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Review Article

From Traditional to Modern: A Narrative Review of AI-Based Approaches of Cardiac Arrhythmia Diagnosis

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ABSTRACT

Cardiac arrhythmia is one of the leading causes of morbidity and mortality in the general population, and thus, early detection of arrhythmia is critical for improving patient outcomes. While the 12-lead ECG was traditionally used as the primary diagnostic tool for arrhythmia, its manual interpretation can be challenging, even for experienced cardiologists. However, with the growing understanding of cardiac arrhythmia, artificial intelligence (AI) algorithms have been developed to analyze ECGs to identify abnormalities and predict the risk of developing arrhythmia. AI can be used for real-time ECG monitoring through wearable devices to alert patients or healthcare providers if an arrhythmia is detected. It has the potential to decrease reliance on cardiologists, shorten hospital stays, and assist patients in rural hospitals with limited access to medical professionals. Although AI is known for its ability to accurately interpret large amounts of data quickly, there are concerns about its use in the medical field. Considering the crucial differences between AI and humans, we discuss the strengths and limitations of using AI to diagnose cardiac arrhythmias.

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INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of mortality in the United States and globally, and is a significant contributor to increased healthcare expenditure.[1,2] Cardiac arrhythmias are defined as irregularities in the heart rate or rhythm and affect around 1.5 to 5 % of the general population worldwide, and their prevalence varies depending on age, gender, lifestyle factors, and other comorbid conditions.[3] Atrial fibrillation (AF), atrial flutter, ventricular fibrillation, ventricular tachycardia, and supraventricular tachycardia (SVT) are

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a few types of cardiac arrhythmias with atrial fibrillation being the most common arrhythmia, affecting around 46 million people globally, three to six million people in the United States, and is the primary diagnosis in more than 454,000 hospital admissions annually.[4,5] Ventricular tachycardia and fibrillation are common causes of sudden cardiac deaths accounting for almost 300,000 deaths in the United States alone.[6] Alan Turning first described the potential use of machines for solving critical problems, and John McCarthy coined and described the term AI in 1956.[7] AI is a broad term that comes under the umbrella of data/computer science. It is an idea of mimicking human behavior by machines. Machine learning (ML) is a subset of AI that explores the fact that machines can learn, adapt, and predict outcomes using structured data, whereas deep learning (DL) is a type of ML that works and makes decisions like the human brain.[8] In the 1960s, the National Library of Medicine (NLM) developed MEDLARS (Medical Literature Analysis and Retrieval System), a groundbreaking precursor to MEDLINE that ultimately led to the creation of PubMed. This innovation was pivotal in advancing how medical literature is accessed and retrieved[9] The initial systems, which displayed the use of AI in medicine, were developed from the 1970s to 1990s, such as CASNET for glaucoma consultation by Rutgers University; MYCIN, which provided a list of potential bacterial pathogens infecting patients and appropriate antibiotics treatment, and DXplain, created by the University of Massachusetts provided differential diagnosis by using different patient information variables.[10] Since then, AI has developed a lot and is now considered one of the greatest allies of doctors in treating patients. The currently available online risk assessment tools like the American Heart Association/ American College of Cardiology (Modified ASCVD score), QRISK, and Reynolds risk score[11] mostly use variables like smoking, hypertension, diabetes, alcohol consumption, and other known factors which are associated with CVD but fail to take into account more complex causal factors which fail to identify more patient population.[12] These tools also heavily rely on the treating physician's experience, knowledge, and judgment. Although a very advanced data processing system that can interpret data and make complex decisions, the human brain has its limits. With increasing amounts of data and information, we need something that can absorb, perceive, analyze, and interpret data. AI, ML, and DL are the key to unlocking and exploiting this extensive and meaningful patient data.[13] The digitalization of health records has paved the way for AI[14], and it is now being integrated with clinical practice to read cardiac imaging like echocardiography and cardiac MRI, and ECGs, speeding up the process while augmenting the physician's ability.[7] The algorithms can be trained to analyze ECG data and detect patterns indicative of arrhythmias and can quickly process large amounts of data and identify subtle abnormalities that might be difficult for human analysts to detect. In addition, AI algorithms are shown to detect more cases of atrial fibrillation versus the usual care in both high-risk (10.6% vs 3.6%) and low-risk patients (2.4% vs 0.9%).[15]

