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Clinical Applications of Artificial Intelligence Based on Cardiovascular Disease

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Abstract: Artificial intelligence has played a significant role in the medical field of cardiovascular diseases, especially in cardiac imaging. Heart diseases affect the function of the heart, causing the heart to be unable to supply blood normally, thus affecting the functions of the body's organs and systems. This paper summarizes the applications of algorithms such as deep learning and machine learning in the clinical treatment of cardiovascular diseases and their differences from two aspects: medical imaging and heart signals. It also reviews how these algorithms assist doctors in making more accurate diagnoses in the early screening, data analysis, and postoperative detection of cardiovascular diseases. It studies the optimization of traditional algorithms and image reconstruction by artificial intelligence-based imaging detection methods, as well as the specific application ways of deep learning in frame selection, segmentation, and disease assessment. Meanwhile, it discusses the advantages of convolutional neural networks (CNN) and recurrent neural networks (RNN) in performing classification tasks in Electrocardiogram (ECG) and puts forward the possibility of using 3D computer simulation synthesis system data to improve the generalization ability of machine learning models. In addition, this paper also introduces the limitations and challenges in the clinical application of AI algorithms in this field as well as their future development, providing a new perspective for the further prevention and control of cardiovascular diseases. The computational methodologies expounded within this review constitute a formidable asset in the realm of medical discoveries, and their translation into the clinical domain holds the potential to precipitate promising advancements.

Keywords: Artificial intelligence, Cardiovascular Disease, Imaging Techniques, ECG.

1. Introduction

Cardiovascular diseases (CVD) constitute a category of disorders affecting the heart and blood vessels. According to the data from the World Health Organization, CVD has a persistently high incidence and mortality rate, accounting for 30% of deaths worldwide [1]. Against the backdrop of an aging society and modern lifestyles, the incidence of cardiovascular diseases has been on the rise year by year, emerging as one of the primary causes of death worldwide. It has imposed an enormous economic burden on individuals, families, and public finances. Therefore, in order to reduce CVD-related deaths and adhere to the principle of early detection and treatment, early screening and accurate judgment have become crucial challenges in the global clinical medical treatment of

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cardiovascular diseases. However, the screening results of cardiovascular diseases often suffer from false positives or false negatives. Besides, for clinicians, despite their rich clinical experience and medical knowledge reserves, issues such as low efficiency and vulnerability to non-professional factors still exist. Artificial intelligence, nevertheless, demonstrates huge potential in this field. AI technologies, via algorithms like machine learning, deep learning, and natural language processing (NLP), play a significant role in assisting doctors to make accurate diagnoses in terms of image reconstruction, predictive screening, and diagnostic evaluation of cardiovascular diseases. Researchers have found that compared with the problems encountered in traditional image analysis, machine learning, by employing techniques and algorithms such as compressed sensing (CS) and deep neural networks (DNN), can enhance the efficiency of image reconstruction [2]. Supervised machine learning can be used to address classification and regression problems. Before learning, weighted factors are usually set, and multiple cross-validations will be carried out subsequently. In machine learning, the support vector machine (SVM) algorithm can serve as one of the basic decisions for automating the evaluation process of coronary artery stenosis [3]. Through fuzzy-based machine learning, rough set theory, and support vector classifiers, machine learning can automatically extract classifications based on neural networks. Based on the PAF prediction database and by using the MIT-BIH arrhythmia database to predict arrhythmia, an accuracy rate of 91.33% has been achieved. Complex classifiers require more features and longer classification time. Although the recurrent neural network (RNN) can classify electrocardiograms, it is rather difficult to train. Thus, the convolutional neural network (CNN) can be combined with RRN to train electrocardiograms [4]. Three-dimensional computer simulations can explain electrocardiogram abnormalities at the organ and cell levels. They permit personalized simulations of electrocardiograms and the generation of data for training [1]. This article undertakes a comprehensive review from the perspectives of cardiovascular magnetic resonance (CMR), coronary computed tomography angiography (CCTA), and electrocardiogram (ECG).

This review is instrumental in facilitating physicians in the treatment process, augmenting diagnostic efficacy, and propelling the prevention and control of cardiovascular diseases. It proffers novel perspectives on the application of AI in CVD for future cardiovascular treatments and furnishes a reference for researchers.

