

Wearable Weightlifting Monitoring System Using ESP32, ESP-NOW, and Fuzzy Logic

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Abstract— This study presents a wearable prototype for real-time monitoring of wrist position and heart rate during weightlifting. The system combines an MPU9250 inertial sensor, a MAX30102 photoplethysmography sensor, two ESP32 modules, ESP-NOW wireless communication, and a fuzzy-logic-based condition classifier. The ESP32-C3 Super Mini operates as the wearable transmitter, while the ESP32-S3 LILYGO T-Display AMOLED acts as the receiver and user interface. The study used a Research and Development (R&D) approach with quantitative functional testing. The reported tests showed that heart-rate detection depended strongly on skin contact, wrist inclination was detected across the tested orientations, and communication remained stable to 20 m without obstacles and to 5 m under the tested obstacle condition. The prototype classified the tested cases as Safe, Warning, or Danger and generated corresponding visual and audible feedback. Because the original experimental record did not include reference-device validation, packet-level communication statistics, measured battery endurance, or the numerical membership and defuzzification parameters of the fuzzy model, the findings are limited to functional prototype evaluation. The main implication is that the device is suitable as a monitoring and feedback prototype for wrist position and heart rate, while further validation is required before broader performance or safety claims are made.

Keywords: wearable monitoring; weightlifting; ESP32; ESP-NOW; fuzzy logic.

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I. INTRODUCTION

Wearable devices are increasingly used to observe exercise performance and basic physiological responses, extending their role beyond general fitness tracking (Chen et al., 2024). Weightlifting is a relevant application because poor movement technique and lifting loads beyond a user’s current capability can increase mechanical stress; the practice commonly described as “ego lifting” is one example of behaviour that may encourage excessive loading (Ludas, 2023). Wearable monitoring can provide immediate information without requiring continuous visual observation, and previous work has shown that wearables can support posture analysis and movement monitoring (Simpson et al., 2019).

For resistance exercise, wrist position and cardiovascular response describe different aspects of the exercise condition. Lifting technique influences force distribution and movement control (Washmuth et al., 2022), whereas heart rate provides a simple indicator of exercise intensity. Age-predicted maximum heart rate can be estimated from $HR_{max} = 208 - 0.7 \times \text{age}$ (SHOOKSTER et al., 2020), and resting heart rate is commonly used as a baseline measure, with typical adult resting values around 60–80 BPM (Healthdirect Australia, 2025). Heart-rate recovery (HRR), defined from the decrease between peak exercise heart rate and recovery values, can also

characterize post-exercise cardiovascular recovery (Petek et al., 2023). In the present prototype, however, HRR is treated as contextual information rather than a classification input because the reported system tests use instantaneous BPM and wrist-tilt error.

The research gap is not simply the use of fuzzy logic. The more specific problem is the integration of physiological and biomechanical signals in a compact wearable system that can issue a real-time condition label. A heart-rate-only monitor cannot indicate whether wrist orientation has deviated, while a posture-only monitor cannot show cardiovascular response. Fuzzy logic is considered useful because it can express gradual transitions between linguistic conditions rather than treating every input as a strictly binary state (Zadeh, 1965). The proposed contribution is therefore the integration of the MAX30102 and MPU9250 in one wearable node, ESP-NOW communication between two ESP32 devices, and a joint condition classifier intended for immediate feedback (Walukow dkk., 2025).

The HR_{max} equation is not used to generate the reported classification thresholds; it is retained only as background for exercise-intensity interpretation (SHOOKSTER et al., 2020). Similarly, the 90° wrist reference and $\pm 30^\circ$ tolerance are design parameters of this prototype rather than universal biomechanical limits. This distinction is important because the current study does not include a

biomechanical validation protocol. The work also supports the broader use of wearable technology for health and well-being applications, consistent with the preventive orientation associated with SDG 3 (Ramadhani Amran et al., 2025).

Accordingly, this study aims to develop and functionally evaluate a wearable weightlifting monitoring prototype that combines wrist inclination and heart rate, transmits data wirelessly through ESP-NOW, and provides Safe, Warning, and Danger feedback. The evaluation focuses on component operation, wireless connectivity, and integrated classification under the test conditions reported in the original experiment.

