Improving Cardiopulmonary Resuscitation (CPR): Integrating Internet of Medical Things (IoMT) and Machine Learning (ML) - A Review

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Abstract

This review explores the pivotal role of cardiopulmonary resuscitation (CPR) in the chain of survival during cardiac events and delves into the challenges and advancements in CPR techniques and technologies. While manual interventions and automated devices have improved survival rates, they present limitations such as rescuer fatigue and lack of real-time feedback. The emergence of the Internet of Medical Things (IoMT) and machine learning (ML) algorithms offers transformative opportunities to enhance CPR rescue efforts by facilitating real-time data acquisition, remote monitoring, and adaptive feedback. However, challenges including interoperability and data security must be addressed for effective integration. The study discusses major findings from related literature, gaps in research, and future directions, highlighting the potential of integrating IoMT and ML to improve CPR outcomes and revolutionize healthcare delivery. Finally, it concludes with recommendations for optimizing CPR strategies and advancing technology for better patient outcomes.

Keywords: Cardiopulmonary Resuscitation, CPR, IoMT, Real-Time, Adaptive Feedback, Machine Learning, Healthcare Integration

1. Introduction

Cardiopulmonary resuscitation (CPR) stands as a pivotal intervention in the chain of survival during cardiac events, serving as the frontline response to restore blood circulation and breathing in individuals experiencing cardiac arrest. Despite its critical role, the efficacy of CPR can be compromised by various factors, including inadequate technique, fatigue, and variability in rescuer proficiency [1]. Such challenges underscore the importance of continually refining CPR techniques and implementing strategies to optimize performance

Existing techniques for CPR rescue primarily rely on manual interventions by trained responders or the utilization of automated external defibrillators (AEDs) and mechanical CPR devices. While these methods have undoubtedly contributed to improving survival rates, they are not without limitations. Manual CPR delivery is susceptible to rescuer fatigue and inconsistencies in compression depth and rate, which can significantly impact patient outcomes [2]. AEDs offer automated rhythm analysis and defibrillation but cannot provide real-time feedback on CPR quality or adapt to individual patient needs. Similarly, mechanical CPR devices provide standardized chest compressions but may be limited in their adaptability to varying patient anatomies and conditions.

The emergence of the Internet of Medical Things (IoMT) represents a paradigm shift in healthcare delivery, offering interconnectedness and data exchange among medical devices, systems, and healthcare professionals [3]. Leveraging IoMT in conjunction with machine learning (ML) algorithms presents a transformative opportunity to enhance CPR rescue efforts. IoMT facilitates the seamless integration and communication of CPR devices, allowing for real-time data acquisition, remote monitoring, and interoperability across healthcare settings [4]. Meanwhile, ML algorithms, particularly Recurrent Neural Networks (RNNs), possess the capacity to analyze complex temporal data, recognize patterns, and generate adaptive feedback tailored to individual patient needs [5].

Despite the promise of IoMT and ML in improving CPR outcomes, several challenges must be addressed to realize their full potential. Interoperability issues among medical devices, data security concerns, and the need for robust ML algorithms capable of handling real-time data streams are among the key challenges facing the integration of IoMT and ML in CPR rescue scenarios [6]. Furthermore, the effective translation of research findings into clinical practice and the seamless integration of technology into existing workflows present additional hurdles.

Against this backdrop, the overarching objective of this study is to develop an IoMT-enabled real-time adaptive feedback system utilizing advanced computational algorithms to enhance CPR performance. By harnessing the connectivity and data-driven capabilities of IoMT and ML, our approach seeks to overcome the limitations of existing CPR rescue techniques and improve patient outcomes during cardiac emergencies. Through rigorous experimentation and validation, we aim to demonstrate the feasibility and efficacy of our proposed system in real-world CPR scenarios, ultimately contributing to advancements in emergency medical care and patient survival rates. In summary, the integration of IoMT and ML presents an opportunity to enhance CPR performance, leading to improved outcomes for patients experiencing cardiac emergencies.

2. Related Work

Section 2 of this paper comprises a concise yet thorough literature survey encompassing CPR techniques, IoMT applications, machine learning in healthcare, and their integration for CPR enhancement.

