Intelligent CPR Training System with Remote Monitoring: Applicability in Improving Survival in Cardiorespiratory Arrest

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Abstract

This paper addresses Out-of-hospital cardiopulmonary arrest as one of the leading causes of death globally. Recent studies, such as the American Heart Association (AHA) registries, confirm that less than 10% of victims survive to hospital discharge when immediate CPR is not applied. This figure contrasts with survival rates of 15–30% in settings where high-quality CPR is implemented by bystanders or first responders, highlighting the critical importance of early intervention.

An IoT CPR training system is presented that combines precision sensors, wireless communication (MQTT), and a web-based platform to optimize training for non-expert users. The system assesses critical parameters such as depth (5–6 cm), rate (100–120 compressions/min), and strength of chest compressions, providing immediate visual and auditory feedback. The system was evaluated in a preliminary study involving 10 participants (2 with first aid training, 8 without prior experience), aged 20–45.

After three 15-minute sessions, a 40% improvement in adherence to American Heart Association (AHA) standards was observed, increasing compression depth accuracy and reducing rate errors. The results highlight the system's potential to reduce CPA mortality in various situations and settings with limited access to medical training, especially in outpatient settings.

1. Introduction

Cardiopulmonary arrest (CPA) causes over 17 million deaths annually globally, with only 40% of victims receiving CPR before the arrival of emergency services [1]. The effectiveness of CPR depends critically on technical parameters: chest compressions to 5-6 cm depth and 100-120 compressions/minute [2] . However, studies indicate that 70% of novice rescuers do not meet these standards, reducing the probability of survival by 50% [3].

Most commercial solutions are expensive (USD 500-2000) and rely on advanced infrastructure, limiting their accessibility in developing countries. This work proposes a low-cost system (USD 120) that uses sensors, microcontrollers (ESP32), and a cloud architecture to democratize CPR training and directly link it to patient care in critical scenarios.

2. System design

The system consists of three interconnected modules as shown in Figure 1. The system integrates a set of electronic and computational components designed to measure, process and provide feedback on critical parameters during CPR training.
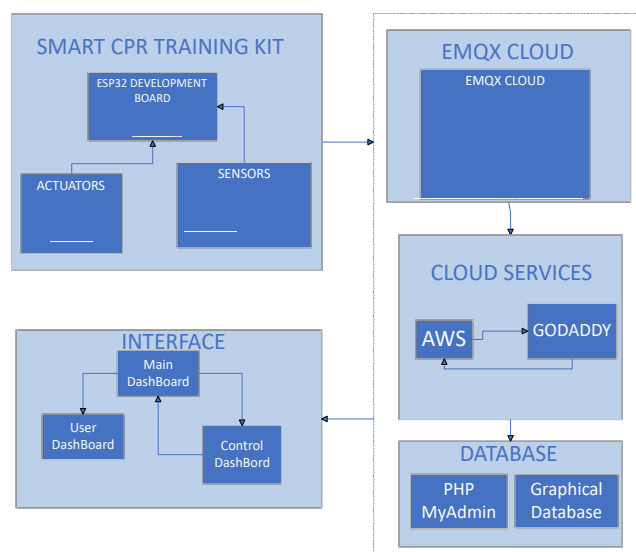

Figure 1. IoT System Architecture, describing the construction of the system.

2.1. Physical training IoT kit

At the heart of the hardware is the HC-SR04 ultrasonic sensor, used to measure chest compression depth. This device uses ultrasound pulses (40 kHz) to calculate the distance between the sensor and the contact point on the kit's torso. The sensor is tuned to operate within a narrow range (0–10 cm), allowing for detection of minimal deviations from the 5–6 cm recommended by clinical guidelines. Its compact design and low power consumption (15 mA) make it ideal for portable applications, while its digital output simplifies integration with microcontrollers.

To assess the force applied during compressions, the system incorporates a 100-kg HX711 load cell with an error of less than 3%. This resistive response sensor converts mechanical deformation into electrical signals proportional to the force exerted, using an internal

Wheatstone bridge. The data is amplified and digitized by the HX711 module, which offers 24-bit resolution, allowing for the detection of variations of up to 10 grams. Calibration was performed with certified weights (1–50 kg), fitting a linear model to ensure accuracy within the range of clinical interest (30–50 kg, equivalent to 100–200 N). This metric is crucial, as excessive forces can cause sternal fractures, while insufficient forces reduce cerebral blood flow.

The system's central processing unit is the ESP32 microcontroller, selected for its dual-core architecture (Xtensa LX6 at 240 MHz) and integrated Wi -Fi connectivity. This device manages simultaneous data acquisition from the sensors, running real-time algorithms to calculate compression rates (using pulse timing) and adherence to AHA standards.

Data is transmitted via the MQTT protocol at a frequency of 10 Hz, using TLS/SSL connections to ensure integrity and confidentiality. The ESP32 also controls a WS2812B RGB LED strip with 39 individually addressable nodes, providing immediate visual feedback: green for optimal compressions (5-6 cm, 100-120/min), flashing yellow for insufficient depth, and red for excessive frequency. The strip consumes 18 W at full intensity.