II. METHOD

The study used a Research and Development (R&D) methodology with a quantitative functional-testing approach. The prototype consists of a wearable sensor node and a separate monitoring node. The sensor node uses an ESP32-C3 Super Mini, MAX30102 heart-rate sensor, and MPU9250 IMU. The monitoring node uses an ESP32-S3 LILYGO T-Display AMOLED and an active-high buzzer. ESP-NOW provides local wireless communication between the two ESP32 devices (Anderson et al., 2025). The design follows the principle of combining physiological and movement information in a single monitoring process (Baklouti et al., 2024; Zhafira & Sardi, 2024; Sumaiya et al., 2024).

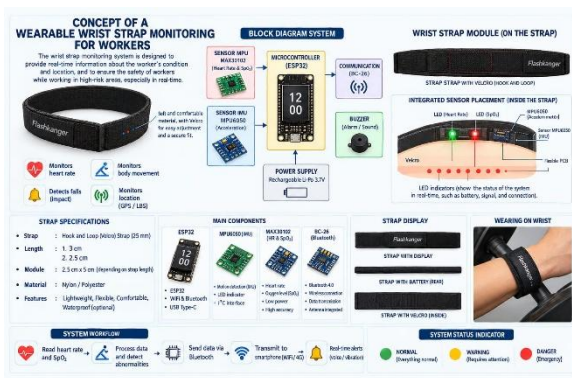


Figure 1. Conceptual arrangement of the wearable monitoring system.

The conceptual arrangement separates sensing from monitoring so that the wearable unit can remain lightweight while the receiver handles display and user feedback. This separation also reduces the need for an internet connection during operation.

The sensor node acquires heart rate through photoplethysmography (PPG) and wrist orientation through the IMU. PPG detects changes in blood volume through optical measurement at the skin surface (Ebrahimi & Gosselin, 2023). The MPU9250 provides accelerometer, gyroscope, and

magnetometer measurements, while the orientation calculation in the original implementation used the accelerometer-derived roll/pitch relationship described in inertial sensing literature (Kok et al., 2017; Madgwick et al., 2011). The resulting BPM and tilt-error values are transferred to the receiver for display and audible feedback.



Figure 2. System block diagram of the wearable monitoring prototype.

A. Hardware Configuration

Table 1. Main hardware components of the prototype

No.	Component	Function / main specification
1	ESP32-C3 Super Mini	Wearable transmitter; RISC-V, Wi-Fi/BLE, ESP-NOW
2	ESP32-S3 LILYGO T-Display AMOLED	Receiver and display; ESP32-S3R8, AMOLED, Wi-Fi/BLE
3	DFRobot Fermion SEN0344 MAX30102	Heart-rate sensing; 3.3 V, I ² C, PPG
4	GY-U9250 MPU9250	Wrist orientation sensing; 9-axis IMU
5	Li-Po 3.7 V 150 mAh	Wearable power source; 150 mAh nominal capacity
6	TP4056 charging module	Battery charging; 4.2 V CC/CV
7	Active-high buzzer	Audible feedback; receiver GPIO10

The ESP32-C3 was selected for the wearable node because of its compact form and wireless capability (Espressif, 2023). The MAX30102 provides PPG-based heart-rate detection, while the MPU9250 supplies inertial measurements for wrist-orientation estimation. The 3.7 V 150 mAh Li-Po battery and TP4056 module were used for portable operation; the charger implements constant-current/constant-voltage charging (NanJing Top Power ASIC Corp., 2023). The battery-life estimate follows $t = C/I$, where t is operating time in hours, C is battery capacity in mAh, and I is average load current (DigiKey, n.d.). The original study did not record a measured endurance test, so this equation is treated as a theoretical estimate only.

$$HR = 60,000 / IBI \text{ (IBI in milliseconds)}$$

The basic heart-rate relation expresses BPM from the inter-beat interval (IBI) (Charlton et al., 2025). For the IMU, wrist tilt was calculated from

accelerometer axes; the deviation used for classification was defined as the absolute difference from the 90° reference:

$$\text{Tilt Error} = |\text{Tilt measured} - 90^\circ|$$

B. Circuit and Software Implementation

The wearable node connects the MAX30102 and MPU9250 to the ESP32-C3 through I²C, with SDA on GPIO4 and SCL on GPIO5. Both sensors are powered from the 3.3 V rail. The receiver obtains the transmitted data through ESP-NOW and displays BPM, tilt, condition status, and connection status. The active-high buzzer is connected to GPIO10 and provides different audible patterns for the condition labels. Fraden (2016) is retained as a general reference for sensor principles and signal conditioning.