A. CPR Techniques and Guidelines

Several studies address various aspects of cardiopulmonary resuscitation (CPR) and defibrillation protocols. One prospective study in Belgian EMS systems identifies poor adherence to CPR guidelines, influenced by provider qualifications and patient outcomes [7]. Another review discusses the transition from ABC to CAB sequence in CPR guidelines, emphasizing CAB's efficacy supported by evidence from systematic reviews and an RCT [8]. A third review outlines interventions for adults with sudden cardiac death, emphasizing early defibrillation and uninterrupted compressions [9]. Additionally, a cross-sectional study in Melaka reveals that BLS training and longer professional experience correlate with higher CPR knowledge levels among general practitioners, despite low possession of AEDs in clinics [10]. Major findings include poor adherence to CPR guidelines, the efficacy of the CAB sequence, the importance of early defibrillation, and the association of BLS training with CPR knowledge levels among general practitioners.

B. Automated CPR Devices

The literature review encompasses studies evaluating automated real-time feedback devices [11], online CPR-AED training in rural areas [12], the impact of AHUP deployment post-cardiac arrest [13], comparison of CPR outcomes with and without the LUCAS device [14], and recommendations for mechanical chest compression devices in CPR [15]. The findings suggest that feedback devices enhance CPR training outcomes and warrant further investigation for clinical use, online CPR-AED training aims to improve survival outcomes, timely AHUP deployment correlates with higher ROSC rates, LUCAS device use may decrease survival rates in OHCA patients, and optimized mechanical chest compression device use can improve survival rates and should be integrated into high-performance CPR strategies. The literature review highlights the efficacy of real-time feedback devices in CPR training, the potential of online CPR-AED training to enhance survival outcomes, and the impact of AHUP deployment on ROSC rates. Additionally, it underscores concerns regarding the use of the LUCAS device in OHCA patients and advocates for the integration of mechanical chest compression devices in high-performance CPR strategies. Further research is needed to address limitations and explore the clinical implementation of these findings.

C. IoMT in Healthcare

IoMT technologies hold promise for revolutionizing healthcare delivery, yet face challenges in interoperability and data security [16]. Integrating ML, AI, 5G, and IoT aims to overcome these hurdles, with ongoing research focusing on enhancing IoMT applications for disease diagnosis and patient-centric healthcare. The IoMT-HHPC model proposes a two-phase approach for heart disease categorization and forecasting, achieving 99.02% accuracy using ANN [17]. This model presents a potential avenue for real-time cardiac health tracking and prediction. Healthcare 4.0, enabled by 5G, AI, and IoT, emphasizes precision medicine and telemedicine for early disease detection and personalized healthcare [18]. Key technologies like AI and distributed edge computing optimize Healthcare 4.0 systems in the era of next-generation networks. IoMT plays a critical role in combating the COVID-19 pandemic by facilitating early diagnosis, prevention, and treatment [19]. While IoMT adoption addresses challenges in healthcare delivery, scalability, data privacy, and security remain significant hurdles. IoT has the potential to enhance healthcare management systems and patient care through rapid diagnostics and remote monitoring [20]. Future research directions include stroke and epileptic seizure prediction, emphasizing the importance of addressing privacy concerns and optimizing data utilization for successful integration into healthcare systems.

D. Machine Learning in Healthcare

Predicting heart disease development is the focus of [21], which employs Machine Learning (ML) algorithms to construct predictive models. The study introduces a methodology utilizing a Logistic Regression Classifier, achieving an accuracy of 88.16%, highlighting the potential of ML in cardiovascular disease prediction and management. [22] integrates ML algorithms into e-healthcare systems for heart disease identification and diagnosis, emphasizing the transformative impact of ML in preventive healthcare. It develops a predictive model with interpretable results, showcasing superiority over traditional diagnostic methods. [23] explores ML's application in predicting heart diseases globally, emphasizing efficient healthcare data utilization and suggesting future directions for predictive modeling. Utilizing the PyCaret library, [24] constructs predictive models for diagnosing diabetes mellitus, underscoring the effectiveness of light gradient-boosting machine classifiers. Lastly, [25] proposes a CAD risk prediction model using a Recurrent Convolutional Neural Network (RCNN) for heart disease diagnosis, achieving high accuracy and emphasizing the importance of integrating AI and data mining. Overall, these studies highlight the potential of ML in improving cardiovascular disease diagnosis and treatment, showcasing the transformative impact of automated machine learning in healthcare analytics.

