## Application of AI Technology in Modeling of Orthopedic Surgery

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**Abstract:** Cardiovascular disease has become one of the biggest health problems in the world. The early symptoms are not obvious, which makes the diagnosis and prevention difficult. However, the high incidence and mortality make people pay more attention to its treatment. In recent years, artificial intelligence technology has developed rapidly and has achieved many applications in the medical field. How to use artificial intelligence technology for early monitoring and prevention of cardiovascular disease is very important for the treatment of this kind of disease. Artificial intelligence models are established through machine learning, deep learning, convolutional neural network and other algorithms to integrate, process and analyze the collected patient physiological data, so as to better explore the role of artificial intelligence in cardiovascular disease monitoring and risk prediction. This paper reviews the algorithms and applications of artificial intelligence in the monitoring and prevention of cardiovascular disease, so as to better provide some reference for the application of artificial intelligence in the prevention and treatment of cardiovascular disease.

**Keywords:** Artificial Intelligence, AI algorithm, cardiovascular diseases, disease surveillance, prevention of disease

**1. Background**

1.1 Overview of Cardiovascular Diseases

With the improvement of China's economic development and people's living standards, cardiovascular disease (CVD) has become a major public health problem, usually including heart failure, hypertension, cardiomyopathy, arrhythmia, etc. Currently, the number of patients with CVD in China is as high as 330 million, and CVD is the leading cause of death, accounting for 46.74% and 44.26% of the total death cases in rural and urban areas respectively, with a year-on-year mortality rate of 0.08-0.45%, seriously threatening human life and health [1]. Among them, there are 245 million cases of hypertension, 13 million cases of stroke, 11.39 million cases of coronary atherosclerotic heart disease, and 8.9 million cases of heart failure. Cardiovascular disease has a high mortality rate, disability rate, and recurrence rate, so early detection of CVD helps improve clinical outcomes. However, traditional medical models are difficult to meet the complex and dangerous CVD. Therefore, it is very important to combine artificial intelligence technology to collect and accurately analyze patient data, and gradually shift to modern precision medicine models for the prevention and treatment of CVD.

1.2 Overview of artificial intelligence technology

The concept of artificial intelligence was first proposed by John McCarthy at the Dartmouth Conference in the 1950s of the 20th world, marking the official birth of artificial intelligence [2]. Artificial intelligence refers to the continuation of computer technology that perceives, acquires, stores and uses knowledge to solve problems by simulating, extending and expanding the operating mechanisms of the human brain. Artificial Intelligence began to be used in the medical field in the 1970s and was trained by analyzing case databases to form diagnostic and treatment processes to solve problems. In the subsequent development, machine learning, deep learning and other algorithmic branches were formed, which improved the ability of AI to process and analyze data, and made progressive breakthroughs. Currently artificial intelligence has been applied in medical imaging, disease monitoring and prevention.

1. **Application of AI in cardiovascular disease surveillance**

Health monitoring system has been known to the world after entering the 21st century, especially in recent years, the remote intelligent health monitoring technology has entered a period of rapid development. The traditional sense of health monitoring refers to the rough judgment of physical function through the patient's physical condition and the hardware medical facilities. Now health monitoring is more and more tend to personalized monitoring, namely through the patient wear remote computing system, continue to collect patients with physiological diversification information and data, then through a variety of big data platform integration, processing, input corresponding disease module algorithm, finally the evaluation of individualized physiological condition, and the process of disease risk prediction. This new monitoring model is intended to help doctors have a more comprehensive understanding of the evolution of patients' health conditions, and to make patients more aware of their own conditions. Combined with the later algorithm model construction, it can provide the most suitable treatment plan for individual patients in real time. Current health monitoring systems are broadly divided into two parts: wearable devices for data collection and algorithms for data analysis[3]. Wearable devices have been widely used in many fields. For the medical industry, their biggest use and initial purpose is to collect patients' physiological information for doctors and experts. Intelligent monitoring equipment is usually easy to carry, real-time recording, and Internet, which can provide people with some basic physiological indicators such as heart rhythm, blood pressure, brain and eye stimulation for people to have a more accurate understanding of their own health conditions. By comparing the application of various field algorithms (including artificial intelligence) in the health monitoring of cardiovascular function[4]. That is, various algorithm models control the hardware devices, and integrate, process and analyze the collected patient physiological data, so as to better explore the practical significance of artificial intelligence in health monitoring and the integrated development of the two in the future, and provide technical support for the realization of disease risk prediction and personalized medicine.

