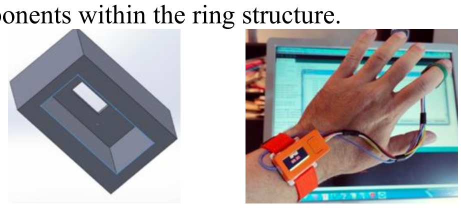


Fig. 5. Wiring Diagram of Smart Ring Prototype

Fig. 6 presents the mechanical design and physical realization of the Smart Ring prototype. Fig. 6(a) shows the three-dimensional CAD model developed using SolidWorks, which was designed to achieve a compact and ergonomic form suitable for finger placement. Fig. 6(b) illustrates the fabricated physical prototype, demonstrating the integration of electronic components within the ring structure.



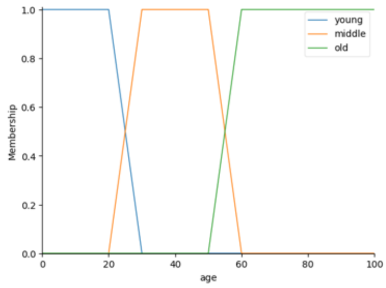
(a) (b)

Fig. 6. Smart Ring Prototype Design (a) 3D CAD Model Using SolidWork, (b) Physical Prototype of the Smart Ring

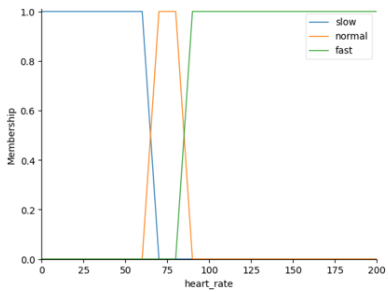
The choice of the finger as the sensor location, as shown in Figure 6(b), is based on its effectiveness in providing reliable physiological measurements. The capillaries at the fingertip provide a direct pathway for photoplethysmography, a common method used in wearable sensors to detect changes in blood volume. This technique is crucial for accurately determining heart rate (HR) and blood oxygen saturation (SpO2) [24].

B. Fuzzy Logic Implementation

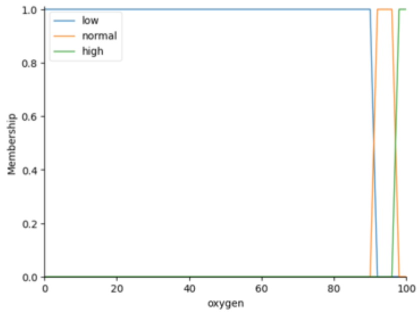
In the process of fuzzification, several aspects need to be considered, such as fuzzy rules and fuzzy sets. Fuzzy rules serve as a reference for classifying the level of bodily fatigue, as outlined in Table III. The results of fuzzification are used as fuzzy inference to apply the final output rules for determining the level of fatigue [25]. The fuzzification process was developed using Python programming, resulting in membership functions for each input, as shown in Fig.7



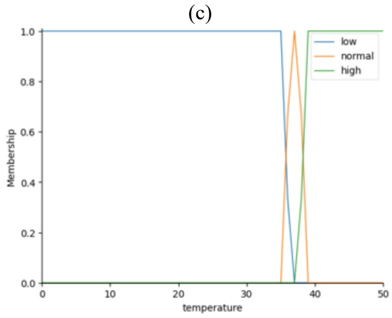
(a)



(b)



(c)



(d)

Fig. 7. Input Membership Functions for Fuzzy Logic-Based Fatigue Classification (a) Age, (b) Heart Rate, (c) Blood Oxygen Saturation (SpO_2), and (d) Body Temperature

Fig. 7 illustrates the input membership functions used in the fuzzy logic system for body fatigue classification. Fig. 7(a) represents the age membership function, which categorizes users into young, middle-aged, and old groups. Fig. 7(b) shows the heart rate membership function, dividing heart rate values into slow, normal, and fast categories. Fig. 7(c) depicts the blood oxygen saturation (SpO_2) membership function, classifying oxygen levels into low, normal, and high. Fig. 7(d) presents the body temperature membership function, which separates temperature values into low, normal, and high ranges. Each membership function plays a distinct role in modeling physiological variations related to fatigue. The membership function output consists of three conditions used to classify the level of bodily fatigue, as depicted in Fig.8