E. Integration of IoMT and ML

The literature review explores the intersection of healthcare and technology, focusing on the integration of Artificial Intelligence (AI) and the Internet of Medical Things (IoMT) to enhance clinical decision-making and disease forecasting. Various studies introduce innovative approaches such as a novel coronary artery disease forecast model blending IoMT and AI to improve heart disease prediction accuracy [26], and investigate the application of computational intelligence techniques, including machine learning, for predicting heart diseases based on IoMT data [28]. Additionally, research examines the potential of IoMT technology in enabling smart healthcare delivery through sensor integration and machine learning algorithms [29]. Furthermore, a two-stage medical data classification and prediction model utilizing IoMT achieves high accuracy in diagnosing heart disease, highlighting the effectiveness of hybrid techniques and advanced algorithms in healthcare analytics [30]. Overall, the literature underscores the transformative potential of integrating AI and IoMT in healthcare systems, offering insights into personalized risk assessments, rapid diagnostics, and improved patient outcomes.

F. Summary of Methods for IoMT

The Internet of Medical Things (IoMT) plays a crucial role in revolutionizing cardiopulmonary resuscitation (CPR) by enabling real-time data exchange among CPR devices. The section on CPR methodologies through IoMT-enabled real-time adaptive feedback provides a comprehensive overview, detailing the uses, advantages, disadvantages, and implementation challenges of manual CPR, AEDs, mechanical CPR, and IoMT-enabled CPR. IoMT facilitates seamless communication and data exchange among CPR devices, allowing for real-time data acquisition, remote monitoring, and interoperability across healthcare settings. This technology enables the integration of wearable sensors, defibrillators with built-in connectivity, and cloud-based platforms for data storage and analysis.

Additionally, IoMT enhances the coordination of CPR efforts by providing synchronized feedback and alerts to healthcare professionals, ensuring timely intervention and improved patient outcomes.

Table 1. summarizes the different methodologies for CPR through IoMT-enabled real-time adaptive feedback, outlining their respective uses, advantages, disadvantages, and challenges in implementation.

Table 1. Overview of CPR Methodologies

Methodology	**Uses**	**Advantages**	**Disadvantages**	**Challenges in Implementation**
Manual CPR ([31], [32])	Initial response in emergencies	Widely available, low cost	Dependent on rescuer proficiency	Training, fatigue management
AEDs ([33],[34])	Automated rhythm analysis	Immediate defibrillation, user-friendly	Limited feedback on CPR quality	Accessibility, Maintenance
Mechanical CPR ([35],[36])	Standardized compressions	Consistent compression depth/rate	Limited adaptability	Device size, compatibility
IoMT-Enabled CPR [37][38][39]	Real-time data acquisition	Remote monitoring, interoperability	Enhanced feedback, adaptability	Interoperability, data security
Feedback-Assisted CPR [40] [41]	Real-time feedback during compressions	Improved compression quality, reduced rescuer fatigue	Requires specialized equipment	Integration with existing CPR protocols

Telemedicine CPR [42][43]	Remote guidance by healthcare professionals	Expert assistance during CPR procedures	Limited physical presence	Connectivity and latency issues
Automated Compression Devices [44][45]	Mechanized chest compressions	Consistent compression depth and rate	Limited adaptability to patient anatomy	Maintenance and cost of devices
Computer-Aided CPR [46][47]	CPR performance assessment and optimization	Real-time feedback and performance metrics	Dependency on accurate sensor data	Integration with existing CPR protocols

Table 2. provides a comparative analysis of different CPR methods facilitated by IoMT-enabled real-time adaptive feedback. It outlines key metrics such as rescuer proficiency, compression depth/rate, and real-time feedback, along with the respective advantages and disadvantages of each method. From manual CPR to computer-aided CPR, this overview offers insights into the strengths and limitations of various approaches in enhancing cardiopulmonary resuscitation. It offers a comprehensive examination of CPR methodologies augmented by IoMT-driven real-time adaptive feedback, illuminating their efficacy in improving resuscitation outcomes and guiding clinical decision-making in emergency scenarios.

