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Advancements and Applications of Convolutional Neural Network Models in Cardiovascular Disease: A Comprehensive Review

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Abstract: In recent years, artificial intelligence (AI) has demonstrated remarkable advancements in the field of cardiovascular disease (CVD), particularly in the analysis of electrocardiograms (ECGs). Due to its widespread use, low cost, and high efficiency, the ECG has long been regarded as a cornerstone of cardiological examinations and remains the most widely utilized diagnostic tool in cardiology. The integration of AI, especially deep learning (DL) technologies based on convolutional neural networks (CNNs), into ECG analysis, has shown immense potential across several cardiological subfields. Deep learning methods have provided robust support for the rapid interpretation of ECGs, enabling the fine-grained analysis of ECG waveform changes with diagnostic accuracy comparable to that of expert cardiologists. Additionally, CNN-based models have proven capable of capturing subtle ECG changes that are often undetectable by traditional methods, accurately predicting complex conditions such as atrial fibrillation, left and right ventricular dysfunction, hypertrophic cardiomyopathy, acute coronary syndrome, and aortic stenosis. This highlights the broad application potential of AI in the diagnosis of cardiovascular diseases. However, despite their extensive applications, CNN models also face significant limitations, primarily related to the reliability of the acquired data, the opacity of the "black box" processes, and the associated medical, legal, and ethical challenges. Addressing these limitations and seeking viable solutions remain critical challenges in modern medicine.

Keywords: Artificial intelligence; Cardiovascular disease; ECG; Convolutional neural networks; Deep learning

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1. Introduction

Cardiovascular diseases (CVDs) represent a significant health challenge in modern society. According to the World Health Organization (WHO), cardiovascular diseases account for 31% of all global deaths annually [1]. In China, the prevalence of CVDs has been steadily increasing, with approximately 330 million individuals currently affected, as reported by the National Center for Cardiovascular Diseases [2]. The burden of CVD is not only a concern for individual health but also presents a substantial challenge for public health systems and medical services.

Machine learning is an important branch of artificial intelligence that trains models to allow machines to learn and make decisions autonomously. Depending on the learning style, machine learning can be divided into three types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [3]. Due to machine learning models need to manually extract features, their learning results are still very dependent on humans. To address these limitations, deep learning (DL) methods have been introduced. Deep learning techniques have rapidly resolved numerous complex problems, particularly in the domain of medical image analysis and processing. Among these, convolutional neural networks (CNNs) have emerged as the most popular DL architecture, especially in medical image analysis [4].

This study explores the performance of CNNs in the classification of ECG signals, focusing on their application in diagnosing and predicting various cardiovascular conditions. CNN is a feedforward network consisting of a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer acts as a feature extractor and uses the extracted features for the classification of subsequent layers. The role of the pooling layer is to reduce the spatial dimension of the input samples while preserving important information. The fully connected layer will establish the weighting of all the outputs of the previous layer and determine the specific target output, and then split the input samples into one-dimensional CNNs for training and testing in classification.

2. Application of convolutional neural network models in cardiovascular diseases

2.1. CNN-based diagnosis and classification of arrhythmias

Recent advances have demonstrated the high diagnostic performance of CNNs in classifying various arrhythmias. A research team at Stanford University (California, United States) has developed a deep convolutional neural network that can be used to classify a variety of different arrhythmias from single-lead ECGs, and its diagnostic performance is superior to that of cardiologists [5]. Che *et al.* proposed an end-to-end deep learning framework combining CNNs with transformer networks to extract temporal information from ECG signals [6]. This model effectively classified arrhythmias such as atrial fibrillation, first-degree atrioventricular block, left or right bundle branch block, premature atrial contractions, premature ventricular contractions, and ST-segment deviations with satisfactory accuracy. Li *et al.* introduced an overlapping segmentation method for ECG signal processing, using Discrete Wavelet Transform (DWT) for denoising and an improved deep residual CNN for automatic arrhythmia classification [7]. Additionally, Kumar *et al.* employed a deep CNN optimized based on Flamingo architecture to classify supraventricular, junctional, and ventricular arrhythmias utilizing Internet of Things (IoT) technology [8]. These studies collectively underscore the efficacy of CNNs in accurately identifying and classifying ECG signal types [9].

2.2. CNN-based prediction of arrhythmias

The Mayo Clinic developed a pioneering AI-ECG algorithm using CNN models trained on nearly 650,000 ECGs to predict paroxysmal atrial fibrillation (AF) in patients with sinus rhythm [10]. A single AI-ECG recording was able to identify patients with underlying paroxysmal AF with an area under the curve (AUC) of 0.87 [10]. A follow-up study examined the role of AI-ECG in predicting future AF risk in undiagnosed patients, comparing the AI-ECG's predictive accuracy with the CHARGE-AF score [11]. The results showed that when the probability of AI-ECG predicting AF exceeded 50%, the 2- and 10-year cumulative incidences of AF were 21.5% and 52.2%, respectively, closely mirroring the predictions of CHARGE-AF [11]. Several AI models have focused on ECG-based AF risk prediction, which can be categorized into three broad types which are the models utilizing clinical variables [12,13], models based on raw ECG data [10,14], and hybrid models combining clinical variables with raw ECG data [15].

