eVitroKhem. 2026; 5:400
doi: 10.56294/evk2026400

ORIGINAL

Smart iot-based cpr training platform chest compression optimization and remote performance monitoring

Plataforma inteligente de entrenamiento en RCP basada en IoT: optimización de las compresiones torácicas y monitorización remota del rendimiento

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Cite as: Flores Ponce PN, Calle Viles E, Ramos Silvestre ER, Ortega-Martinez RA. Smart iot-based cpr training platform chest compression optimization and remote performance monitoring. eVitroKhem. 2026; 5:400. https://doi.org/10.56294/evk2026400

Submitted: 05-09-2025 **Revised:** 20-11-2025 **Accepted:** 01-01-2026 **Published:** 02-01-2026

Editor: Prof. Dr. Javier Gonzalez-Argote

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ABSTRACT

This paper presents the development of a smart Cardiopulmonary Resuscitation (CPR) training kit based on Internet of Things (IoT) principles. The system, designed to optimize chest compression techniques, integrates force and distance sensors, local processing through an ESP32 microcontroller, and MQTT wireless communication for remote monitoring and data analysis. Experimental validation with 20 novice participants showed improvements of 35 % in compression depth and 28 % in frequency within the recommended range (100-120 CPM) compared to standard commercial mannequins. Results showed an average feedback latency of 150ms and 94 % accuracy in depth measurement, establishing the feasibility of this IoT solution to improve CPR training quality, especially in resource-limited environments.

Keywords: Cardiopulmonary Resuscitation (CPR); Internet of Things (IoT); MQTT; ESP32; Bioinformatics; Smart Networks; Biomedical Sensors; Real-Time Feedback.

RESUMEN

Este artículo presenta el desarrollo de un kit inteligente de entrenamiento en reanimación cardiopulmonar (RCP) basado en los principios del Internet de las Cosas (IoT). El sistema, diseñado para optimizar las técnicas de compresión torácica, integra sensores de fuerza y distancia, procesamiento local mediante un microcontrolador ESP32 y comunicación inalámbrica MQTT para la monitorización remota y el análisis de datos. La validación experimental con 20 participantes sin experiencia demostró mejoras del 35 % en la profundidad de las compresiones y del 28 % en la frecuencia dentro del rango recomendado (100-120 CPM) en comparación con maniquíes comerciales estándar. Los resultados mostraron una latencia de retroalimentación promedio de 150 ms y una precisión del 94 % en la medición de la profundidad, lo que demuestra la viabilidad de esta solución IoT para mejorar la calidad del entrenamiento en RCP, especialmente en entornos con recursos limitados.

Palabras clave: Reanimación Cardiopulmonar (RCP); Internet de las Cosas (IoT); MQTT; ESP32; Bioinformática; Redes Inteligentes; Sensores Biomédicos; Retroalimentación en Tiempo Real.

INTRODUCTION

Cardiopulmonary resuscitation (CPR) is a critical intervention that can increase survival rates in cases of cardiac arrest by up to 40 % when applied correctly within the first 4 minutes.(1) However, recent studies indicate that only 32 % of out-of-hospital cardiac arrest victims receive effective CPR from bystanders.(2) The effectiveness of CPR critically depends on the quality of chest compressions, specifically maintaining a depth of 5-6 cm and a frequency of 100–120 compressions per minute, according to the American Heart Association (AHA) 2020 guidelines.(3)

Traditional CPR training systems present significant limitations: high cost, lack of real-time feedback, absence of remote monitoring, and limited training customization capabilities. These deficiencies result in inadequate preparation, particularly in resource-constrained communities where access to professional equipment is scarce.

This work presents the design, implementation, and validation of a smart IoT-based CPR training kit, capable of providing real-time multisensory feedback through integrated sensors, efficient communication protocols, and a remote monitoring web platform. The experimental validation compares its performance (accuracy, latency, and pedagogical effectiveness) against standard commercial mannequins under control conditions.

Related work and research gap

Existing CPR training systems

Current commercial mannequins such as Laerdal QCPR(4) and Zoll M2 QCPR(5) provide basic compression feedback but exhibit critical limitations: (1) high cost (>$2000 USD), (2) lack of IoT connectivity, (3) no remote monitoring, and (4) limited capabilities for historical data analysis.