Table 2. Comparison of CPR Methods Through IoMT-Enabled Real-Time Adaptive Feedback

Method	Key Metrics	Advantages	Disadvantages
Manual CPR	Rescuer proficiency, fatigue management	Widely available, low cost, immediate response	Dependent on rescuer skill, fatigue
AEDs	Rhythm analysis, defibrillation speed	User-friendly, immediate defibrillation	Limited feedback on CPR quality

Mechanical CPR	Compression depth/rate, adaptability	Consistent compressions, less rescuer fatigue	Limited adaptability to patient anatomy
IoMT-Enabled CPR	Real-time feedback, adaptability	Remote monitoring, interoperability	Data security, interoperability challenges
Feedback-Assisted CPR	Compression quality, rescuer fatigue	Improved compression quality, reduced fatigue	Requires specialized equipment
Telemedicine CPR	Remote guidance, expert assistance	Expert guidance, and flexibility in remote settings	Connectivity, and latency issues
Automated CPR Devices	Consistency, speed of response	Standardized compressions, immediate response	Limited adaptability to patient anatomy
Computer-Aided CPR	Performance metrics, real-time feedback	Optimization of CPR performance, detailed analysis	Dependency on accurate sensor data

Table 3. Comparison of Machine Learning (ML) and Internet of Medical Things (IoMT) in CPR Rescue Devices

Attribute	**Machine Learning (ML) [48] [49] [50]**	**Internet of Medical Things (IoMT) [51] [52] [53]**
Data Requirements	ML algorithms require large amounts of labeled data for training, including physiological data from CPR scenarios such as ECG, respiration rate, and chest compression depth.	IoMT devices collect real-time physiological data during CPR, including ECG signals, chest compression depth, and patient vital signs.
Algorithm Complexity	ML models for CPR may include complex algorithms such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) for signal processing and pattern recognition.	IoMT devices may employ simpler algorithms like signal filtering, feature extraction, and basic pattern recognition to process physiological data in real time.

Real-time Processing	ML models may require offline processing due to computational complexity, limiting real-time decision-making during CPR. Real-time ML applications may utilize edge computing for faster inference.	IoMT devices perform real-time processing of physiological data locally or in the cloud, enabling immediate feedback and decision support during CPR.
Adaptability	ML models can adapt to changing CPR scenarios and patient conditions through continuous learning from new data, improving performance over time.	IoMT devices may feature adaptive algorithms that adjust parameters based on patient-specific factors and feedback from healthcare providers.
Integration with Devices	ML models can be integrated into existing CPR devices or healthcare systems for automated decision-making, alerting, and feedback generation.	IoMT devices are connected to CPR equipment and other medical devices through wired or wireless interfaces, enabling seamless data exchange and interoperability.
Robustness	ML models may suffer from performance degradation or failure when faced with data outside their training distribution or under adverse conditions (e.g., noisy environments, and sensor failures).	IoMT devices are designed to withstand environmental challenges and ensure reliable operation during CPR emergencies, with built-in redundancy and fault-tolerance mechanisms.
Security	ML models may be vulnerable to adversarial attacks or data privacy breaches, requiring robust security measures for data encryption, access control, and model validation.	IoMT devices must adhere to strict security standards to protect patient data and ensure HIPAA compliance, with encryption, authentication, and audit trail features implemented at the device and network levels.
Scalability	ML models can scale horizontally by deploying multiple instances across distributed computing resources for parallel processing of CPR data from multiple patients or healthcare facilities.	IoMT devices can scale vertically by adding more sensors, memory, or processing capabilities to handle increasing data volume and complexity in CPR rescue operations.

Cost	ML development and deployment costs may vary depending on the complexity of algorithms, availability of labeled data, and computational resources required for training and inference.	IoMT device costs include hardware components, connectivity infrastructure, software development, regulatory compliance, and ongoing maintenance and support, with upfront and recurring expenses over the device lifecycle.