AI has certainly revolutionized the field of medicine and beyond, but it has its own disadvantages that cannot be overlooked. Although AI systems are capable of producing highly accurate results, their reliability is inherently dependent on the quality and completeness of the data they are trained on. In instances where the data is biased or incomplete, the outputs generated may be misleading or erroneous. Secondly, while AI does aid the physician, there is a general loss of human touch and empathy, which is the cornerstone of patient care. In addition, a solution in AI costs between 20,000 USD and 1,000,000 USD, which is far out of reach for any small institution in a resource-restrained country.[16] Finally, there is a big concern for the ethical implications of AI, as when the healthcare records are uploaded to the cloud, there is a concern for privacy and risk of patient data breach. Considering the important differences between AI and humans, we discuss the strengths and limitations of using AI to diagnose cardiac arrhythmias.[17]

Overview of AI in diagnosing cardiac arrhythmias

AI typically uses sensors or electrodes to measure the electrical impulses generated by the heart and convert this data into a visual representation of the heart's electrical activity.[18] The two most commonly used signals are ECG and Photoplethysmography (PPG), with PPG being a more modern signal used in wearable devices like watches, wristbands, and smartphones.[19] ML, DL, and Convolutional Neural Networks (CNN) are some of the most popular AI techniques (Figure 1) used for arrhythmia diagnosis. These techniques leverage large amounts of data to train models that can accurately classify different types of arrhythmias based on ECG signals.[20] ML is a subfield of AI that involves developing algorithms that can automatically learn and improve from experience and large data sets without being explicitly programmed to diagnose cardiac arrhythmias. Several ML algorithms can be used for arrhythmia diagnosis, including supervised, unsupervised, and