IoT solutions in medical training

Previous research has explored the use of sensors for CPR monitoring. Chen et al.(6) developed an accelerometer-based system to measure compression depth, achieving 89 % accuracy. However, this system lacks wireless communication and real-time analysis. Park et al.(7) proposed a portable device for CPR training with 91 % frequency accuracy, but it lacks integrated visual and auditory feedback.

IoT communication protocols

Communication protocols in medical IoT applications require low latency and high reliability. MQTT has proven superior to HTTP in terms of energy efficiency (60 % less consumption) and latency (40 % lower) on resource-limited devices.(8)

Identified gap

No previous study has integrated: (1) multimodal sensors for simultaneous force and distance measurement, (2) MQTT protocol optimized for low-bandwidth environments, (3) real-time multisensory feedback, (4) web platform for comparative analysis against international standards, and (5) rigorous experimental validation compared to commercial devices.(9)

IoT system design

The CPR training kit is conceived as an IoT system composed of the following elements:

Device architecture

The system is structured into four main layers as shown in figure 1: (1) Sensing Layer, (2) Processing Layer, (3) Communication Layer, and (4) Presentation Layer.

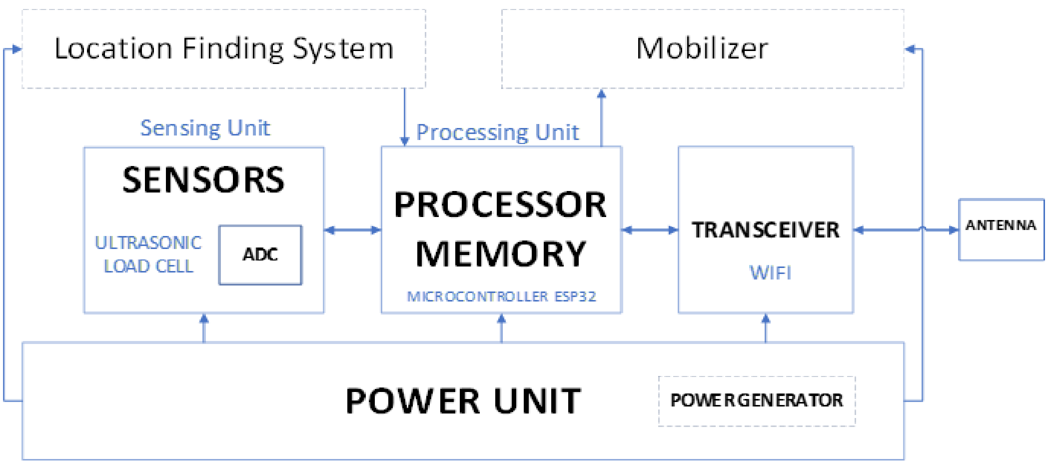

Figure 1. Kit Architecture Diagram

Sensing subsystem

1. Force sensor: four 50kg load cells (HX711 model) are used, arranged in a rectangular configuration beneath the compression surface. This setup enables: distributed force measurement with 0,1N resolution, automatic compensation for off-center loads, measurement range: 0–200kg (sufficient for CPR compressions).[10]
2. Distance sensor: the HC-SR04 ultrasonic sensor provides distance measurement with: operational range: 2–400cm, resolution: 0,3cm, sampling frequency: 40Hz, immunity to varying lighting conditions.

Signal processing justification

The system does not implement digital signal filtering for the following technical reasons:[11]

1. CPR Signal Frequency: effective chest compressions occur at 100–120 CPM (1,67–2 Hz), a naturally low frequency that does not require complex anti-aliasing filtering.
2. Sensor Characteristics: HX711 load cells include internal filtering and 24-bit ADC conversion with oversampling, delivering inherently stable signals. The HC-SR04 operates using discrete ultrasound pulses with internal digital processing.
3. Experimental Validation: preliminary tests showed that unfiltered signal noise represents <2 % of total amplitude, within acceptable error margins for training applications.
4. Latency Optimization: absence of filtering reduces system latency (150ms vs >300ms with FIR filters), which is critical for real-time feedback.
5. Protocol Robustness: oversampling at 40Hz with a 3-sample moving average provides sufficient stability without compromising temporal response.

