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Exploring the impact of artificial intelligence driven solutions on early detection of cardiac arrest

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ABSTRACT

The advancement of medical science and technology has yet not evolved up with a concrete solution towards early detection of cardiac arrest from practical deployment. It is noted that artificial intelligence (AI) has been proving a potential contributor to address this state of diagnosis emergency. In current era of research work, there has been various implementation model and review work has been carried out towards advocating AI for determining early onset of cardiac arrest; however, there are various contradiction and shortcoming which is quite challenging to be extracted. Hence, the current manuscript presents a review of existing methodology by presenting core taxonomies of recent AI-methods towards early detection of cardiac arrest. Various standard dataset has been studied too to find associated advantages and limitation that restrict the actual potential of AI to prediction. The outcome presents novel highlights of research gap, trade-off, and crisp highlights of effectiveness of existing AI approaches as a study contribution.

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1. INTRODUCTION

This study pertains to a severe medical emergency known as cardiac arrest leading to stoppage of circulation of blood in human body. It can be determined by various standard symptoms viz. severe pain in chest, no breathing, no pulse, sudden loss of consciousness. The standard treatment exercised are advanced cardiac life support system, defibrillation, and cardiopulmonary resuscitation (CPR). However, it is very rare case to observe success rate of early prediction method in medical science as it demands dominantly proactive measures. Artificial intelligence (AI), which is capable of solving complex real world problem, has significant contribution towards various predictive and sophisticated analysis in critical diseases [1]. In perspective of cardiac arrest, electrocardiograph data (ECG) can be monitored by AI to determine the abnormalities in heart rate as an indicators towards arrhythmias. Various types of wearable devices using AI can be also deployed towards tracking various direct or indirect indicators or vital signal in real time for continuous monitoring. The sole intention is to trace any form of early warning sign. AI in form of machine learning, deep learning, natural language processing (NLP) can be significantly used for analyzing biosignals for predicting the state of criticality of patient along with proper classification [2]. When a patient is admitted to hospital, AI-based monitoring tools can be used for real-time tracking of all the trends of vital signal for speeding up the process of early detection. Apart from ECG data, various other form of input data e.g. radiological scan data can be also used towards investigating internal problems within heart for determining any form of cardiovascular issues. Adoption of AI algorithm suits well especially in the case of large dataset towards constructing a risk assessment model based on imaging studies, laboratory results, vital signals and medical history.

Various related work has been carried out in this regard to understand the existing contribution of AI in early detection of cardiac arrest. The work carried out by Alamgir *et al.* [3] have discussed various approaches of AI where machine learning approaches played a dominant role in prediction of cardiac arrest. The study by Almansouri *et al.* [4] inferred better detection performance could be done by combining AI with image analysis and yet it demands more validation, which is currently missing in existing studies. Sun *et al*. [5] advocated various scope of AI towards diagnosing cardio vascular diseases (CVD); however, authors stated impending shortcomings of AI technology to be overcomed. Holmstrom *et al.* [6] have presented a framework of AI towards evaluating threat of cardiac arrest where the authors have used deep learning method.

Various problems and challenges have been encountered while reviewing existing AI-based literatures which are as follows: i) existing AI models have been implemented on limited labeled data which affects the decision making, ii) a perfect diagnostic approach towards early onset of cardiac arrest demands its system to be both real-time and perform continuous monitoring; however, there is a significant trade-off between them, iii) existing AI-based solution towards adaptability and generalization is sub-optimally accomplished owing to non-inclusion of patient variability and environmental factor. Apart from this, existing review work doesn't offer clear insight of core taxonomies of recent approaches while not much comparative discussion is carried out towards the issues pertaining to its dataset.

Therefore, the goal of the proposed study is to present a compact and point-to-point discussion of current state of AI based methods towards early onset of cardiac arrest. The value-added contribution are as follows: i) the study has reviewed and presented core taxonomy of AI-based approaches towards detecting cardiac arrest, ii) reviewed methods have been presented with respect to their effectiveness and limitations, iii) Various dataset adopted towards current form of investigation has been presented with all their specification and issues as well, iv) a crisp discussion of research gap and trade-off has been presented to understand the current stance of existing AI methodologies.