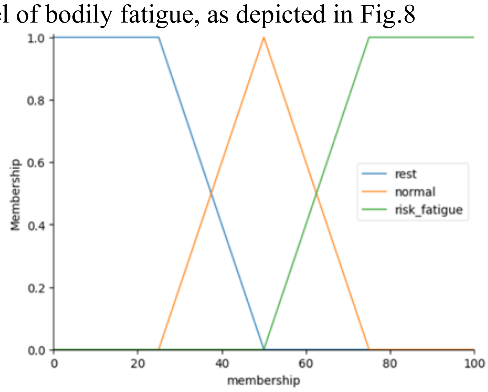


Fig. 8. Output Membership Function for Body Fatigue Classification

Fig. 8 illustrates the output membership function used in the fuzzy logic system to classify body fatigue levels. The output variable represents the overall fatigue condition and is divided into three linguistic categories: rest, normal, and risk. Each category corresponds to a specific range of output values that indicate the user's physical condition based on the combined influence of heart rate, blood oxygen saturation (SpO_2), body temperature, and age. The defuzzification process converts the fuzzy output into a crisp value, which is then used to determine the final fatigue category and trigger alerts when the risk threshold is exceeded.

C. Smart Ring Application

In previous research, android-based smart ring applications have been created and developed using the flutter framework with the Dart programming language. In the smart ring application, there is an interface that consists of several variable displays that show information to users such as the latest update time of the monitoring and evaluation process, user location, body fatigue level category, and start & stop buttons that function to manage monitoring and evaluation of data generated by the MAX30100 sensor. When the user starts the body condition monitoring process, there is an option by pressing the start or stop button which means whether they want to monitor and evaluate the results through the smart ring application on the smartphone, otherwise the data generated by the MAX30100 sensor is only stored in the database and not displayed in the application [24].

The smart ring application also displays 3 fatigue indicator data on the widget, namely temperature, SpO2 level, and heart rate. The value is not constant and continues to change along with the process of monitoring the user's body condition while using the smart ring [26]. The user interface of the smart ring application can be seen in Fig. 9.

Fig. 9. User Interface Smart Ring Application[24]

The smart ring application can also generate real-time notifications when the user's status evaluation is in the fatigue risk category and provide summary information of body condition data measurements as shown in Fig. 10.

Fig. 10. Alert Page When A User is at Risk of Fatigue[24]

D. Quantitative Evaluation and Data Analysis

In this study, a trial was conducted with a total of two users who belonged to the young age category, namely 25 years and middle age 35 years by wearing a smart ring prototype on their fingers and activating GPS and smart ring applications. Users are asked to use the smart ring before bed rest, during daily activities and are also asked to do sports movements, namely middle-distance running. Based on the test results, it can be seen that fuzzy logic has been successfully applied to classify the category of body fatigue level conditions based on the data obtained by the smart ring prototype. Which then the classification results are sent to the smart ring application.

TABLE IV. BODY FATIGUE CLASSIFICATION RESULT FOR A 25-YEAR-OLD SUBJECT

Age (years)	SpO2 (%)	Heart Rate (bpm)	Temperature (^{0}C)	Fatigue Category
25	96	67.65	36.00	rest
25	96	76.00	36.31	rest
25	96	71.95	37.00	rest
25	96	70.75	36.63	rest
25	96	28.55	35.88	rest
25	96	98.56	36.81	normal
25	97	100.31	37.10	normal
25	97	100.32	37.10	normal
25	97	100.65	37.21	normal
25	97	100.65	37.19	normal
25	95	146.1	37.55	risk
25	95	146.12	37.55	risk

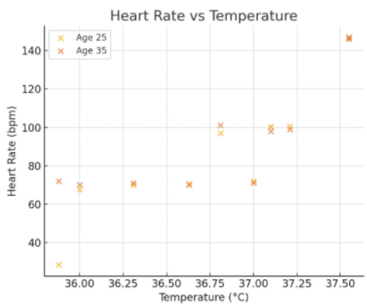
Table IV presents the fatigue classification results obtained from a 25-year-old subject during different activity conditions. The classification shows a clear transition from rest to normal and risk categories as heart rate and body temperature increase, accompanied by a decrease in SpO_2.