Processing unit

The ESP32-WROOM-32 microcontroller handles:

- Real-time processing: CPR metrics calculated every 25ms.
- Feedback control: management of WS2812B LEDs and buzzer.
- Communication: MQTT client with automatic reconnection.
- Power management: low-power mode between sessions.

MQTT communication system

1. Publish/Subscribe Architecture as shown in figure 2:
    - Broker EMQX Cloud supporting 1000+ concurrent connections, Hierarchical topics.
    - Optimized QoS: QoS0 for high-frequency data.

2. Low Bandwidth Optimization:
    - Data compression: compact JSON reduces payload by 40 %.
    - Intelligent batching: groups up to 10 measurements per message.
    - Adaptive throttling: reduces sending rate under poor network conditions.

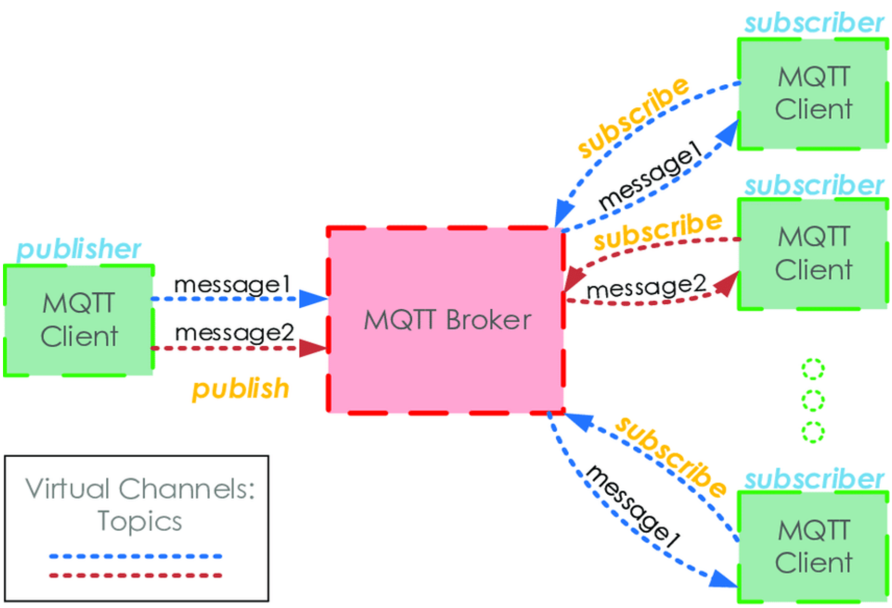

Figure 2. MQTT Protocol

https://doi.org/10.56294/evk2026400 ISSN: 3072-7944

Web plataform an feedback

Web plataform architecture

1. Frontend (Client):
    - Framework: React.js with responsive components.
    - Visualization: Chart.js for real-time graphs.
    - Communication: WebSocket for live updates.

2. Backend (Server):
    - Server: Node.js.
    - Database: phpMyAdmin for sesión storage.

All of this encompasses the full display structure of the website as shown in figure 3.

