

A Survey on Recent Research development on Design and Development of Smart Gloves for Real-Time CPR Monitoring Using ESP32 and MPU6050

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Abstract: High-quality cardiopulmonary resuscitation (CPR) requires appropriate chest-compression rate, depth, recoil and minimal interruption. Wearable sensing can provide immediate feedback without requiring bulky external instrumentation. This literature review investigates recent IEEE and closely related research on smart gloves, CPR feedback, inertial measurement units (IMUs), wearable healthcare sensing, edge processing and intelligent CPR assessment, with emphasis on an ESP32 and MPU6050 implementation. A 2024 IEEE Access smart-glove study demonstrated real-time monitoring using e-textile pressure sensors and IMUs, including compression depth, rate, recoil and interruptions. More recent 2025–2026 research has expanded toward wearable feedback, multimodal AI, computer vision, robust IMU processing and edge intelligence. The review identifies a research opportunity for a low-cost ESP32–MPU6050 smart glove that performs real-time compression detection and feedback while explicitly addressing calibration, orientation, drift, motion artifacts, recoil and external validation. A modular extension using a force/pressure sensor is recommended to strengthen depth estimation. The paper proposes a research methodology, gap-to-solution matrix, experimental plan, evaluation metrics and future roadmap including TinyML, multimodal fusion, BLE/mobile analytics and energy-aware operation.

Keywords: CPR monitoring, smart glove, ESP32, MPU6050, IMU, wearable healthcare, chest compression, real-time feedback, edge AI, TinyML.

I. INTRODUCTION

Cardiac arrest is a time-critical emergency in which early and effective CPR is essential. However, maintaining consistent chest-compression characteristics is difficult for many rescuers. Recent wearable feedback studies show that embedded sensing can improve CPR performance. A 2024 smartwatch-based study reported significant improvements in compression depth and rate when feedback was available compared with unaided CPR. [1]

The transition from rigid CPR measurement devices to wearable form factors is particularly important. Guridi Sotomayor et al. developed a smart glove using e-textile pressure sensors and IMUs and demonstrated detection of compression depth, rate, chest recoil and interruption. The work also considered wearability and hand adaptability. [2] This establishes a strong research precedent for a glove-based CPR system.

The proposed project focuses on a low-cost embedded architecture using ESP32 and MPU6050. The ESP32 provides processing, BLE/Wi-Fi connectivity and a practical platform for real-time algorithms. The MPU6050 provides three-axis acceleration and gyroscope data. The principal technical challenge is converting noisy inertial measurements into reliable CPR quality parameters while controlling gravity effects, sensor bias, integration drift, orientation changes and non-CPR hand movement.

Recent IEEE literature shows that wearable healthcare research is moving toward edge intelligence and multimodal sensing. A 2026 IEEE Access systematic review found that IMUs dominate wearable movement analysis but highlighted small datasets, heterogeneous protocols, limited external validation and weak standardization as persistent problems. [3] These observations are directly relevant to the proposed CPR glove and motivate a rigorous multi-subject validation strategy.

II. LITERATURE REVIEW METHOD

The literature was organized into five themes: CPR compression measurement and feedback; smart gloves and wearable CPR systems; IMU signal processing; ESP32/edge wearable healthcare; and AI-assisted CPR assessment. Priority was given to IEEE Xplore publications from 2024–2026, while older papers were retained only when they established foundational measurement concepts. Recent literature was then mapped to specific design requirements and research gaps for the proposed system.

III. LITERATURE REVIEW

A. Smart Gloves for CPR

The most directly relevant IEEE work is the 2024 IEEE Access paper “A Proof-of-Concept Study on Smart Gloves for Real-Time Chest Compression Performance Monitoring.” It combines pressure sensing and IMUs to monitor compression depth, rate, recoil and interruptions and reports a lightweight, hand-adaptable prototype. [2] The study establishes that glove-based sensing can provide a practical alternative to rigid feedback devices.

For the proposed ESP32–MPU6050 system, this paper also identifies an important methodological issue: inertial sensing alone does not directly measure displacement. A new system must therefore distinguish between motion-derived depth estimation and directly measured depth. A pressure or force sensor can be added as an optional second channel to create a stronger multimodal architecture.

B. Wearable CPR Feedback

Wearable feedback is supported by the 2024 smartwatch CPR study, which showed improved compression-depth and rate effectiveness when users received real-time guidance. [1] A 2025 study also developed a wearable CPR audio-visual feedback device capable of displaying compression depth and frequency in real time. [4] In 2026, a medical latex glove-type feedback device was evaluated with 30 participants and demonstrated improved adherence to displayed depth guidance relative to a conventional feedback device. [5]

These findings suggest that feedback must be treated as an integral part of the system, not merely as an output display. For the ESP32 glove, tactile vibration and audio feedback are attractive because the rescuer may not be able to continuously look at a display.