TABLE V. BODY FATIGUE CLASSIFICATION RESULT FOR A 35-YEAR-OLD SUBJECT

Age (years)	SpO2 (%)	Heart Rate (bpm)	Temperature (^{0}C)	Category
35	96	70	36.00	rest
35	96	71	36.31	rest
35	96	71	37.00	rest
35	96	70	36.63	rest
35	96	72	35.88	rest
35	96	101	36.81	normal
35	97	98	37.10	normal
35	97	99	37.10	normal
35	97	98	37.21	normal
35	97	100	37.19	normal
35	95	147	37.55	risk
35	95	146	37.55	risk

Table V presents the body fatigue classification results for a 35-year-old subject under various activity conditions. Similar to the younger age group, the results indicate a progressive transition from the rest to normal and risk categories as physiological stress increases. The rest condition is characterized by a stable heart rate of approximately 70 bpm, SpO_2 levels around 96%, and body temperature below 3. These findings suggest that the selected physiological parameters provide consistent fatigue indicators regardless of minor age differences within the adult population.

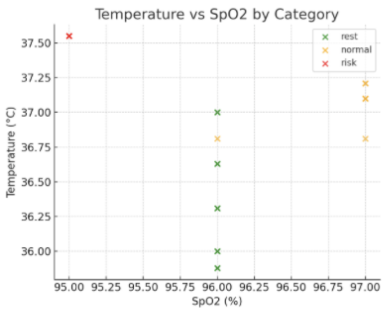
The study reveals that at both ages 25 and 35, the pattern of body fatigue categories remains relatively consistent. The "risk" condition is characterized by a decrease in blood oxygen saturation (SpO2), a significant increase in heart rate, and a rise in body temperature. Threshold values that indicate the transition from "rest" to "normal" and subsequently to "risk" categories can serve as reliable indicators of physical fatigue. These thresholds are useful for monitoring physical activity and can be applied in occupational health settings to help prevent overexertion and ensure well-being. The interpretation of the three visualization graphs of body fatigue data based on age, body temperature, heart rate, and SpO2 can be seen in Fig.11.



(a)

ISSN 2355-3286

(b)



(c)

Fig. 11. Visualization of Body Fatigue Indicators (a) Heart Rate Trend, (b) Blood Oxygen Saturation (SpO_2), (c) Body Temperature Response during Physical Activity

Based on the data visualization and analysis at Fig.11, it is evident that body fatigue can be effectively assessed using three physiological parameters: heart rate, body temperature, and blood oxygen saturation (SpO2). The data shows a consistent pattern where increased body temperature and decreased SpO2 levels correlate with elevated heart rates, which serve as indicators of body stress or fatigue. In particular, when the body temperature rises to around 37.5°C and SpO2 drops to 95%, heart rates exceed 145 bpm—placing the condition into the "risk" category. Meanwhile, individuals in the "rest" category tend to maintain a body temperature below 37°C, SpO2 at 96%, and a heart rate around 70 bpm.

Across both age groups (25 and 35 years old), the trends remain consistent, suggesting that these physiological markers are reliable regardless of minor age differences within adult populations. This supports the idea that fatigue detection models can be generalized for young adults. In summary, heart rate, body temperature, and SpO2 are key indicators that can be used together to monitor physical fatigue, identify health risks, and potentially guide preventive actions or rest recommendations.

As an initial validation, the result of body temperature and heart rate measurements from the smart ring were compared with manual measurements using a digital thermometer and medical pulse oximeter [27]. Results showed an average deviation of ± 1.3^{0}C for temperature and ± 5 bpm for heart rate, which is within the tolerance of non-invasive monitoring.

E. Comparison with Medical Reference Device

To evaluate the accuracy of the proposed Smart Ring, a comparative analysis was conducted using certified medical reference devices. Heart rate and blood oxygen saturation (SpO_2) measurements obtained from the Smart Ring were compared with a fingertip medical pulse oximeter, while body temperature readings were compared with a digital medical thermometer. These reference devices are commonly used in clinical and home healthcare settings and serve as standard non-invasive measurement tools. [28] [29]

TABLE VI. COMPARISON BETWEEN SMART RING AND MEDICAL REFERENCE DEVICE

Parameter	Smart Ring (Mean)	Medical Device (Mean)	Mean Absolute Error
Heart Rate (bpm)	98.4	101.9	± 5.0 bpm
SpO_2 (%)	96.2	97.7	± 1.5 %
Body Temperature (^{0}C)	36.9	38.2	± 1.3 (^{0}C)

Based on Table.VI the comparison results indicate that the Smart Ring demonstrates measurement performance comparable to certified medical reference devices. The observed mean absolute error of ±5 bpm for heart rate and ±1.5% for SpO_2 aligns with acceptable tolerances reported for non-invasive wearable sensors. According to ISO 80601-2-61, pulse oximetry devices are considered acceptable when SpO_2 error remains within ±2%. Similarly, the observed temperature deviation of ±1.3 °C falls within the range reported for wearable temperature monitoring systems. These findings suggest that the Smart Ring provides reliable physiological measurements suitable for fatigue monitoring applications, although it is not intended to replace clinical diagnostic equipment.