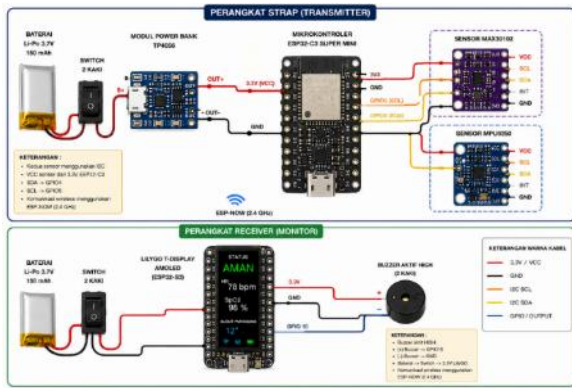


Figure 3. Schematic implementation of the transmitter and receiver circuits.

The software sequence is: sensor acquisition, basic signal screening, tilt-error calculation, condition classification, ESP-NOW transmission, display update, and buzzer control. Sensor acquisition is repeated while the system is powered. The current manuscript did not preserve numerical sampling-rate, filtering, smoothing, transmission-interval, or packet-timing settings; therefore, these parameters are not reconstructed here.

The flow is continuous: the transmitter reads both sensors, evaluates the current condition, and sends the latest state to the receiver. The receiver refreshes the visual status and controls the buzzer according to the received classification. The flow therefore represents a monitoring loop rather than a one-time measurement procedure.

C. Experimental Procedure and Evaluation Measures

Testing was performed progressively so that sensing, communication, feedback, and integrated classification could be observed separately before system-level interpretation. For the MAX30102, the strap was evaluated without skin contact, with correct

contact, with loose contact, and after light exercise movement. For the MPU9250, the wrist was positioned near the reference angle and then intentionally deviated in forward, backward, and larger-angle positions. For wireless communication, the transmitter and receiver were tested at 0.5, 1, 3, 5, 10, and 20 m under unobstructed and obstacle/body conditions. The receiver status and displayed data were then observed at each distance.

For quantitative validation, the intended error metrics are absolute error and percentage error relative to a reference instrument. These measures can be expressed as:

$$\text{Absolute Error} = |X_{\text{sensor}} - X_{\text{reference}}|$$

$$\text{Percentage Error (\%)} = \frac{|X_{\text{sensor}} - X_{\text{reference}}|}{X_{\text{reference}}} \times 100$$

For ESP-NOW, communication quality can be quantified from packet counts using packet-delivery ratio (PDR):

$$\text{PDR(\%)} = \frac{\text{Packets Received}}{\text{Packets Sent}} \times 100$$

Mean latency, reconnection time, RSSI, mean error, MAE, RMSE, standard deviation, and repeatability would strengthen the evaluation. These measurements were not part of the original experiment, so no numerical values are added to avoid introducing unsupported data. The same principle applies to battery testing: the theoretical relation $t = C/I$ is provided, but measured operating duration is not claimed.

C. Condition Classification

The reported firmware behaviour combines BPM and tilt error. BPM below 50 is treated as Check Sensor; 50–129 BPM is the defined Safe interval; 130–159 BPM is Warning; and BPM ≥ 160 is Danger. Tilt error $\leq 30^\circ$ is Safe, $>30^\circ$ to 45° is Warning, and $>45^\circ$ is Danger. These boundaries are system-specific design parameters rather than validated physiological or biomechanical limits.

Table 2. Condition rule matrix represented by the reported classification behaviour.