C. Multimodal CPR and AI

The 2026 IEEE ICHI paper on the Universal CPR AI Assistance Response Engine (U-CARE) represents a newer research direction. It combines smartphone-based guidance, LLM-assisted verbal guidance and computer vision to assess compression rate, depth and hand placement. [6] The system illustrates the move from single-sensor feedback toward multimodal intelligent assistance.

A low-cost ESP32 glove should not attempt to reproduce the complete U-CARE architecture. Instead, its value is as a deterministic sensing layer: CPR events can be detected locally with low latency, while a smartphone can optionally provide advanced analytics, historical tracking and AI coaching.

D. IMU and Wearable Signal Processing

Recent IEEE wearable sensing research shows that IMU signals are vulnerable to motion artifacts and sensor-contact changes. A 2025 IEEE Access study used dual IMUs and deep learning for robust respiratory-rate estimation under movement. [7] Although the target application differs from CPR, the signal-processing lesson is important: frequency-domain features, sensor fusion and artifact-aware algorithms can improve robustness.

The 2026 IEEE Access systematic review of wearable-sensor machine learning similarly emphasizes that many studies rely on small or private datasets and within-dataset validation, while external validation is limited. [3] The proposed CPR glove should therefore use subject-wise and session-wise evaluation and should report performance on participants not used for model/threshold tuning.

E. Edge AI and Low-Power Wearables

A 2026 IEEE review of ultra-low-power FPGA-based architectures for wearable health monitoring identifies power-aware design, lightweight machine learning, dynamic voltage/frequency scaling, clock gating and memory-aware processing as important strategies for edge healthcare. [8] Although ESP32 is not an FPGA, the principle of local

processing with minimized wireless transmission is applicable. A practical glove should process primary CPR events locally and transmit only compact features or summary data when possible.

IV. COMPARATIVE LITERATURE ANALYSIS

Study	Platform	Sensing	Main output	Contribution	Gap
Smart glove, 2024 [2]	Glove	Pressure + IMU	Depth, rate, recoil, interruption	Closest direct benchmark	Different hardware; proof-of-concept scale
Smartwatch CPR, 2024 [1]	Smartwatch	Accelerometer	Depth, rate, variability	Shows wearable feedback benefit	Not glove/ESP32
Wearable feedback, 2025 [4]	Wearable	Embedded sensing	Depth + frequency + feedback	Real-time feedback	Different architecture
Glove CPR device, 2026 [5]	Medical glove	Glove-integrated sensing	Depth + rate	Recent glove evidence	Different sensing/validation
U-CARE, 2026 [6]	Phone + AI	Vision + multimodal	Rate, depth, hand placement	Advanced intelligent feedback	Higher complexity
Dual-IMU study, 2025 [7]	Wearable	Dual IMU + DL	Motion-derived signal	Artifact robustness	Different target
Wearable ML review, 2026 [3]	Multiple wearables	IMU/EMG/etc.	Movement analysis	Identifies validation gaps	Not CPR-specific
Edge-AI review, 2026 [8]	Wearable/FPGA	Edge AI	Real-time inference	Power-aware direction	Not ESP32-specific

V. MOST RECENT RESEARCH GAP ANALYSIS

Gap 1—Low-cost inertial CPR monitoring: Recent systems increasingly use multimodal pressure/IMU sensing, computer vision or more advanced wearable processors. There remains a practical opportunity for a low-cost ESP32–MPU6050 platform, provided that measurement limitations are explicitly characterized.

Gap 2—Depth estimation reliability: Double integration of acceleration is susceptible to bias and drift. Therefore, an MPU6050-only design should not claim direct clinical depth measurement without reference validation. A calibrated force/pressure channel is a strong future extension.

Gap 3—Recoil monitoring: Basic systems often emphasize rate and depth. The 2024 smart-glove study demonstrates the importance of including complete recoil and interruptions. [2] The proposed system should therefore report recoil as a first-class metric.

Gap 4—Motion artifacts: Wrist rotation, repositioning, glove movement and sensor placement can generate false compression events. Recent IMU literature demonstrates the broader importance of artifact-resistant processing. [7]

Gap 5—External validation: Recent wearable ML research identifies limited external validation as a persistent weakness. [3] The proposed study should include multiple participants and sessions and should reserve unseen participants for final testing.

Gap 6—Feedback latency and usability: Wearable CPR research indicates that immediate feedback can improve performance. [1], [4] The proposed work should quantify end-to-end latency and user acceptance rather than reporting only sensor accuracy.