IV. CONCLUSION

This study has successfully developed an IoT-based Smart Ring for real-time body fatigue monitoring using heart rate, blood oxygen saturation (SpO_2), and body temperature parameters. Quantitative evaluation results show that the Smart Ring achieves an average measurement deviation of ±5 bpm for heart rate, ±1.5% for SpO_2, and ±1.3 °C for body temperature when compared with standard medical devices. These error values fall within acceptable limits for non-invasive wearable monitoring systems. Experimental results from two adult subjects aged 25 and 35 years demonstrate consistent fatigue classification patterns. The fatigue risk condition is quantitatively characterized by heart rate values exceeding 145 bpm, body temperature above 37.5 °C, and a decrease in SpO_2 to approximately 95%. These thresholds confirm the effectiveness of the fuzzy logic-based classification model in identifying fatigue levels across different adult age groups. Overall, the proposed Smart Ring provides a reliable and affordable solution for early fatigue detection and real-time health monitoring. Future work will involve larger-scale user testing and clinical validation to further improve measurement accuracy and generalizability. Although the Smart Ring demonstrates comparable accuracy to non-invasive medical reference devices, it is intended for fatigue monitoring and early warning purposes rather than clinical diagnosis.

ACKNOWLEDGMENT

The authors would like to thank the Department of Mechatronics and Artificial Intelligence at Universitas Pendidikan Indonesia for providing facilities and support for this research.

REFERENCES

[1] D. van Hoogmoed *et al.*, “Physical and psychosocial correlates of severe fatigue in rheumatoid arthritis,” *Rheumatology*, 2010, doi: 10.1093/rheumatology/keq043.

[2] Brent A. Williams, Brent A. Williams, Brent A. Williams, and Brent A. Williams, “Abstract MP035: The Clinical Epidemiology of Fatigue in Newly Diagnosed Heart Failure,” *Circulation*, 2017, doi: 10.1186/s12872-017-0555-9.

[3] Maarten Van Herck *et al.*, “Fatigue is Highly Prevalent in Patients with Asthma and Contributes to the Burden of Disease,” *J. Clin. Med.*, 2018, doi: 10.3390/jcm7120471.

[4] E. Sivari and S. Surucu, “Prediction of heart attack risk using linear discriminant analysis methods,” 2023, doi: 10.51271/jceees-0002.

[5] I. L. A. G. S. Yadav, S. Wakode, and S. Khasimbi, “The role of stress in the development of cardiovascular diseases,” *J. Nurs. Healthc.*, 2023, doi: 10.33140/jnh.08.01.01.

[6] J. Jalaludin, “Editorial: Stress Can Lead to Cardiovascular Disease,” 2023, doi: 10.55958/jcvd.v18i4.132.

[7] Ana Cristina Perez Moreno *et al.*, “Fatigue as a predictor of outcome in patients with heart failure: analysis of CORONA (Controlled Rosuvastatin Multinational Trial in Heart Failure).,” *Jacc-Heart Fail.*, 2014, doi: 10.1016/j.jchf.2014.01.001.

[8] L. Aljihmani *et al.*, “Classification of Fatigue Phases in Healthy and Diabetic Adults Using Wearable Sensor,” *Sensors*, 2020, doi: 10.3390/s20236897.

[9] Oura Health Ltd, “Oura Ring: Smart Ring for Sleep, Readiness & Activity Tracking.” Oura Health Ltd, 2022. [Online]. Available: https://ouraring.com

[10] GO2SLEEP, “GO2SLEEP Smart Ring for Sleep Monitoring. Sleepon.” 2021. [Online]. Available: https://sleepon.us

[11] Motiv Inc, “Motiv Ring: Fitness, Sleep, and Heart Rate Tracker.” 2019. [Online]. Available: https://mymotiv.com

[12] Muhammad Niswar *et al.*, “A Low Cost Wearable Medical Device for Vital Signs Monitoring in Low-Resource Settings,” *Int. J. Electr. Comput. Eng.*, 2019, doi: 10.11591/ijece.v9i4.pp2321-2327.