2. Cardiovascular Disease Influencing Factors and Hazards

Being the world's biggest cause of death, cardiovascular disease has complex and diverse influencing factors involving genetics, lifestyle, environmental factors and other aspects. First, genetic inheritance has a significant impact on the development of cardiovascular disease. Studies have shown that several hereditary risk factors, such as cholesterol levels, triglyceride levels, hypertension, obesity, diabetes, and genetic variants of metabolic syndrome, are closely related to the susceptibility to cardiovascular disease [5]. In addition, poor lifestyle habits are a crucial factor in the rising incidence of cardiovascular disease. Unhealthy lifestyles such as excessive obesity, alcoholism, smoking, sedentary behavior and lack of exercise directly or indirectly increase the risk of CVD. Some studies have shown that abdominal obesity is an independent risk marker for cardiovascular disease, which promotes the development of atherosclerosis, heart failure and arrhythmia, which in turn leads to mortality [4]. In addition to genetics and lifestyle, environmental factors also play an important role in the development of cardiovascular disease. For instance, it has been demonstrated that exposure to specific heavy metals, including lead, cadmium, and arsenic, as well as air pollution, affects blood vessel function and has a role in the development of cardiovascular disorders like atherosclerosis [1]. According to estimates from the World Health Organization, 16.6 million people worldwide lose their lives to cardiovascular disease each year, with low- and middle-income nations accounting for more than three-quarters of these deaths. This places an enormous economic burden on individuals, families

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and public finances. Therefore, there is an urgent need for early detection and treatment options to lower risk factors and CVD mortality. In the field of clinical medicine around the world, early screening and precise diagnosis of cardiovascular illnesses have grown in importance and require immediate attention. In light of this, the field of artificial intelligence (AI) presents a potential solution to this problem. Through thorough data analysis and post-operative monitoring throughout the course of therapy, deep learning and machine learning algorithms can further optimize clinical decision-making and treatment outcomes while increasing the effectiveness and accuracy of early screening for cardiovascular illnesses.

3. Image-based detection methods

Currently, imaging technologies are widely used in the early screening and diagnosis of cardiovascular diseases, especially in the precise segmentation of key anatomical structures such as ventricles, valves and coronary arteries, as well as the quantitative assessment of a series of physiological and pathological parameters (e.g., left ventricular ejection fraction, myocardial perfusion defects, and coronary artery stenosis degree) [6]. Meanwhile, AI algorithms, after deep learning and training, are able to analyze and recognize image data more accurately and construct data-driven inference and prediction models, thus showing great potential in the field of CMR image reconstruction, CCTA and echocardiography.

Firstly, for CMR image reconstruction, Bustin et al. proposed the use of a machine learning reconstruction method to optimize the traditional nonlinear optimization process. The authors analyze the differences in the models by comparing and contrasting the differences in the basic assumptions of the traditional image reconstruction in which acquisition is difficult and there are many influencing factors, so there is the problem of long scanning time and low efficiency, the differences in the basic assumptions of the mature techniques such as compressed sensing (CS) and low-rank reconstruction, and the differences in the models of the newly proposed deep neural network (DNN) as an implicit or explicit a priori method. Ultimately, it is concluded that these methods aid in enhancing reconstruction accuracy and efficiency while lowering noise artifacts in clinical applications related to CMR image reconstruction. There are still certain drawbacks, though, including the absence of clinical validation, issues with the reconstruction network's generalization and reconstruction quality, the scarcity of particular training datasets, unfinished work on non-rigid motion modeling, and potential future developments [2]. Secondly, Al'Aref et al. proposed that machine learning models can be used for frame selection, segmentation, disease assessment, and assessment of coronary artery flow function as well as atherosclerotic lesions through machine learning models. The authors analyzed the specific ways in which deep learning can be applied by algorithms in the assessment of hemodynamics in coronary artery disease (CAD), the calculation of FFR by CT angiographic features, and the automation of arterial calcification scoring (CAC). In addition, the differences between the latest proposed deep learning algorithms and traditional machine learning models and cardiovascular experts were compared. As a result, the findings show that machine learning methods can be applied broadly to maximize the data concerning the degree of stenosis in particular atherosclerotic lesions that are derived from imaging modalities like coronary CCTA. Furthermore, it is anticipated that fully automated machine learning methods for image analysis would make processing extremely big image datasets easier [3]. Finally, Alsharqi et al. suggest that machine learning holds great potential for enhancing the diagnostic performance of echocardiography. The authors discuss the potential of Q-Learning, Random Forest (RF), Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Naive Bayes, Principal Component Analysis (PCA), Reinforcement Learning (RL) and Autoencoders in image recognition, pathology pattern classification, automatic quantification, and the future direction of AI-assisted interpretation of echocardiograms. It has been shown that machine learning models can improve the accuracy and efficiency of echocardiographic assessment.