Gap 7—Edge/cloud balance: Current CPR research is moving toward multimodal AI and connected assistance. [6] The proposed glove can provide a low-power local measurement layer while a smartphone/cloud system performs optional analytics.

VI. GAP-TO-SOLUTION MATRIX

Research issue	Literature limitation	Proposed solution	Validation
Low-cost real-time CPR	Advanced devices can be complex	ESP32 + MPU6050 embedded platform	Cost, latency, power
Compression detection	IMU noise/orientation	Filtering + orientation compensation	Precision/recall/F1
Depth	Integration drift	Reference-calibrated estimation + optional FSR	MAE/RMSE/bias
Recoil	Often omitted in basic systems	Return-motion analysis	Sensitivity/specificity
Motion artifacts	Non-CPR movement causes false events	Artifact rejection + robust features	False-positive rate
Feedback	Latency/usability often underreported	Vibration/buzzer/OLED/BLE	Latency/usability
Generalization	Small/private datasets	Multi-subject/session validation	External-test accuracy
Energy	Wireless transmission costs energy	Local processing + duty-cycled BLE	Battery/energy per session

VII. PROPOSED SYSTEM ARCHITECTURE

The proposed smart glove consists of an MPU6050 mounted in a mechanically stable location, an ESP32 microcontroller, a feedback unit and an optional wireless/mobile interface. The MPU6050 communicates with the ESP32 through I2C. The ESP32 performs calibration, filtering, event detection, rate estimation, motion-derived depth/recoil estimation and feedback generation. BLE can transmit summary metrics to a mobile application.

A recommended research version should include an expansion interface for an FSR, pressure sensor or flexible force sensor. This permits direct comparison between an IMU-only configuration and a multimodal configuration. Such a comparison would strengthen the research contribution by showing the trade-off among cost, accuracy, complexity and energy.

Component	Function	Research consideration
ESP32	Processing, BLE/Wi-Fi	Real-time processing and wireless communication
MPU6050	3-axis accelerometer + gyroscope	Orientation, bias and placement calibration
Vibration motor	Tactile feedback	Immediate rate/depth/recoil alerts
Buzzer	Auditory feedback	Distinct error patterns
OLED (optional)	Local display	Rate/depth/quality display
Battery + regulator	Portable power	Measure energy consumption
FSR/pressure sensor (extension)	Force/contact sensing	Improve depth/recoil estimation

VIII. PROPOSED SIGNAL-PROCESSING METHODOLOGY

1. Acquire synchronized accelerometer and gyroscope samples at a fixed sampling rate.
2. Estimate sensor bias and calibrate the IMU before each experimental session.
3. Filter the raw signals to suppress high-frequency noise and isolate the compression-motion band.
4. Estimate orientation and compensate the gravity component.
5. Detect compression peaks and troughs using adaptive thresholds and timing constraints.
6. Calculate instantaneous and moving-average compression rate.
7. Estimate displacement/depth using calibrated motion integration and/or a sensor-fusion model.
8. Detect recoil from the return trajectory and settling behavior.
9. Detect interruptions/hands-off periods.
10. Generate tactile/audio/visual feedback and optionally transmit summary data over BLE.

IX. MATHEMATICAL MODEL

For consecutive compression peaks at times t_i and $t_{(i+1)}$, the instantaneous compression rate can be expressed as $R_i = 60/(t_{(i+1)} - t_i)$, where R_i is in compressions per minute. A robust median or moving average over several cycles can stabilize the displayed rate.

After gravity compensation, linear acceleration $a(t)$ can be integrated to estimate velocity and displacement. In simplified form, $v(t) = \int a(t) dt$ and $x(t) = \int v(t) dt$. In practice, bias and drift make unconstrained double integration unreliable; therefore the algorithm should use calibration, filtering, physical constraints and reference-based correction. The resulting value should be reported as estimated displacement unless independently validated.

A recoil indicator can be computed from the post-compression return trajectory. Features may include return time, residual displacement, return slope and post-compression stability. These features can later be combined with pressure release data.