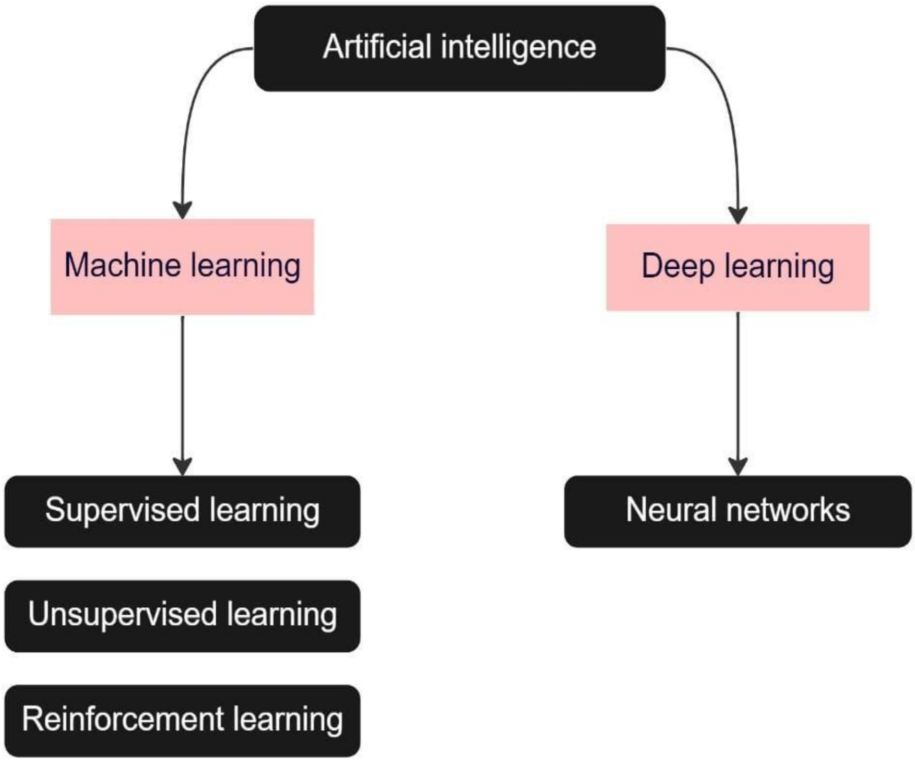

Figure 1: Classification of AI

reinforcement learning.[19] In supervised learning, the algorithm is trained using labeled data and then makes predictions on new, unlabeled data.[21] Labeled data refers to a dataset where each ECG recording has been manually labeled or classified by a human expert which indicates the presence or absence of arrhythmias, type of arrhythmia and has the advantage which includes high accuracy and the ability to handle large amounts of data.[22] On the contrary, in unsupervised learning, the algorithm is trained on unlabeled data that refers to a dataset where ECG recordings are not labeled or classified.[23] This approach can be useful for detecting arrhythmias that are not well-known or understood, as it can identify patterns that may not be apparent through manual labeling. In reinforcement learning, the algorithm learns by interacting with an environment and receiving feedback in the form of rewards or penalties, and it can be used to optimize treatment decisions or to design personalized treatment plans. The advantages of reinforcement learning include learning from experience and handling complex dynamic environments; however, it can be computationally expensive and require significant amounts of training data.[24]

DL uses artificial neural networks with multiple layers to learn and extract features from data and automated arrhythmia detection using DL techniques such as CNN has the potential to improve the accuracy and speed of diagnosis.[25,26] The proposed CNN model is designed to automatically extract features from long-duration ECG signals and classify them into one of the five classes: normal sinus rhythm, atrial fibrillation, other rhythms, atrial flutter, and ventricular fibrillation. The CNN approach has several advantages over traditional ML approaches for ECG analysis. First, it can automatically extract features from raw ECG signals without manual feature engineering.[27] Second, it can handle long-duration ECG recordings, which are more representative of real-world scenarios than short-duration ECG segments. Short-duration ECG segments, typically lasting a few seconds or minutes, are commonly used in clinical settings to diagnose heart abnormalities but may not capture the full range of heart activity over a longer period. Long-duration ECG recordings, lasting 24 hours or more, can provide a more comprehensive view of a person's heart activity, capturing variations that occur throughout the day and in response to different activities and stressors. This allows for a more accurate and representative picture of a person's heart health in real-world scenarios.[28] As the world becomes increasingly reliant on technology, AI algorithms will undoubtedly revolutionize the healthcare industry, providing accurate and efficient diagnosis that will save countless lives.

Advantages of AI-based approaches in cardiac arrhythmias

For a long time, medicine has relied on the decisions made by healthcare workers. Although we often come across the phrase, 'prevention is better than cure,' the traditional form of medicine is more focused on treating diseases. AI-based models help prevent the devastating outcomes of cardiac arrhythmias by accurately predicting the risk of getting one. The PULSE-AI trial, which is a prediction algorithm for atrial fibrillation in the United Kingdom, correctly predicted and diagnosed 45,493 new cases in high-risk individuals and also demonstrated cost-effectiveness when compared to routine screening and diagnosis of atrial fibrillation.[29]

Cardiac arrhythmia diagnosis requires long hours of monitoring, yielding to high costs and discomfort to patients, and AI has provided immense support in diagnosing impending or previously undocumented episodes of AF in patients with normal sinus rhythm, contributing to a reduction in the incidence of stroke and sudden cardiac death. An electrocardiograph with AI that could detect the presence of the ECG signature of AF during normal sinus rhythm was successfully established as a screening tool in a large study with approximately 180,000 patients with normal sinus rhythm by Attia et al at the Mayo Clinic, Rochester, in 2019. This AI-based electrocardiograph had an overall accuracy of 79.4% (79.0-79.9) in identifying AF, which increased to 83.4% when it was the first ECG following an episode of AF ;an Area Under Curve of 0.87 (95% CI 0.86-0.88) and sensitivity and specificity of 79.0% and 79% respectively.[30]