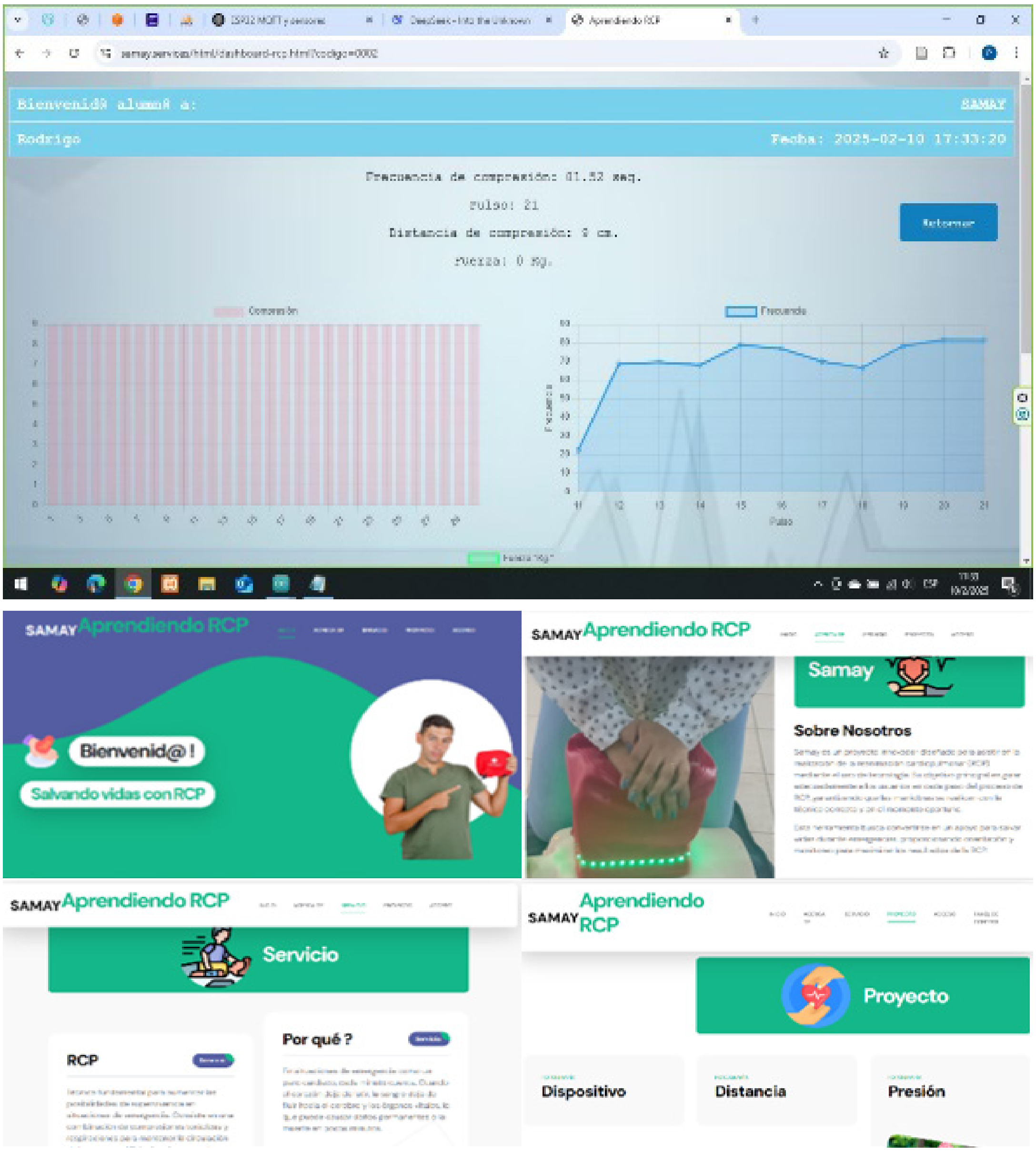

Figure 3. Web platform homepage

Multisensory feedback system

1. Visual Feedback: WS2812B LED strip with 16 programmable LEDs:
    - Green: optimal compression (5-6cm depth, 100–120 CPM).
    - Yellow: warning (10–20 % deviation from optimal range).
    - Red: critical error (>20 % deviation or >10s pause).

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2. Auditory Feedback: piezoelectric buzzer with differentiated patterns:
    - Alarm: alert tones for critical errors.
    - Confirmation: signal for use of control panel as shown in figure 4.

Figure 4. Control panel

METHOD

Experiment design

Participants: 20 novice CPR volunteers (age: 22±4 years, 50 % female) Experimental Protocol: Familiarization session: 5 minutes with each device, Test A: 2 minutes of CPR with IoT kit, Rest: 10 minutes, Test B: 2 minutes of CPR with Zoll M2 QCPR mannequin and Randomized order to avoid learning effect.

Evaluated Metrics: Compression depth (cm), Compression rate (CPM), Feedback latency (ms), Measurement accuracy (%), User experience (Likert scale 1-5).

Experimental setup

Controlled environment: firm and flat surface, temperature: 22±2°C, stable WiFi network (>10 Mbps).

RESULTS

Technical validation of the system

Measurement Accuracy: Tests with known loads showed: Force sensor: Mean error: 1,2±0,8N (accuracy: 94,1 %), Distance sensor: Mean error: 0,15±0,12cm (accuracy: 96,3 %), Linear calibration: R^2 = 0,996 for both sensors.