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Furthermore, among other metrics, these algorithms may precisely measure a number of attributes, including the degree of heart valve disease and the ischemic burden of coronary artery disease. Furthermore, in order to enhance patient outcomes, this technology is anticipated to be utilized in clinical practice more frequently in the future [7].

4. Methods Based on Electrocardiogram Signals

Electrocardiogram (ECG) signals are commonly used techniques in clinical screening for capturing and recording the electrical activity of the heart. By analyzing EEG signals, doctors can diagnose and treat heart diseases more effectively. In recent years, artificial intelligence (AI) has been extensively utilized in the clinical monitoring of diseases such as arrhythmia and atrial fibrillation. Especially in remote monitoring devices, due to the high sensitivity of ECG signal abnormalities to the devices, false alarms often occur. Therefore, artificial intelligence plays an important role in helping doctors interpret ECG recordings [8].

As most ECG recordings now rely on computer analysis, this not only requires the analysis results to be fast and accurate but also demands that the analysis process is not affected by device and individual differences among patients. Neural network-based techniques, especially deep learning, have achieved automatic classification from raw ECG data without the need for manual feature extraction. CNN and RNN have been widely used in the classification tasks of ECG. Research has found that a 3-layer deep genetic integrated classifier can detect 17 types of arrhythmia with an accuracy rate reaching 99.37% [9]. And a 10-layer deep CNN model can identify patients with myocardial infarction with an accuracy rate of 99%. However, complex classifiers usually require more training and optimization time.

To improve classification efficiency and solve the problems in traditional classification methods, researchers have designed deep learning models to address the heartbeat classification tasks of electrocardiograms. Extracting ECG features and classifying them are the key steps in achieving accurate diagnosis. Traditional machine learning algorithms may have certain limitations in generalization ability. Therefore, a hybrid algorithm combining CNN and RNN has been proposed to fully utilize their respective advantages. CNN is used to extract sequential features from ECG signals, while RNN is responsible for processing these features and completing the heartbeat classification task. In addition, through the application of transfer learning, the model performance can be further optimized, the problem of insufficient model generalization can be solved, and thus the classification accuracy can be improved [9].

While RNN is appropriate for sequential time series data, CNN is typically used to interpret spatial data, such as photographs. When the input time series data has a big dimension, RNN's computational efficiency will be comparatively low. In order to lower the dimension of the input signal and subsequently feed the extracted features into an RNN for prediction, CNN is often used as a feature extractor. In particular, two successive 1D convolutional layers process the raw information before passing it into the convolutional module to increase the model's sensitivity even further. The Squeeze-and-Excitation (SE) module may be used to successfully increase the model's attention to significant elements. By capturing information at various levels from the feature set through convolutional layers, residual blocks assist avoid the vanishing gradient issue and improve the network's expressiveness. To avoid overfitting, a Batch normalization layer is added to the model to stabilize the training process.

After CNN extracts the features of the raw signal, these features are input into RNN for classification. Long Short-Term Memory (LSTM), as a special type of RNN, can model time series data from both forward and backward directions, effectively avoiding overfitting. Finally, the output vector of RNN is input into a softmax layer with 5 neurons to perform the heartbeat classification task [9].