Structural changes in the heart, like myocyte hypertrophy, fibrosis, or chamber dilation, cause subtle changes in ECG that can be detected by deep neural network-based ECGs that can easily go unrecognized by the human eye. AI has also made it possible to interpret ECGs with greater accuracy compared to the usual reading of ECGs by cardiologists. Hannan et al's deep neural networks significantly outperformed a group of ordinary cardiologists in terms of accuracy when interpreting ECGs for aberrant cardiac rhythms such AF, atrio-ventricular block, bigeminy, ectopic atrial rhythm, idioventricular rhythm, and junctional rhythm with an all-rhythm class area under curve (AUC) of greater than 0.91.31 AI-based ECG helps find discernible patterns on ECG in order to enable cardiologists to accomplish routine tasks and also adds value by leveraging the physiologic signal for risk assessment, illness screening, or the diagnosis of other non-cardiac diseases.[32] Human errors can occur during human interpretation of sonography and image interpretation, including poor hand-eye coordination, unskilled eye image interpretation, and subtleties of imaging individuals with different body types or medical conditions. Therefore, AI-enabled usage of resources can lead to a decrease in comparable human mistakes, one of the leading causes of mortality in the US.[33] These issues may be resolved while also enhancing clinical decision-making effectiveness and lowering the price of diagnosis and treatment with AI-based algorithms.[34] In general, AI-enabled early identification of individuals at risk for developing cardiac arrhythmias or early detection of cardiac arrhythmias can result in rapid and aggressive treatment starting with stringent follow-up, which can enhance clinical outcomes.

Challenges and limitations of the AI-based approach

AI has become an integral part of the healthcare industry in this modern era. ML is quickly expanding in the field of medicine and has the potential to completely change how doctors and other medical professionals approach patient care. Although AI has growing advantages in diagnosing arrhythmia, there are also certain potential limitations and challenges to using it (Figure 2).

Dependence on Data Quality: One critical factor affecting the accuracy of ML algorithms used to diagnose cardiac arrhythmias is data quality. The data used to train the algorithm must be of high quality. The algorithm's accuracy may be compromised if the data is noisy or contains artifacts, such as those in ECG signals.[35,36]

Risk of overfitting: Another challenge that arises with ML algorithms is the risk of overfitting. These algorithms are trained to recognize patterns and relationships in the given data, which they then use to predict outcomes for new data. However, if the algorithm becomes too specialized in the training data and fails to generalize well to new data, it results in overfitting. An algorithm trained on a specific patient population may not work well with a different population with different characteristics. This limitation can affect the algorithm's performance in diagnosing cardiac arrhythmias accurately.[19,37]

Figure 2: Challenges of using AI

Lack of interpretability: A significant challenge associated with using ML algorithms in healthcare is their lack of interpretability. Some algorithms can be complex and opaque, making it challenging for healthcare providers to understand how the algorithm arrived at its diagnosis or prediction. This lack of interpretability can create a barrier to adopting ML in healthcare, as healthcare providers need to be confident in the algorithm's output to trust it. It is especially challenging in healthcare, where an incorrect diagnosis or treatment recommendation can have severe consequences. Some algorithms, like decision trees or linear regression models, are easier to interpret as they rely on simple mathematical models. In contrast, others, like DL neural networks, are difficult to interpret, making it challenging to unravel the complex calculations and layers of abstraction.[25,38,39]

Technical expertise: Finally, implementing and maintaining ML algorithms in healthcare requires technical expertise due to their complexity. Healthcare providers may need to invest in specialized training programs or hire data science and ML experts to ensure effective use of these algorithms in diagnosing cardiac arrhythmia and other healthcare applications. These specialized training programs involve data science and computer programming.[32]

FUTURE CONSIDERATIONS

AI clinical applications in medical imaging and diagnostics are rapidly expanding. It has been demonstrated that an AI-enabled ECG can identify patients with various cardiac rhythm abnormalities. In an emergency, an AI-enabled ECG may aid in the rapid identification of potentially life-threatening electrolyte imbalances and help triage patients at risk of cardiac arrest who may require more intensive monitoring.[40]