Heart rate state	Tilt state	Result
Safe	Safe	Safe
Safe	Warning	Warning
Safe	Danger	Danger
Warning	Safe	Warning
Warning	Warning	Warning
Warning	Danger	Danger
Danger	Safe	Danger
Danger	Warning	Danger
Danger	Danger	Danger

The original experimental record does not retain the numerical membership functions, membership degrees, inference strengths, or a defuzzified output value. To avoid inventing

undocumented parameters, the revised manuscript makes this limitation explicit. The classification evidence is therefore interpreted as functional rule-based fuzzy logic consistent with the linguistic states, rather than as a fully reproducible numerical fuzzy-inference specification. A complete future implementation should document membership functions, inference, and defuzzification parameters so that the model can be independently reproduced.

The physical arrangement places the MAX30102 on the inner side of the strap for skin contact and keeps the sensing electronics within the wearable assembly. The receiver is separated from the wrist strap so the user or trainer can view the status and hear the alarm without handling the sensor unit.

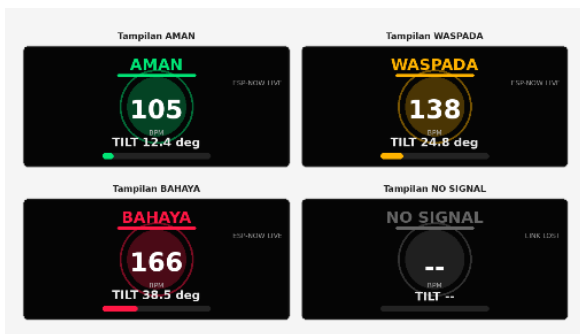


Figure 4. Receiver monitoring interface used for visual feedback.



Figure 5. Physical implementation and wrist-worn configuration of the prototype.

III. RESULTS

The evaluation covered heart-rate sensing, wrist-angle sensing, ESP-NOW connectivity, buzzer response, and integrated condition classification. Because the original dataset contains one reported observation for several component conditions, the results are presented as functional observations rather than statistical estimates of accuracy or reliability.

A. Heart-Rate and Wrist-Tilt Tests

The MAX30102 produced a BPM value when the strap was properly positioned and no value when contact was insufficient. This behaviour is consistent with the sensitivity of PPG to the sensor-skin interface (Allen, 2007). The results should not be interpreted as measurement accuracy because no reference monitor or pulse oximeter was used for comparison.

Table 3. Reported MAX30102 functional test results.

No.	Condition	BPM	Status	Observation
1	Strap not worn	0	Check Sensor	No pulse detected
2	Strap worn correctly	89	Safe	BPM detected
3	Strap worn loosely	0	Check Sensor	Poor skin contact
4	After exercise movement	117	Safe	BPM increased after activity

Table 4. MPU9250 wrist-tilt test results.

No.	Measured tilt	Tilt error	Status
1	89.9°	0.1°	Safe
2	79.9°	10.1°	Safe
3	97.6°	7.6°	Safe
4	70.3°	19.7°	Safe
5	54.5°	35.5°	Warning
6	45.5°	44.5°	Warning
7	29.5°	60.5°	Danger

The MPU9250 differentiated the tested wrist orientations, with status changes occurring at the predefined tilt-error boundaries. An earlier version of the manuscript contained a conflicting extreme value of 69.5° in the integrated-test table; the value has been reconciled here to the component-test record of 60.5°. Orientation estimation with IMUs is established as a suitable approach for position and orientation monitoring (Kok et al., 2017; Madgwick et al., 2011). The present thresholds remain prototype-specific, and Seitz and Haff (2015) is treated only as contextual strength-training literature rather than as a basis for the angle limits.

B. ESP-NOW and Feedback Tests

The reported communication test showed stable reception up to 20 m in unobstructed conditions. With the tested building/body obstacles, reception remained stable to 5 m, became intermittent near 10 m, and was lost at 20 m. The original test did not record packet counts, packet-delivery ratio, latency, reconnection time, or RSSI; consequently, communication performance is reported qualitatively. Cosma and Radoi (2021) is not used as direct evidence for ESP-NOW performance because

its topic is gait representation, not this wireless protocol.

Table 5. ESP-NOW connectivity observations from the reported test.