Hill NR *et al.* (2019) conducted a retrospective cohort study involving adults aged ≥ 30 years without a history of AF, assessing the performance of various models, including published risk models (Framingham, ARIC, CHARGE-AF), machine learning models (neural networks, random forests, support vector machines, etc.), and Cox regression models [12]. They analyzed data from 2,994,837 patients using a neural network model, achieving an AUROC of 0.827, which was 0.102 higher than the best available model, CHARGE-AF. Similarly, a UK study validated a machine learning algorithm in the DISCOVER registry, which included patients aged ≥ 30 years without an AF diagnosis in the past 5 years [13]. The algorithm identified 60,413 patients suitable for risk assessment, of which 3.0% (17,880 patients) were diagnosed with AF by the end of the study. The model achieved an AUC of 0.83, a negative predictive value of 99.1%, and a sensitivity of 75.0%. For patients aged ≥ 65 years, the negative predictive value was 96.7%, and sensitivity was 91.8%.

Attia *et al.* developed an AI-enabled ECG system using CNNs to detect ECG features indicative of AF during normal sinus rhythm, analyzing data from 180,922 patients and 649,931 normal sinus rhythm ECGs [10]. The AI ECG identified AF with an AUC of 0.87, a sensitivity of 79.0%, a specificity of 79.5%, an F1 score of 39.2%, and an overall accuracy of 79.4%. Another study trained a deep neural network using 12-lead digital ECG traces collected from 430,000 patients between 1984 and 2019, predicting new AF within one year in patients without a history of AF, achieving an AUROC of 0.85 [14]. Khurshid *et al.* compared the 5-year AF probability predictions of ECG-AI with the CHARGE-AF clinical risk score, as well as a combined ECG-AI and CHARGE-AF (CH-AI) score, validating that AI-based AF risk prediction models using 12-lead ECGs can effectively quantify future AF risk [15]. Combining clinical risk factors with AI models provides the highest predictive accuracy. In conclusion, CNNs have shown promising results in identifying and predicting the risk of atrial fibrillation in patients with normal sinus rhythm.

2.3. CNN for screening ventricular dysfunction

CNN models have been applied successfully to screen for ventricular dysfunction using ECG data. Attia *et al.* trained a CNN to identify patients with ventricular dysfunction, defined as left ventricular ejection fraction (LVEF) ≤ 35%, using only 12-lead ECG data from 44,959 patients at the Mayo Clinic [16]. The model achieved an AUC of 0.93, with a sensitivity of 93.0%, specificity of 86.3%, and overall accuracy of 85.7%. Additionally, patients identified as "false positives" by the model had a 10% increased risk of developing ventricular dysfunction within five years. Adedinsewo *et al.* tested an AI-powered ECG algorithm on 1,606 patients presenting with acute dyspnea in the emergency department [17]. The algorithm correctly identified the underlying causes of dyspnea, including left ventricular dysfunction, with an accuracy of 85.9% for LVEF < 35% and 86% for LVEF < 50%. Vaid *et al.* also applied deep learning algorithms to detect left and right ventricular dysfunction with encouraging results [18]. Furthermore, the EAGLE study, a randomized controlled trial, is currently screening for left ventricular dysfunction using a deep learning system that analyzes 12-lead

ECGs [19]. A recent study demonstrated the potential of CNNs in screening for heart failure with reduced ejection fraction (HFrEF) based on ECG data with highly promising accuracy [20]. However, external validation revealed lower accuracy and a higher false positive rate, particularly in ECG subgroups with tachycardia, atrial fibrillation, and conduction delays.

2.4. Application of CNN in aortic stenosis

Kwon *et al.* developed a deep learning algorithm capable of detecting aortic stenosis using 12-lead and single-lead ECGs, achieving an AUC of 0.86–0.88 and a negative predictive value of over 99% in the aortic stenosis screening process [21]. Similarly, Cohen-Shelly *et al.* created a deep learning algorithm that identified moderate to severe aortic stenosis in asymptomatic individuals with high sensitivity, specificity, and a negative predictive value of 99% [22]. The study also highlighted the superiority of the algorithm in identifying asymptomatic subjects, a task where traditional auscultation by physicians often falls short, as only 39% of physicians correctly identified a murmur. Harmon *et al.* conducted a recent retrospective study demonstrating the AI-ECG algorithm's ability to predict disease progression in aortic stenosis by analyzing TP interval and T/U wave morphology [23].

2.5. Application of CNN in cardiomyopathy

Recent studies have evaluated the application of deep learning algorithms for diagnosing hypertrophic cardiomyopathy (HCM) using 12-lead ECGs. One such model achieved a negative predictive value of 99%, sensitivity of 87%, specificity of 91%, and an AUC of 0.96, indicating its potential for HCM screening in the general population [24]. Tison *et al.* developed a deep-learning model to detect multiple conditions, including HCM, pulmonary hypertension (PAH), cardiac amyloidosis (CA), and mitral valve prolapse (MVP) using standard 12-lead ECGs [25]. The model distinguished PAH (AUC: 0.94) and HCM (AUC: 0.91) with high accuracy, though its performance was less robust in distinguishing CA (AUC: 0.86) and MVP (AUC: 0.77).