AI-enabled technology may help identify arrhythmia, improve accessory pathway localization and automatically detect atrial fibrosis by segmenting AF intracardiac electrograms and LGE-MRI images.[41] The integration of rhythm recognition during cardiopulmonary resuscitation (CPR) represents a significant and promising advancement in the future application of machine learning within automated external defibrillators (AEDs). This technology has progressed from adaptive filters that remove CPR artifacts to creating end-to-end SAAs (Shock advice algorithms).[42] Current models have not been able to completely eliminate 'hands-off' time because they frequently require rhythm reconfirmation in the absence of chest compressions.[43] Bystander AED use occurs in only 2% of out-of-hospital cardiac arrest cardiac arrests in the United States.[44] Another potential future application of AI is drone delivery of AEDs to increase AED availability and reduce time to initial defibrillation. A recent simulation study in rural Canada discovered that drone-delivered AEDs reduced time to defibrillation by 1.8 to 8.0 minutes, which would have a significant impact on mortality. AI could be used to calculate the best geographical location and patrol routes to provide the most AED access.[45] We anticipate that this technology will be integrated into clinical practice in the near future. AI diagnostic applications in wearable devices can efficiently analyse these data. Real-time data from wearable devices has spurred research into new AF treatments like pill-in-pocket anticoagulation. This improves AF management and rhythm control.[46] ML methods can analyse data from multiple sources to predict life-threatening arrhythmia or heart failure episodes faster than rule-based algorithms. Thus, ML algorithms improved at-risk patient anticoagulation guidelines and cardiac device therapy patient selection.[19] AI can still be applied to genomic and proteomic data, histological characterization, and drug discovery for arrhythmia. Growing data sets may allow researchers to identify "virtual twins" of AF patients, providing a new perspective on AF in patients with similar profiles and advancing AF treatment personalization.[20] AI and ML have transformed the field of Electrophysiology, from arrhythmia detection and diagnosis to risk prediction and management. Significant work remains to be done in order to better understand AI's capabilities, pitfalls, and appropriate deployment in order for it to be integrated clinically.[32] This represents a genuine opportunity for basic scientists, clinicians, epidemiologists, computer scientists, and regulators to collaborate in the development of robust infrastructure that enables open, accessible platforms for further creative development.

CONCLUSIONS

AI is revolutionizing the field of medicine, and the diagnosis of cardiac arrhythmia is no exception. The 12-lead ECG is no longer the sole diagnostic tool, and AI has emerged as a promising tool to assist healthcare professionals in diagnosing arrhythmias with high accuracy and speed. ML, DL, and CNNs are some of the most popular AI techniques that have been used for arrhythmia diagnosis. ML involves developing algorithms that can automatically learn and improve from experience without being explicitly programmed. While in supervised learning, the algorithm is trained using labeled data, in unsupervised learning, the algorithm is trained on unlabeled data. CNN can automatically extract features from raw ECG signals without the need for manual feature engineering, and it can handle long-duration ECG recordings, which are more representative of real-world scenarios. With the advancement of technology, the diagnosis of arrhythmia can be more effective and accurate, but its dependence on the quality of data, risk of overfitting, lack of interpretability, technical expertise, and high cost are still some of the factors that need to be looked upon. While AI cannot replace a diligent doctor's experience, skill, empathy, or personal touch, it has the potential to make staggering progress in the diagnosis of arrhythmia, considering the astonishing extent, speed, and capability for its growth. More research and development are required to precisely detect various types of arrhythmias, which can result in a significant transformation of the healthcare system.

Conflict of Interest

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Authors' Contribution

VG, SGK, SB, SG, and VM assisted in article concept and design, acquisition of data, drafting of the manuscript, and final approval. VG, SGK, SB, SG, VM, FA and RJ assisted in article concept and design, analysis and interpretation of data, revision of the manuscript for important intellectual content, and final approval. FA and RJ further assisted in the revisions of the final manuscript.

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