[13] S. Adibi, *Mobile Health: A Technology Road Map*. 2015. doi: 10.1007/978-3-319-12817-7.

[14] “Sensing Materials: 2D Semiconductors for Biosensing,” 2023. doi: 10.1016/b978-0-12-822548-6.00049-2.

[15] F. Fang, S. Aabith, S. Homer-Vanniasinkam, S. Homer-Vanniasinkam, and M. K. Tiwari, “High-resolution 3D printing for healthcare underpinned by small-scale fluidics,” 2017. doi: 10.1016/B978-0-08-100717-4.00023-5.

[16] “Machine Learning-Based Automatic Cardiovascular Disease Diagnosis Using Two ECG Leads,” 2023, doi: 10.48550/arxiv.2305.16055.

[17] N. J. Camm, “Machine Learning Model Predicting the Likelihood of a Patient Developing Cardiovascular Disease Based on Their Medical History and Risk Factors,” *Am. J. Biomed. Sci. Res.*, 2023, doi: 10.34297/ajbsr.2023.18.002429.

[18] P. Lukowicz, U. Anliker, J. A. Ward, G. Tröster, E. Hirt, and C. Neufelt, “AMON: a wearable medical computer for high risk patients,” 2002, doi: 10.1109/ISWC.2002.1167230.

[19] S. Alharbi *et al.*, “Oxygen saturation measurements from green and orange illuminations of multi-wavelength optoelectronic patch sensors,” *Sensors*, 2018, doi: 10.3390/S19010118.

[20] T. Tamura, Y. Maeda, M. Sekine, and M. Yoshida, “Wearable Photoplethysmographic Sensors—Past and Present,” *Electronics*, 2014, doi: 10.3390/ELECTRONICS3020282.

[21] D. Castaneda, A. Esparza, M. Ghamari, C. Soltanpur, and H. Nazeran, “A review on wearable photoplethysmography sensors and their potential future applications in health care.,” *J. Biosens. Bioelectron.*, 2018, doi: 10.15406/IJBSBE.2018.04.00125.

[22] Y.-X. Zhao, Z.-X. Lu, Y.-Z. Hsieh, S.-S. Lin, and P.-Y. Chiang, “The Wearable Physical Fitness Training Device Based on Fuzzy Theory,” *Appl. Sci.*, 2021, doi: 10.3390/APP11219976.

[23] L. Zhang, J. Xie, A. Antonidoss, and M. Anbarasan, “Activity classification and analysis during sports training session using fuzzy model,” *J. Intell. Fuzzy Syst.*, 2021, doi: 10.3233/JIFS-219042.

[24] L. Venica, E. N. Irawan, and D. I. H. Putri, “IoT with Firebase: Smart Ring Android App Using MAX30100 for Fatigue Detection,” *J. Electr. Electron. Inf. Commun. Technol.*, vol. 6, no. 1, pp. 8–15.

[25] E. P. Nikmatuzaroh, R. Setiawan, and N. F. Hikmah, “Multimodal Instrumentations as Fatigue Detection Using Fuzzy Logic Method,” *J. Biomim. Biomater. Biomed. Eng.*, 2022, doi: 10.4028/p-jm1fkf.

[26] R. de la Vega, H. Anabalón, C. Jara, E. Villamil-Cabello, M. Chervellino, and Á. Calvo-Rodríguez, “Effectiveness of Mobile Technology in Managing Fatigue: Balert App.,” *Front. Psychol.*, 2021, doi: 10.3389/FPSYG.2021.704955.

[27] “Yuwell. (2020). YX102 Fingertip Pulse Oximeter User Manual. Jiangsu Yuyue Medical Equipment & Supply Co., Ltd.”

[28] *ISO 80601-2-61:2017, Medical electrical equipment – Particular requirements for basic safety and essential performance of pulse oximeter equipment.*

[29] J. Allen, “Photoplethysmography and its application in clinical physiological measurement,” *Physiol. Meas.*, vol. 28, no. 3, pp. R1–R39, Mar. 2007, doi: 10.1088/0967-3334/28/3/R01.