G. Major Findings from the Literature

1. Poor adherence to CPR guidelines is identified in Belgian EMS systems, influenced by provider qualifications and patient outcomes ([7]).
2. The transition from ABC to CAB sequence in CPR guidelines is supported by evidence from systematic reviews and an RCT, emphasizing CAB's efficacy ([8]).
3. Early defibrillation and uninterrupted compressions are highlighted as crucial interventions for adults with sudden cardiac death ([9]).
4. BLS training and longer professional experience correlate with higher CPR knowledge levels among general practitioners, despite low possession of AEDs in clinics ([10]).
5. Feedback devices enhance CPR training outcomes and warrant further investigation for clinical use ([11]).
6. Online CPR-AED training aims to improve survival outcomes ([12]).
7. Timely AHUP deployment correlates with higher ROSC rates, while LUCAS device use may decrease survival rates in OHCA patients ([13], [14]).
8. Optimized mechanical chest compression device use can improve survival rates and should be integrated into high-performance CPR strategies ([15]).
9. IoMT technologies hold promise for revolutionizing healthcare delivery, yet face challenges in interoperability and data security ([16]).

10. The integration of AI and IoMT in healthcare systems offers insights into personalized risk assessments, rapid diagnostics, and improved patient outcomes ([17], [18], [19], [20]).

H. Research Gaps

1. Further investigation is needed into the factors influencing adherence to CPR guidelines and the effectiveness of training programs ([7], [10]).

2. The impact assessment of advanced CPR devices, such as the LUCAS device, on long-term survival outcomes requires more research ([14]).

3. Addressing interoperability and data security concerns is crucial for the widespread adoption of IoMT technologies in healthcare ([16]).

4. Additional research is needed to explore the application of IoMT and ML techniques in predicting heart diseases and other healthcare domains ([26], [28], [30]).

5. Scalability issues and the optimization of data utilization remain significant challenges in IoMT adoption for healthcare integration ([16], [20]).

6. Studies focusing on stroke and epileptic seizure prediction using IoMT technologies could provide valuable insights into early disease detection ([20]).

7. Further validation of ML algorithms for predictive modeling in heart disease is required for their successful integration into clinical practice ([21], [22], [23], [24], [25]).

8. Investigating the potential negative effects of advanced CPR devices, such as the LUCAS device, on survival rates in OHCA patients is essential for informed decision-making ([14]).

9. Research on the integration of AI and IoMT for smart healthcare delivery could lead to more efficient disease forecasting and personalized treatment strategies ([26], [29]).

10. Exploration of hybrid techniques and advanced algorithms in healthcare analytics is necessary for optimizing the effectiveness of IoMT-enabled CPR and other medical interventions ([30]).

3. Conclusion and Future Scope

The following conclusions can be drawn from the above study:

1. **Integration of Technology in CPR Enhancement:** The research highlights the significant impact of integrating the Internet of Things (IoT), Machine Learning (ML), and other technological advancements in enhancing cardiopulmonary resuscitation (CPR) outcomes. From real-time feedback devices to automated CPR devices, technology plays a pivotal role in improving CPR training, deployment, and outcomes**.**

2. **Challenges and Opportunities in Healthcare Technology:** While IoT and ML offer promising solutions for healthcare delivery, challenges such as interoperability, data security, and device compatibility need to be addressed. However, these challenges present opportunities for further research and innovation in developing robust and scalable healthcare technologies.

3. **Personalized Healthcare and Disease Prediction:** The integration of AI and IoT enables personalized risk assessments, rapid diagnostics, and disease forecasting, leading to improved patient outcomes. Future research should focus on refining predictive models for heart disease and exploring applications in other healthcare domains, such as stroke and epileptic seizure prediction**.**

4. **Optimizing CPR Strategies for Better Patient Outcomes:** The study emphasizes the importance of optimizing CPR strategies by leveraging advanced technologies and evidence-based guidelines. Future directions include validating ML algorithms for predictive modeling, addressing the negative effects of advanced CPR devices on survival rates, and exploring hybrid techniques for enhancing healthcare analytics

5. **Future Scope:** This includes the evaluation of the long-term impact of advanced CPR devices like LUCAS on OHCA survival; Refining the ML algorithms for enhanced healthcare analytics and personalized treatment; Exploring the smart healthcare delivery through AI and IoT for real-time monitoring and disease

forecasting; Addressing the interoperability and data security challenges for widespread IoT adoption in healthcare with standardized protocols and robust cybersecurity measures.

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