X. EXPERIMENTAL DESIGN

Experiment	Variable	Measurements	Analysis
Sampling-rate study	Sampling frequency	Detection accuracy, CPU load	Accuracy/cost trade-off
Placement study	Glove sensor position	Rate/depth error	Repeated-measures comparison
Filter study	Cutoff/window	Precision, recall, latency	Sensitivity analysis
Depth validation	Reference depth	MAE, RMSE, bias	Regression + Bland–Altman
Rate validation	Reference rate	BPM error	MAE/RMSE/correlation
Recoil study	Complete/incomplete recoil	Sensitivity/specificity	Confusion matrix
Artifact study	Wrist/hand movement	False detections	F1/false-positive rate
Feedback study	Feedback/no feedback	CPR quality	Within-subject comparison
Battery study	BLE/Wi-Fi modes	Current/runtime	Energy/session

XI. EVALUATION METRICS

- Compression rate: MAE, RMSE and percentage error in compressions/minute.
- Depth: MAE, RMSE, bias and limits of agreement against an independent reference.
- Compression detection: precision, recall, F1-score and false-positive/negative rates.
- Recoil: sensitivity, specificity and percentage of compressions meeting the defined recoil criterion.
- Interruption: hands-off duration and detection latency.
- Feedback: end-to-end latency from event detection to vibration/audio/display.
- Embedded performance: CPU utilization, memory use, packet loss and sampling stability.
- Energy: current consumption, battery runtime and energy per monitored session.
- Usability: comfort, fit, perceived intrusiveness, interpretability and workload.

XII. PROPOSED RESEARCH CONTRIBUTION

- Low-cost glove-integrated CPR monitoring using ESP32 and MPU6050.
- Real-time compression-cycle detection with orientation and drift compensation.
- Combined monitoring of rate, estimated depth, recoil and interruption.
- Immediate tactile/audio feedback with optional BLE mobile dashboard.
- Optional pressure/FSR channel for multimodal depth and recoil validation.
- Multi-subject and multi-session evaluation designed around external-validation principles.
- Energy-aware local processing to reduce unnecessary wireless transmission.

XIII. FUTURE DEVELOPMENT

The first future direction is multimodal sensing. Adding an FSR or flexible pressure sensor can provide complementary force/contact information and reduce dependence on double integration for depth estimation. The comparison between IMU-only and IMU+pressure versions can itself become an experimental contribution.

The second direction is TinyML. A compact classifier can distinguish true compression cycles from wrist repositioning, tremor and non-CPR movements. Recent wearable ML literature supports the use of IMU-derived features but also warns that small datasets and non-subject-wise validation can exaggerate performance. [3] Therefore, TinyML development should use participant-independent testing.

The third direction is edge/mobile cooperation. The ESP32 can perform deterministic event detection locally while a smartphone receives compressed features, displays session trends and performs optional advanced analytics. This balances low latency and energy efficiency with computational flexibility.

The fourth direction is multimodal intelligent CPR assistance. The 2026 U-CARE study demonstrates the trend toward computer vision, language-based assistance and objective CPR feedback. [6] A future glove can provide the wearable sensor stream to such a multimodal platform while preserving local tactile feedback.

The fifth direction is validation and translation. A research-grade prototype should progress from laboratory manikin testing to diverse participants, different glove sizes, different hand positions and eventually controlled clinical simulation. Any medical-device claims would require appropriate regulatory, safety and clinical validation beyond an academic prototype.

XIV. FUTURE DEVELOPMENT ROADMAP

Phase	Development	Expected output
1	ESP32 + MPU6050 acquisition	Stable sensor pipeline
2	Calibration + filtering	Clean motion signals
3	Compression detection	Reliable rate monitoring
4	Depth + recoil estimation	Multi-parameter CPR assessment
5	Vibration/audio/OLED feedback	Closed-loop coaching
6	BLE mobile dashboard	Session-level analytics
7	FSR/pressure fusion	Improved depth/recoil robustness
8	TinyML artifact rejection	Robust real-world detection
9	Multi-subject validation	Generalization evidence
10	Advanced clinical simulation	Translation feasibility

XV. CONCLUSION

Recent literature confirms that CPR monitoring is moving toward wearable, multimodal and intelligent systems. The 2024 IEEE Access smart-glove study is the closest benchmark for the proposed work because it combines IMUs and pressure sensing to monitor depth, rate, recoil and interruption. [2] 2025–2026 research further demonstrates the value of wearable feedback, multimodal AI, robust IMU processing and edge intelligence. [3]–[8]

The proposed ESP32–MPU6050 smart glove therefore has a credible research pathway when its novelty is defined around low-cost embedded implementation, robust signal processing, real-time feedback and rigorous validation—not simply the selection of ESP32 and MPU6050 components.

The most important research gap is the need for a reproducible, low-cost glove architecture that explicitly evaluates compression rate, motion-derived depth, recoil, interruption, motion artifacts, feedback latency, energy consumption and generalization across users. An optional pressure sensor can address the fundamental limitation of inertial-only

depth estimation. The resulting system can form a practical platform for future TinyML, multimodal sensing and connected CPR-assistance research.

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