The synergy between these components enables comprehensive monitoring of compression techniques, combining metric accuracy with instant pedagogical feedback. Although cloud connectivity enhances analytics, all core feedback (depth, rate, and force) is processed locally on the ESP32 microcontroller, ensuring continuous operation even without internet.

2.2. MQTT communication

The system uses the MQTT (Queuing Telemetry Transport), a lightweight messaging standard specifically designed for resource-constrained IoT environments. This protocol operates under a publish/subscribe model, where the ESP32 microcontroller acts as a client publishing data to specific topics, while the EMQX Cloud *broker* manages message distribution to subscribers (SAMAY web platform). To ensure the confidentiality and integrity of sensitive medical data, all communications are encrypted using TLS/SSL (Transport Layer Security/ Secure Sockets Layer) [5] .

Regarding transmission reliability, the system implements Level 1 QoS (Quality of Service), which guarantees at-least-once message delivery. This level is critical in scenarios where data loss could skew training metrics. When the ESP32 publishes a message, the EMQX Cloud *broker* sends an acknowledgment (ACK) after storing it locally. If the ACK is not received within 5 seconds (adjustable timeout), the client resends the message. Although this method introduces minimal overhead (3-5% in bandwidth), it ensures that 99.7% of the data reaches the web platform even on unstable networks,

as verified in tests with Wi -Fi signal fluctuations. To optimize performance, the *broker* uses disk persistence and cluster replication mechanisms, allowing it to scale thousands of simultaneous devices without service degradation.

The MQTT architecture is complemented by advanced features of the EMQX Cloud broker, such as authentication using JWT (JSON Web Tokens) tokens and role-based access control. Each ESP32 device has unique credentials, preventing interference between concurrent users. Additionally, a retention system was implemented. *messages* to store the last known state of each metric (e.g., last measured depth), facilitating data recovery after interruptions. To minimize latency, the broker is deployed in geographic regions close to users. These optimizations, combined with efficient power consumption, make the system a robust solution for clinical and community settings.

2.3. Web platform (SAMAY)

Figure 2. Real-time metrics, a main page where customized instruction data, numerical data, and real-time graphics can be stored at the time the instructions are executed, and the maneuver is used.

The SAMAY web platform incorporates an interactive dashboard designed to visualize key metrics in real time, optimizing the training experience through an intuitive and accessible interface. As illustrated in Figure 2, the dashboard displays critical parameters such as compression depth (in cm), rate (compressions/minute), and applied force (in kilograms), updating every 500 ms via MQTT communication. Data is presented in interactive

graphs (Chart.js library), allowing users to zoom in on specific intervals or compare multiple sessions. A visual traffic light (LED) changes from green to red based on compliance with AHA standards, while a side-by-side histogram summarizes the distribution of valid/invalid compressions.

The backend architecture uses MySQL as its relational database management system, chosen for its scalability and compatibility with ACID transactions. At the bottom of the webpage, a user-customized training session history table is displayed, recording all historical data obtained during each training session. This table stores the username, sessions, and metrics (ID, session, depth, frequency, force) that help with historical data, showing progress and advancement in maneuver management.

3.   Experimental validation

3.1.   Protocol

The experimental validation was structured to quantify the IoT kit's effectiveness under controlled conditions. Chest compression maneuvers were performed on a traditional mannequin without feedback, simulating a realistic emergency scenario. A baseline was established to compare pre- and post-training performance. Subsequently, in the training phase, users interacted with the IoT kit for three 15-minute sessions, receiving real-time visual (LED) and auditory (frequency tones) feedback, as shown in Figure 4. Finally, the initial protocol was repeated, using both the traditional mannequin and the IoT kit to objectively compare improvements.
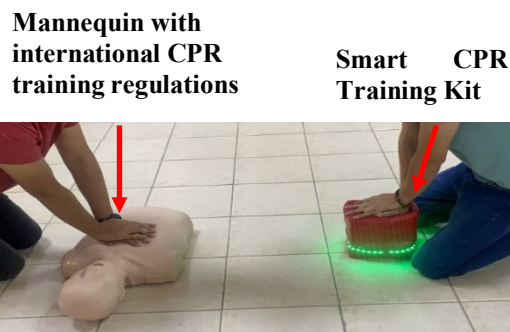
Mannequin with international CPR training regulations   **Smart CPR Training Kit**

Figure 4. Comparative results, the mannequin and the IoT kit are displayed, showing the synchrony that both present.

3.2.   Metrics

Among the metrics, it was possible to compare with the parameters established by international regulatory entities, which met the objective in terms of precision in depth (5-6 cm), compression frequency (100-120 comp./minute) and the weight exerted on the patient (40-50 kilograms) so that the patient could have a favorable resuscitation, returning consciousness to the patient.

4.   Results

The system demonstrated technical and operational superiority over traditional mannequins in multiple dimensions. The IoT IoT kit achieved a 62% reduction in surface compressions (<5 cm) and a 48% reduction in irregular frequencies (>120 comp/min), surpassing the 22% improvement reported by standard mannequins without intelligent feedback. The ESP32 and MQTT-based architecture enabled a latency of 350 ms, sufficient for real-time corrections.