Distance	Condition	Receiver	Data
0.5 m	No obstacle	Live	Yes
1 m	No obstacle	Live	Yes
3 m	No obstacle	Live	Yes
5 m	No obstacle	Live	Yes
10 m	No obstacle	Live	Yes
20 m	No obstacle	Live	Yes
0.5 m	Obstacle/body	Live	Yes
1 m	Obstacle/body	Live	Yes
3 m	Obstacle/body	Live	Yes
5 m	Obstacle/body	Live	Yes
10 m	Obstacle/body	Unstable	Intermittent
20 m	Obstacle/body	No signal	No

The buzzer followed the condition labels: no sound for Check Sensor, Safe, and No Signal; a single warning beep for Warning; and continuous sound for Danger. The receiver display and buzzer therefore provided the intended immediate feedback without requiring the user to observe the screen continuously.

C. Integrated Classification

Table 6. Revised integrated classification cases.

BPM	Tilt error	Result
114	0.1°	Safe
84	10.1°	Safe
94	7.6°	Safe
94	19.7°	Safe
90	35.5°	Warning
89	44.5°	Warning
112	60.5°	Danger



Figure 6. Representative receiver outputs for the tested classification cases.

The integrated cases confirm that the status changed when the tilt error moved from the Safe interval into Warning and Danger ranges. However, most reported BPM observations remained within the defined Safe interval. Therefore, the present data do not demonstrate the independent effect of high or low heart rate on the final class. A stronger fuzzy-classification evaluation should include low-BPM/small-tilt, high-BPM/small-tilt, low-BPM/large-tilt, high-BPM/large-tilt, and moderate-

BPM/moderate-tilt combinations and report agreement against a reference classification.

The limited dataset also affects the interpretation of repeatability. For each condition, the manuscript reports the observed response rather than a distribution across repeated trials. As a result, the tables are useful for confirming functional state transitions, but they cannot establish statistical confidence intervals or measurement stability. This distinction is maintained throughout the revised manuscript so that observed operation is not confused with validated performance.

The classification logic can be understood as a two-input decision process: heart-rate state contributes information about physiological load, while tilt state contributes information about wrist deviation. When either input moves to a more critical state, the resulting label becomes more conservative. This design is consistent with the relational objective of considering the relationship between movement and physiological response (Fat, 2024), but its effectiveness still requires tests in which both inputs vary across the full operating range.

IV. DISCUSSIONS

The central technical result is the feasibility of combining a PPG heart-rate sensor and an IMU in a compact wrist-worn node and linking the node to a separate ESP32 display through ESP-NOW. The component tests show that each subsystem can contribute to a real-time feedback chain, but they do not by themselves establish sensor accuracy, clinical validity, or general exercise-safety performance.

For heart-rate sensing, the strong dependence on strap contact is expected for optical measurements because motion and the sensor-skin interface can alter signal quality (Allen, 2007). This is particularly important during weightlifting, where wrist movement and pressure can change during a repetition. The MAX30102 therefore functions adequately as a prototype sensor, but a reference-device comparison is needed before error, MAE, RMSE, repeatability, or accuracy can be reported.

For wrist orientation, the MPU9250 provided distinguishable readings across the tested positions, and IMU-based orientation monitoring is appropriate for wearable motion analysis (Kok et al., 2017; Madgwick et al., 2011). The 90° reference and 30°/45° boundaries should nevertheless be understood as system-specific parameters. They are operational thresholds selected for this prototype, not universal safety limits for all resistance-training movements. The same caution applies to the strength-training context represented by Seitz and Haff (2015).

The fuzzy component is the least fully validated part of the present study. The intended

advantage of fuzzy logic is to combine multiple inputs in linguistic terms and support gradual transitions (Zadeh, 1965; Sanggola et al., 2022; Silitonga & Wahyudi, 2055). Yet the available experimental record contains mainly crisp interval labels, and the BPM values do not cover enough of the input space to demonstrate how physiological information changes the final output. Thus, the current evidence supports functional integration but not a quantified claim of fuzzy-classification superiority over a conventional threshold classifier.

Wireless behaviour also depends on the environment. The observed reduction in stable range under obstacles indicates that the prototype is more suitable for nearby indoor monitoring than for long-distance operation. Because packet-level measurements were not collected, the study cannot quantify delivery efficiency or latency. A future test should transmit a known number of packets at repeated distances and report packet-delivery ratio, mean latency, reconnection time, and, where available, RSSI.