2.6. Application of CNN in myocardial infarction and ischemic heart disease

AI models combining CNNs with long short-term memory (CNN-LSTM) architectures have demonstrated strong performance in classifying myocardial infarction (MI) and ischemic heart disease. For example, Chen *et al.* (2022) evaluated the performance of a CNN-LSTM model on 697 pre-hospital 12-lead ECGs, achieving evaluation indices such as accuracy (0.992), precision (0.889), specificity (0.994), recall (0.941), AUC (0.997), and F1 score (0.914) [26]. This study also highlighted a reduction in diagnostic delay and faster response times compared to physicians (37.2 ± 11.3 vs. 113.2 ± 369.4 seconds, $P < 0.001$). Similarly, Chen *et al.* trained CNNs to identify and localize myocardial infarction using 12-lead ECGs, achieving an accuracy of 82.7% based on a dataset of 15,285 ECGs for training, 6,552 for validation, and 205 for testing [27]. Tadesse *et al.* proposed an end-to-end deep learning approach capable of diagnosing MI events as acute, recent, or old, using time-based information [28]. Additionally, Gumpfer *et al.* developed a deep learning model to detect myocardial scarring (MS) from 12-lead ECGs, achieving an accuracy of 78%, sensitivity of 70%, and specificity of 84.3% when compared to MRI data from 114 patients [29].

2.7. Application of CNN in electrolyte abnormalities

CNNs have also been applied to detect electrolyte abnormalities using ECG data. Galloway *et al.* trained

CNNs to identify pathological serum potassium levels by analyzing ECG traces, defining hyperkalemia as K+ ≥ 5.5 mmol/L [30]. The model, with 11 convolutional layers, demonstrated good diagnostic efficacy for hyperkalemia, achieving a negative predictive value of 99%, AUC of 0.853 to 0.883, and sensitivity of 88.9% to 91.3%. Lin *et al.* applied an 82-layer CNN model to detect changes in serum potassium levels [31]. Hypokalemia, associated with hyperkalemia, is characterized by ECG changes such as prolonged PR interval, ST-segment depression, T-wave flattening or inversion, QTc interval prolongation, and U-wave appearance. The deep learning model outperformed physicians in detecting potassium dysregulation, with sensitivity ranging from 84.5% to 95.6%. Attia *et al.* explored the possibility of using a single-lead ECG to estimate potassium levels in the absence of blood samples [32]. Their study yielded serum potassium level estimates based on T-wave morphology, excluding patients with biphasic, bimodal, or inverted T-waves, with a mean error of 0.50 ± 0.42 mmol/L. This research opens avenues for developing wireless, non-invasive monitoring technologies capable of alerting patients at risk of fatal arrhythmias, particularly those with kidney failure or on dialysis.

3. Prospects and challenges of CNN in cardiovascular disease

The application of artificial intelligence (AI) in cardiology, particularly deep learning (DL) techniques, has opened new avenues for diagnosing and predicting cardiovascular diseases. DL, a subset of machine learning (ML), leverages neural networks with numerous interconnected neurons in each layer, enabling the discovery of data features that may be imperceptible to human experts.

Despite these advances, significant challenges remain in optimizing AI tools for reliable and safe clinical use. One major concern is the "black box" nature of DL models, where the decision-making process is often opaque and difficult to interpret. This lack of transparency poses risks for irrational decision-making and raises ethical concerns. The development of explainable AI (XAI) is crucial to making these processes more transparent and trustworthy.

Overfitting is another challenge, where models trained on specific datasets may fail to generalize across broader populations. This issue highlights the need for robust models capable of handling diverse and potentially contradictory inputs for accurate classification. Furthermore, misleading or misclassified data can lead to incorrect model predictions, emphasizing the importance of rigorous data validation and model training.

Addressing these challenges is essential for ensuring that AI tools can be reliably integrated into clinical practice without constant human supervision. By overcoming these limitations, AI and DL technologies have the potential to revolutionize the prevention, diagnosis, and treatment of cardiovascular diseases.

4. Summary and outlook

The integration of artificial intelligence, particularly convolutional neural networks, into cardiology, has proven to be a valuable tool in supporting healthcare professionals and enhancing the quality of care. AI and machine learning technologies are not intended to replace healthcare professionals; rather, they serve as powerful tools that can improve the accuracy and efficiency of diagnosis and treatment, making the practice of medicine more rewarding and effective.

Incorporating AI into standard 12-lead ECGs, which is an inexpensive, widely available, and non-invasive test and can reduce diagnostic time and enable continuous monitoring through wearable devices. This capability facilitates the early diagnosis, prediction, and management of cardiovascular diseases, ultimately improving patient outcomes.

As AI technologies continue to evolve, their role in cardiology will likely expand, offering new opportunities for innovation in patient care. The future of AI in cardiovascular medicine promises not only enhanced diagnostic capabilities but also the potential for personalized treatment strategies that could transform the landscape of modern medicine.

Disclosure statement

The authors declare no conflict of interest.

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