2. METHOD

A desk research methodology has been used for this purpose where manuscripts pertaining to detection of cardiac arrest using varied AI methodology has been collected. Figure 1 shows that initially abstract screening has been performed towards primary filtering which also carry out identification of issues. Presence of any duplicated study has been eliminated followed by performing secondary filtering which consists of in depth study of actual experimental details given in the filtered manuscript with respect to adopted research method and accomplished study outcome. Inclusion criteria used are only AI based journals published between 2020-2024 while exclusion criteria is any conference papers or papers without detailed information of adopted methods, dataset, or results. The outcome of adopting this method is extracted research gap and trade-off that assists in understanding the effectiveness of existing AI-models.

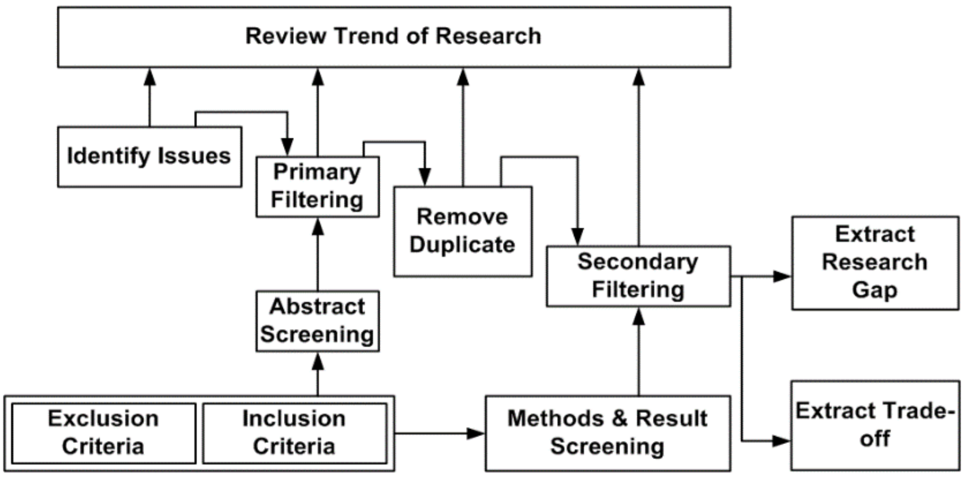

Figure 1. Adopted methodology

3. RESULTS AND DISCUSSION

There are various types of AI schemes targeting towards early diagnosis of cardiac arrest. All these reviewed approaches uses its input from various sources, which is transformed to digitized state followed by applying different forms of machine learning approaches (as shown in Table 1). Irrespective of different methodologies, the agenda of these AI approaches remains same which is to determine the early onset of cardiac arrest. Following are the taxonomies of the reviewed AI-based approaches reportedly used for identifying early detection of cardiac arrest:

a) Analysis of electrocardiogram (ECG) signal: researchers have implemented deep neural networks (DNNs) and convolutional neural networks (CNNs) to classify ECG signals in real-time (Krasteva *et al*. [7], Ahmed *et al*. [8], Deng *et al*. [9]). Machine learning models can see patterns in ECG data that denote when a patient may go into cardiac arrest. These models are trained to detect subtle arrhythmias and other precursors to a cardiac arrest. Long short-term memory (LSTM) networks has also been extensively used in this regards especially for time-series ECG data analysis (Zacarias *et al*. [10]). These networks are adept at learning from sequential data and can learn to predict when a cardiac event will happen by recognizing time-dependent patterns that precede an arrest.

b) Wearable device based approaches: devices like smartwatches or chest straps that are powered by AI have sensors that track heart rate, rhythm, and other vital signs in real time (Alimbayeva *et al*. [11], Chowdhury *et al*. [12]). On some occasions these devices utilize AI algorithms to detect possible early signs of cardiac arrest or severe arrhythmias and warn medical health care teams or caregivers. These wearables are empowering real-time monitoring of heart health, potentially leading to earlier interventions that can stop a heart from going into full cardiac arrest.

c) Predictive modelling approach: based on large datasets, researchers are using machine learning models to predict the risk of cardiac arrest (Nguyen and Byeon [13], Yu *et al*. [14], Ogunpola *et al*. [15]). These models can assess the risk for an oncoming heart attack by examining several data points about several patients (demographic data, medical history, ECG data, and blood pressure). Similarly, it can be trained on previous case data to highlight underlying patterns that may serve as early indicators of a potential cardiac event.

d) Joint operation of signal and data processing: AI with higher signal processing techniques also helps to enhance the quality and accuracy of the data obtained from ECG, photoplethysmogram (PPG), and other sensors (Beh *et al*. [16], Pinto *et al*. [17]). AI models take signals and enhance a signal by filtering noise to increase the detection of critical findings that suggest a cardiac arrest event in the making.