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In addition, 3D computer simulations can synthesize system data, which can be used as verification data in classification studies. By generating synthetic data, researchers can expand the training set, thereby improving the generalization ability and accuracy of machine learning models. In remote monitoring, 3D computer simulations can effectively handle unknown heartbeat patterns, reduce false alarms, and thus optimize the time and resources of nursing staff. Moreover, 3D computer simulations can also study the effects of drugs on ECG. For example, Lyon used 3D computer simulations to study the effects of drugs on electrocardiogram signals. They simulated the conductance blockages of hERG and fast sodium channels. Overall, 3D computer simulations not only provide powerful data generation and analysis capabilities for electrocardiogram analysis but also play an important role in the diagnosis and monitoring of heart diseases [10].

5. Existing limitations and future prospects

Despite significant advances in the clinical application of AI algorithms in cardiovascular diseases, several limitations and challenges remain. First, in medical image analysis, deep learning models usually rely on a large amount of labeled data for training, especially when dealing with rare diseases, where insufficient samples may lead to poor training results. To cope with this challenge, migration learning becomes an effective solution. By pre-training visual models such as ResNet, DenseNet, and Vision Transformer on large-scale general-purpose visual datasets such as ImageNet and migrating them to medical image datasets for fine-tuning, the models are able to borrow general-purpose visual knowledge such as edges, shapes, and so on and adapt them to specific medical features, which improves the learning effect in the case of small samples. Meanwhile, data augmentation combined with generative models such as Generative Adversarial Networks (GANs) further extends the diversity of datasets, thus effectively mitigating the small sample problem. Further strengthening the impact of learning with few samples, the emergence of multimodal learning also makes it possible to combine medical pictures with clinical writings, genetic data, and other information to improve the model's capacity for generalization through shared representation learning. The small sample problem in medical image analysis can be effectively resolved by combining various strategies. Secondly, in healthcare, the decision-making process of AI models requires a high degree of interpretability, especially in clinical decision-making. Due to the complexity of transfer learning models, ensuring their transparency and trustworthiness becomes more difficult, and thus specialized technological tools are needed to enhance interpretability. Common techniques such as Local Interpretable Model-agnostic Explanations (LIME), Shapley Additive explanations (SHAP), Grad-CAM, and knowledge graphs can improve the transparency of the models and enhance physicians' trust. However, it is still a challenge to provide clear explanations that meet medical requirements when dealing with deep learning models. Also, privacy protection of patient data is a key issue in healthcare AI. Techniques such as differential privacy, federated learning, and homomorphic encryption have provided effective guarantees for data security, but how to ensure privacy while maintaining the efficiency and accuracy of AI models remains a research hotspot. With the advancement of technology, future medical AI systems will pay more attention to the balance between privacy protection and interpretability, while improving the accuracy of diagnosis and treatment and ensuring that patients' privacy is fully protected. Lastly, it is important to pay attention to the problem of bias in healthcare AI models. It will have a direct impact on the model's accuracy, fairness, and popularity. Bias typically arises in a number of areas related to data collection, model training, and assessment. Bias in the medical field can result in the unjust treatment of particular groups, including particular genders, races, ages, or illnesses kinds, which can have an impact on patient outcomes.

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6. Conclusions

This paper outlines artificial intelligence's role in early heart disease detection and diagnosis, with an emphasis on using deep learning techniques to analyze ECG signals and imaging techniques. Firstly, the study examines the primary risk factors for cardiovascular diseases, such as genetics, lifestyle, and environment, and highlights how these factors affect public health. The use of AI algorithms based on imaging and ECG data is then described in depth in the study. These methods are crucial for hemodynamic analysis, lesion evaluation, disease detection, and clinical decision optimization. However, despite significant advances in AI for CVD diagnosis, some limitations remain. Due to the dependence of deep learning models on a large amount of labeled data, the training effect in the case of fewer samples is still problematic. Second, the interpretability, data privacy protection and bias of medical AI models are important issues that must be addressed today. In addition, more technological innovations are needed to ensure the reliability and safety of deep learning models in clinical environments. The use of AI in early cardiovascular disease detection, therapy optimization, and patient monitoring will grow in depth as technologies like data sharing, transfer learning, and multimodal learning continue to advance. In summary, this analysis serves as a helpful guide for future research directions in related domains in addition to providing a thorough overview of current AI technologies in the detection of cardiovascular illness.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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