The system should therefore be described as a monitoring and feedback prototype. It does not establish that weightlifting is medically safe, does not evaluate injury reduction, and does not replace professional coaching or validated physiological instruments. These limitations are consistent with the original device scope and should remain explicit in interpretation. The practical implication is narrower: the prototype can present wrist-position and heart-rate information in real time and can alert the user when predefined prototype conditions are reached.

Several limitations are methodological as well as technical. First, the heart-rate results depend on a stable PPG contact surface, so movement artefacts and strap pressure may influence the signal. Second, the IMU thresholds were selected for the prototype and were not validated against a goniometer, inclinometer, or reference IMU. Third, the wireless test reports connection state but not packet-level performance. Fourth, the fuzzy method is not completely reproducible from the original record because membership parameters and defuzzification outputs were not preserved. Finally, the battery section contains an estimate rather than an endurance experiment. These limitations define the boundary of the present contribution and provide direct targets for the next development stage.

The most useful next experiment would be a repeated, reference-based evaluation in which heart rate and wrist angle are collected simultaneously over several repetitions and exercise intensities. The resulting dataset could support sensor error analysis, classification agreement, and a fully documented fuzzy inference model. Such a protocol would allow

the system to move from a functional prototype toward a quantitatively validated wearable monitoring platform.

From an engineering perspective, the present prototype identifies several design decisions that should be preserved in the next iteration. First, separating the sensor node from the display node is useful because the wearable assembly can concentrate on sensing and local processing, while the receiver can provide a larger visual area and audible feedback. This architecture also keeps the monitoring loop local and does not depend on an internet service. Second, the placement of the MAX30102 on the inner wrist surface should be treated as a mechanical design requirement rather than a minor installation detail. Stable contact is directly associated with whether a usable PPG signal can be obtained (Allen, 2007; Mamahit dkk., 2023; Mamahit, 2024). A revised strap should therefore control sensor position and contact pressure while remaining comfortable during repeated exercise.

Third, the wrist-angle reference should be calibrated for the movement and user rather than treated as a universal value. The MPU9250 can provide orientation information, but the useful threshold depends on how the sensor is mounted, the starting posture, and the exercise movement. A calibration routine before testing could establish the user-specific reference position and reduce systematic offset. The existing 90° reference is adequate for the current prototype test because it is the design reference used to calculate tilt error, but its biomechanical validity requires a separate validation study.

Fourth, the fuzzy component should be documented directly in the firmware and experimental protocol. A reproducible implementation should record the linguistic input sets, numerical membership functions, rule base, inference operator, aggregation method, and defuzzification procedure. The test plan should then deliberately vary both inputs so that the classifier is evaluated not only when tilt changes but also when heart rate moves across its operating regions. This is especially important because the current results are dominated by cases in which BPM remains in the defined Safe interval. Without broader input coverage, the benefit of combining two variables cannot be isolated from the effect of a single threshold.

Finally, future testing should treat the complete system as an engineering measurement chain. Sensor validation, wireless transmission, power consumption, and user feedback should be measured under repeated trials rather than reported from isolated observations. Such a design would make it possible to compare the theoretical battery estimate with measured endurance,

calculate packet-delivery ratio and latency, quantify sensor error against reference devices, and determine whether the classification output is consistent across users and exercise conditions. These additions would strengthen both reproducibility and the practical value of the prototype without expanding its claims beyond a wearable monitoring and feedback system.

V. CONCLUSION

A wearable weightlifting monitoring prototype was successfully developed using an ESP32-C3 transmitter, ESP32-S3 LILYGO receiver, MAX30102 heart-rate sensor, MPU9250 inertial sensor, ESP-NOW communication, a display interface, and an audible buzzer. Under the reported test conditions, the system detected heart-rate signals when skin contact was adequate, detected changes in wrist inclination, transmitted data reliably over the tested unobstructed distances, and produced the intended Safe, Warning, and Danger feedback.

The study also shows clear limits. The original experiment did not include reference-device validation, repeated statistical measurements, packet-level wireless metrics, measured battery endurance, or the numerical membership and defuzzification parameters required for independent reproduction of a complete fuzzy inference system. The prototype should consequently be treated as a technical monitoring and feedback device rather than a validated safety or medical instrument. Future work should add reference-based sensor validation, repeated communication trials, battery measurements, broader classification cases, and a fully documented fuzzy model.

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