e) Multi-media analytical approach: some studies specifically examine the potential of AI in analyzing videos, using computer vision methods to monitor visual indicators of cardiac arrest and such as loss of consciousness, unusual posture or lack of movement (Premkumar *et al*.,[18], Decoodt *et al*. [19], Li *et al*. [20]).

f) Decision support system-based approaches: various types of medical devices e.g., monitoring system and defibrillators are integrated with AI for catering up the proactive diagnostic demands during emergency event (Javeed *et al*. [21], Lee *et al*. [22]). Such types of integrated system is used for assisting resuscitation, forecasting event of cardiac arrest, and scrutinize patient’s information.

g) Early warning system: there are various types of data-driven approaches using AI for developing early warning system for predicting cardiac arrest (Chae *et al*. [23], Elvas *et al*. [24]). Such system performs its prediction computed from multiple input sources obtained from patient’s data, monitoring devices, hospital and medical records. The outcome assists in timely intervention.

Table 1. Summary of AI approaches in reviewed literatures

AI approaches	Advantages	Limitation
Analysis of ECG signal	Increased accuracy, automated diagnosis, supports real-time analysis	Complex model interpretability, higher dependence on data quality
Wearable device based approaches	Non-invasive, continuous monitoring	Restricted detection in critical event, has accuracy fluctuation
Predictive modelling approach	Enhances preventive care, highly customizable, enhanced risk assessment	Higher bias possibilities, highly dependent on historical data
Joint operation of signal and data processing	Improved overall accuracy, comprehensive monitoring	Sensor compatibility, increased computational complexity
Multi-media analytical approach	Identification of visible symptoms, non-intrusive screening	Could miss essential information
Decision support system-based approaches	Enhances clinical outcomes, helpful during critical moments	Higher dependency towards data quality, poor clinical acceptance
Early warning system	Proactive intervention, holistic monitoring	Implementation complexity, outliers

3.1. Trends on dataset

There are various types of dataset adopted in existing study which are mainly in waveform database (WFDB) or in comma separated value (CSV) format. Majority of the dataset is constructed based on ECG signals considering varied form of specifications (spec) as exhibited in Table 2. While some dataset assists towards indirect diagnosis of cardiac arrest while some are meant for direct determination of cardiac arrest. Apart from the limiting factors associated with existing dataset, one notable fact is that they are quite imbalanced and not all dataset has magnified size of information that is essential for sophisticated AI algorithms.

Table 2. Trends on adopted dataset for cardiac arrest

Dataset	Specification	Advantages	Limitation
Physionet 2017/2020 [25]	Size: 1000-10000 EGS signals Format: WFDB, CSV Spec: blood pressure, pulse oximeter and respiratory rate..	Open access, large scale, real-world data, comprehensive	Limited labelling, imbalanced classes, variation in data quality
MIT-BIH Arrhythmia [26]	Size: 48 records for two-channel ECG signals Format: WFDB, CSV Spec: different types of arrhythmia	Widely used, high-quality data	No vital signs, short duration, restricted to arrythmia only
The Framingham Heart Study [27]	Size: 5000 records with 100 attributes Format: CSV, Spec: demographic data, cholesterol, diabetes and physical activity.	Longitudinal data, widely adopted, assists broader context analysis	Lacks any specific labels for cardiac arrest
The Cleveland Heart Disease dataset [28]	Size: 303 records with 14 parameters Format: CSV Spec: common features (type of chest pain, maximum heart rate, and blood pressure)	Supports binary classification, compact dataset size, includes diverse features	Limited to binary classification, doesn't possess temporal data, restricted data points
Shenzhen Hospital Data [29]	Size: 10,000+ records Format: raw signal, CSV Spec: medication, lab result, common data (heart rate, blood pressure, respiratory rate, pulse oximetry and ECG))	Large sized data, multimodal data, assists in real-time analysis	Incomplete labelling, increased data complexity, access restriction
TROIKA dataset [30]	Size: 8 subjects with 16 hours ECG recording Format: time-series, CSV Spec: arrhythmias, signals from wearbles	Supports detection of ambulatory cardiac arrest, supports classification of arrhythmia	Short data length, less data variability, limited scope due to few subjects
AHA (American Heart Association) Heart disease dataset [31]	Size: 1000-10000 records Format: CSV Spec: classification of risk of heart disease, family history, gender, age, cholesterol	Efficient for risk assessment, widely available, enriched clinical data	Restricted temporal data, doesn't explicitely focus on cardiac arrest
PTB Diagnostic ECG database [32]	Size: 549 records Format: WFDB Spec: arrythmia, myocardial infaction	Realistic data, diverse condition of cardiac arrest, high quality 12-lead ECG data	Smaller size, doesn't focus on early detection, ECG with only minutes of recording
ECG-ID [33]	Size: 90 subjects Format: WFDB Spec: labelled identifier of subject, 12-lead ECG data	Ideal for research, subject identification, high quality data	Lacks temporal data, data from 90 subjects only, focused on subject identification and not cardiac arrest