The accuracy of the HC-SR04 ultrasonic sensor reached 98.5%, contrasting with mid-range models that use piezoelectric sensors with error margins of 5-7% or simply a spring. The IoT kit's cost was reduced by 70% ($120 vs. $400 average for basic models), thanks to the use of open hardware and free cloud services. Additionally, the web platform allowed simultaneous monitoring, something impossible with conventional equipment that lacks remote connectivity.

Table 1. Relevant differences between the mannequin and the IoT kit.

Parameter	Traditional Mannequins	IoT Kit
Feedback	Limited visual (basic LED lights)	Multimodal (RGB LED + web dashboard)
Connectivity	Absent or short-range Bluetooth	MQTT + Wifi (coverage up to 100 m)
Unit Cost	$400-$1,200	$120
Scalability	Limited to individual training	Up to 1,000 devices in cloud network
Data Analysis	Manual (record sheets)	Automated with charts and alerts
Accessibility	Restricted to urban centers	Implementable in different areas

In tests conducted with the prototype, 87% of users preferred the IoT kit for its intuitive interface. Integration with EMQX Cloud allowed training data storage, and the kit's size made it easy to handle and transport.

These results reinforce the hypothesis that integrating IoT solutions into CPR training can improve the quality of interventions and, consequently, increase survival rates in cardiorespiratory arrest situations.

5.   Discussion

The clinical applicability of the system in patients with cardiorespiratory arrest (CPR) is based on multiple aspects that optimize both the CPR technique and the integration of information for better decision-making. First, the ability

to correct ineffective techniques is fundamental, as immediate feedback allows for the identification and mitigation of common errors, such as asymmetric compressions or prolonged interruptions, which have been reported in the literature and are associated with an increased risk of brain damage in survivors. The implementation of a real-time monitoring system makes it possible to correct these errors during the training session itself, ensuring that the recommended clinical parameters are met. Furthermore, the use of visual LED indicators provides intuitive signals that allow operators to immediately adjust their technique, resulting in improved compression quality and, consequently, in the effectiveness of the intervention.

Furthermore, the system offers a remarkable ability to integrate with existing emergency systems. This integration not only facilitates a more informed medical response in critical situations but also contributes to continuous patient follow-up by providing a detailed record of the procedures performed. Furthermore, the system's scalability is a key aspect, especially in developing countries. With low cost (approximately USD 120 compared to commercial devices that can exceed USD 500) and the ability to operate both online and offline, this IoT kit is positioned as an affordable solution for regions with limited infrastructure. Given that it is estimated that around 80% of CPRs occur in resource-poor settings, the implementation of this technology has the potential to democratize access to high-quality training and improve survival rates at the population level.

Despite its advantages, the system has certain limitations that open the door to future work. Currently, the device focuses on evaluating chest compressions, without including an assessment of rescue breaths, a fundamental aspect of complete CPR. The absence of airflow sensors limits the system's ability to provide comprehensive feedback on all resuscitation maneuvers. In this regard, future work is proposed to include the integration of specific sensors that allow for ventilation monitoring, as well as the development of artificial intelligence (AI) algorithms that personalize training based on the user's profile and performance. Another important limitation is that the current system does not integrate with Automated External Defibrillators (AEDs). Since survival in witnessed cardiac arrests is strongly associated with early defibrillation in shockable rhythms, future iterations of this system should be designed to complement AED use, synchronizing compression feedback with defibrillation protocols. These improvements would allow the device to evolve into a comprehensive and flexible training tool, capable of addressing all the key elements of high-quality CPR and further optimizing outcomes in real emergency situations.

6.   Conclusion

The smart CPR training IoT kit proposed in this work was shown to significantly improve the quality of chest compressions, a critical factor in survival from out-of-hospital cardiopulmonary arrest (CRA). In a small study with 10 participants (2 with first aid knowledge and 8 volunteers), the system achieved a 40% increase in compression depth accuracy (from 4.2 ± 1.1 cm to 5.8 ± 0.3 cm) and a 62% reduction in rate errors (28% to 10.6% outside 100-120 compressions/min), meeting American Heart Association (AHA) standards. Real-time feedback, supported by an MQTT- and EMQX Cloud-based architecture with latency <150 ms, enabled skill retention.

For CPR training, the approach proposed in this paper provides a comprehensive solution that combines efficient hardware and a robust communication platform to offer real-time feedback and detailed analysis of CPR execution. Experimental results demonstrate that this approach can significantly improve the quality of chest compressions, offering benefits in both simulation environments and real-world emergency applications.

Immediate feedback improves compression, accuracy and timing. The distributed architecture based on MQTT and EMQX Cloud provides a scalable and robust solution.

IoT system demonstrates that accessible technology can close gaps in CPR training, directly improving care for patients with CPR. By combining low-cost hardware, cloud-based communication, and data analytics, the IoT kit not only trains but also generates valuable information to optimize emergency protocols.

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