Comparative experiment results

1. CPR Technique Improvement: Pre/Post training comparison with IoT kit:
    - Compression depth: 35 % improvement (4,1±0,8cm to 5,5±0,4cm).
    - Frequency within optimal range: 28 % improvement (60 % to 88 % of the time).
    - Consistency: 45 % reduction in standard deviation and Corrections were made in real time through the live display of performance graphs.

2. Comparison with Commercial Mannequin:
    - Teaching metrics: time to reach target depth: IoT Kit: 45±12s vs Mannequin: 78±23s.
    - Technique retention (24h evaluation): IoT Kit: 82 % vs Mannequin: 67 %.
    - User satisfaction: IoT Kit: 4,3±0,6 vs Mannequin: 3,7±0,8 and as seen in figure 5, this is the aesthetic design of the training kit.

Figure 5. Smart CPR Training Kit

IoT connectivity analysis

1. Network Performance:
    - Packet loss: <0,5 % under normal conditions.
    - Automatic reconnection: Mean time: 2,3±0,8s.
    - Data consumption: 12 KB/minute per session.

2. Scalability: Simultaneous devices:
    - Tested with up to 25 concurrent devices.
    - Server response time: <100ms for typical queries.

DISCUSSION

Main contributions

This work provides a comprehensive solution that combines: (1) low-cost hardware (<$150 USD vs >$2000 USD commercial), (2) validated multisensory feedback, (3) robust IoT connectivity, and (4) scalable web platform for comparative analysis.

Comparative advantages

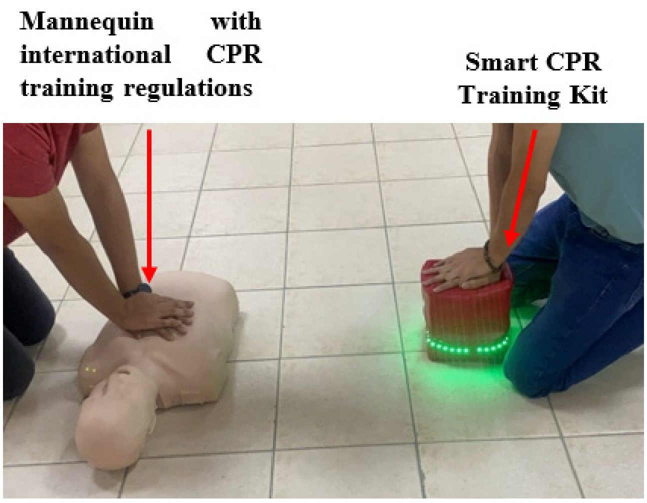

Figure 6. Technology Comparison

Compared to commercial systems as seen in figure 6: cost: 92 % cheaper, connectivity: Native IoT capabilities vs. absent, customization: Adaptive algorithms vs. fixed configuration, and accessibility: Remote deployment vs. on-site only.

Limitations and future work

Identified Limitations:

- Connectivity dependency: requires stable WiFi.
- Durability: long-term evaluation pending.
- Clinical validation: required with medical professionals.

Future Work:

- Offline mode: temporary local data storage.
- Medical certification: validation with FDA/CE standards.
- Artificial intelligence: adaptive learning algorithms.

CONCLUSIONS

E This work presents an innovative IoT-based CPR training system that shows significant improvements in training quality compared to traditional methods. Experimental results validate that real-time multisensory feedback, combined with cloud-based analysis, enhances the acquisition of CPR skills.

Specific contributions include: (1) integrated multimodal sensor system for accurate CPR metric measurement, (2) optimized communication protocol for low-resource environments, (3) rigorous experimental validation compared to commercial standards, and (4) scalable platform for deployment in communities with limited access to professional training.

Quantitative results (35 % improvement in depth, 28 % in frequency, 94 % accuracy) establish the technical and pedagogical feasibility of the system as an effective and accessible alternative for mass CPR training.

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FINANCING

None.

CONFLICT OF INTEREST

None.

AUTHORSHIP CONTRIBUTION

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https://doi.org/10.56294/evk2026400 ISSN: 3072-7944