3.2. Identified research gap

After reviewing the existing AI-based approaches, it is noted that there is a fair possibilities towards framing up early detection of cardiac arrest; however, there are certain prime research gap that demands to be addressed. The prime origination of the gap is related to the dataset itself while the secondary origination of gap relates to the complexities associated with the conventional AI approaches. All these gaps, when addressed, is anticipated to yield a robust and efficient solution towards early cardiac arrest. The prime research gaps identified are as follows:

a) Few availability of labelled data: from perspective of deep learning in AI, higher volumes of well-labelled data. In absence of labelled data, the generalization of the model is challenging to be ensured as well as complexity associated with situation of cardiac arrest cannot be effectively represented.

- Opportunity: there is a demand of collaboration among AI laboratories, research institution, and clinical settings towards accomplishing common goal of standardized and labelled dataset.

b) More biased and imbalance dataset: almost majority of dataset explored suffers from imbalance data with a possession of more event of normal heart condition and much less event of cardiac arrest. This eventually results in biasing and sub-optimal predictive performance of AI models owing to lack of inclusion of rare or underrated cases.
   - Opportunity: one possible way to minimize this gap is towards using class re-weighting as well as generation of synthetic data. More studies towards diversification of dataset demands to be carried out towards enhancing generalization ability.

c) Lacks practical supporting of consistent monitoring: for a model of cardiac arrest detection to be accurate, it is necessary to perform decision making while carrying out real-time monitoring in parallel. Unfortunately, majority of AI frameworks are created to perform post hoc analysis which doesn't serve the demands of realistic detection. Owing to inclusion of sophisticated operation, AI models induce latency, may be small, but not enough to cater up for emergency situation reliably.
   - Opportunity: one feasible way to address this gap is to construct a novel machine learning model with discrete characteristics supporting low latency monitoring consistently on real-time. Another feasibility is towards adopting streaming analytics and edge computing for low latency operations for consistent monitoring.

d) Integration of multimodal data: one interesting observation in the review shows that adoption of multimodal could potentially optimize the detection performance of cardiac arrest. For this purpose, various attributes viz. clinical notes, patient history dan respiration rate should be considered while modelling. Although, all these information resides within some of the standard dataset, existing AI solution is yet found to emphases only towards ECG as single signal modalities. This biased adoption restricts the detection performance contextually.
   - Opportunity: studies towards adopting various modalities should be encouraged.

e) Lacks integration with clinical workflows: for an optimal and reliable analysis, it is necessary for an AI model to be clinically integrated with workflow of hospital. For an example, an AI model can be possibly integrated with clinical tools, electronic health records, and other form of notification system. No such model is yet witnessed which eventually results in delayed action or possible missed warning.
   - Opportunity: if not such integration is feasible for short-time research work, there is still higher hopes considered wider and diverse set of dataset with an inclusion of modules to replicate the real-time scenario even in simulation mode. Such study patterns can take the AI model more applicable for better chances of clinical integration.

3.3. Identified research trade-off

From the discussion of identified research gap in prior sub-section 3.2, it is noted that there are still better opportunity towards improvising the shortcomings. However, such opportunity towards designing a solution should also address various trade-off, which is actually more challenging. The prime origination of such trade-off mainly arises from the legacy issues of AI itself along with severe degree of sophistication demanded for a true detection of cardiac arrest. Following are some of the critical trade-off:

- Prediction and monitoring: prediction on real-time emphasizes on identifying critical events following by generating notifications in critical circumstances. However, monitoring over long-term is more associated with collecting sequential data followed by trend analysis essential for predicting risk in future. Hence, AI models towards instantaneous prediction can miss identifying the risk attributes that can be actually captured using long-term monitoring approaches, while the latter is also associated with large resource consumption.
- Generalization and specialization: any explicit model focusing on specialization can offer increased detection rate; however, their applicability is questionable when subjected to different clinical settings. On the other side, the model claiming for generalization, when subjected to specific case may under perform.
- Performance in real-time and accuracy: the AI models emphasizing on real-time performance demands a low-latency system while AI model focusing to accomplish higher accuracy focusses on complexities and patterns of data which eventually takes more computational resources and time. Hence, AI-models with higher accuracy could be eventually slower while model focusing on real-time performance can actually miss out critical information necessary for detecting early onset of cardiac arrest.

All the above-mentioned trade-off equally demands an importance to be addressed. A better modelling by joint consideration of trade-off and gaps could lead to efficient AI model towards early detection problem.

This review emphasized the wide spectrum of AI-based techniques being investigated for the early diagnosis of cardiac arrest. A crucial finding is that, while great progress has been achieved in developing AI solutions, the field is still in its early phases of real-world implementation. AI approaches, such as deep learning models like CNNs and LSTMs, wearable device-based monitoring, and predictive modeling, have demonstrated promise in detecting early indicators of cardiac arrest. However, obstacles remain, particularly in terms of dataset constraints, model generalization, real-time monitoring capabilities, and connection with clinical operations. Furthermore, despite advances in AI, an ongoing difficulty in most techniques is the imbalanced and frequently poorly labeled datasets, which limit AI models' capacity to effectively generalize across varied clinical situations. Furthermore, low-latency models that can operate in real-time emergency circumstances are becoming increasingly important for prompt intervention.

Compared to earlier studies in this sector, this review contributes to a better knowledge of the obstacles and potential advancements in AI-driven cardiac arrest detection. While previous evaluations focused on the particular application of AI approaches, this study takes a more in-depth look at the integration of varied datasets, taxonomies of AI techniques, and the trade-offs between real-time performance and model correctness. Recognizing specific gaps, such as the need for labeled data, multimodal integration, and clinical workflow integration, this analysis presents new ideas and direction that are consistent with the current status of the field. Previous research has primarily demonstrated the potential of AI in detecting arrhythmias and predicting cardiac events from ECG data, but this study focuses on the broader scope of multimodal and wearable device-based approaches, which are becoming more viable in the field of cardiac health monitoring. The findings of this analysis highlight the complex interplay between data quality, real-time requirements, and clinical acceptance, which has not been adequately addressed in previous publications.

4. CONCLUSION

To summarize, while AI-driven technologies for early identification of cardiac arrest hold significant promise, overcoming difficulties such as data quality, model interpretability, real-time monitoring, and clinical integration is critical to realizing their full potential. Addressing these shortcomings through new research will improve the accuracy and dependability of AI models while also paving the path for more effective and prompt treatments in urgent cardiac care. The future of AI in cardiac arrest detection depends on constant collaboration among researchers, healthcare professionals, and physicians to develop solid, practical, and ethical solutions that can save lives. At present, there are various degrees of study models harnessing AI towards detection of cardiac arrest using different types of data. It has been noted that there are various scales of innovative approaches evolved from machine and deep learning approaches mainly in this perspective; however, there are also shortcomings which is necessary to be addressed. The contribution and novelty of this review work are as follows: i) the study presents a very crisp discussion on newly identified taxonomy of AI-based methods towards detection of cardiac arrest to find associated benefits and unsolved issues, ii) different from existing review work, the current paper has presented discussion of dataset along with their limitation to assist future researchers choosing the necessary dataset for their study, iii) highlights of research gap with possible opportunity has been stated, and iv) point-to-point briefing of identified core trade-off has been presented which are essential to be addressed in upcoming studies. The future work will be towards addressing the problems identified in current review work using newly constructed models of machine learning along with flexible constraint modelling. More importance will be given to select prominent attributes under dynamic environment to select most dominant indicator towards early detection of cardiac arrest.

Looking ahead, there are various intriguing study topics. First, the issue of dataset imbalance can be addressed using approaches such as synthetic data generation and advanced data augmentation algorithms, which help to balance the prevalence of cardiac arrest cases with normal heart condition data. Another way to improve prediction accuracy is to integrate multimodal data sources, such as ECG, patient history, vital signs, and even video analysis. Research efforts should also be directed on developing AI models with lower latency for real-time detection and intervention, as well as investigating edge computing for more efficient data processing. In addition, AI solutions must be effectively integrated into healthcare operations. This involves seamless integration with electronic health records (EHRs) and other monitoring systems to enable real-time decision-making and help physicians provide prompt interventions. Future study could look into the ethical implications of AI in healthcare, specifically data privacy, model openness, and the acceptability of AI-generated suggestions in clinical contexts.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author.

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