At present, the most used clinical health monitoring system is the device to monitor cardiovascular function, namely the traditional ECG conductivity and various forms of blood pressure collection system. Because requires patients to wear the corresponding monitoring equipment is equivalent to patients in a normal state imposed a pressure (or increase physiological, or increase psychological burden), this is because wearable devices are composed of internal microprocessor and sensors, its weight, size, shape and contact with the human body, and many other factors affect the performance of the device and the patient's wearable experience. Problems involved in this aspect are usually improved by the design and manufacturing of equipment and the application of new materials, such as changing the ordinary patch with the ultrasonic patch, which can improve the patient's wearing comfort and better monitor the blood pressure of the deep arteries. By reducing weight and expanding data storage and endurance capacity, the ECG conductive equipment has changed from the original patient wearing detection in the testing room to a more accurate recording method of all-day wearing monitoring. However, most of the hardware updates belong to other fields such as material mechanics, and the update of general equipment is accompanied by a large change in the price, so it takes a long time to enter the wide area clinic, so we will not make too much introduction here. More and more industry insiders believe that the performance of monitoring devices is not only related to hardware, but also the data processing of its internal algorithm model also determines the upper limit of device operation. The following is the introduction of the information acquisition system in the field of ECG monitoring and blood pressure monitoring and the attempt of artificial intelligence to improve its performance.

2.1 Data set selection

Since health monitoring involves signal analysis of real human body, the training set of the algorithm model used to train data processing in ECG and blood pressure monitoring must be realistic and comprehensive enough, so that the information collected by the monitoring equipment can be more used in later disease analysis prediction and clinical decision making. However, data such as electrocardiogram, patient medical records and cardiovascular history are all highly privatized information, so it is difficult to obtain comprehensive data from large-scale populations, and it is difficult to achieve large-scale language training. In the retrieved literature, most of the new monitoring algorithms were trained and tested by MITDB [5-6]. The dataset was obtained by 47 subjects for two days, including different waveforms and images of abnormal heart conditions in each time period, which can simulate all types of arrhythmias and heart disease in the clinic. At present, the performance test of the new monitoring system is basically trained with the same limited data set of MITDB to compare the accuracy of predicting cardiovascular disease types with other systems, so as to judge the feasibility of the algorithm in clinical monitoring.

2.2 Overview of denoise of ECG signals

Devices involved in any signaling will need to consider how to avoid or reduce the loss or deterioration of signals during the conduction process. In health monitoring, cardiology patients, for example, the electrocardiogram is the most commonly used tool to monitor patient heart function, currently used routine 12 cardiac lead system, through the electrode patch relative to the patient of the heart, using the potential difference between the electrode recorded heartbeat rhythm and waveform (including P wave, QRS wave group and T wave and U wave). Because this method is widely collected from various parts of the patient body surface electrical signals, in the actual case, the environment of the patient change, the use of drugs, cause equipment to receive outside the ECG signal interference (the outside signal refers to any signal non purposeful, can be produced by the patient itself or other environmental components), so that the collected data information effective information reduction, clutter, is not conducive to the analysis of the real health of patients. And some patients are not suitable for the use of electrode electrostatic patch, special circumstances can also cause allergies, suction electrode caused by blisters and other adverse reactions. The arm band electrocardiogram modified from the cuff sphygmomanometer can solve the various problems mentioned above, but the most difficult problem to overcome is the greater influence of the arm EMG signal [6]. Various signal noise will disturb the algorithm training and the prediction results, and affect the performance of the monitoring equipment. In order to eliminate the interference of various chaotic electrical signals to the data acquisition, the data differentiation degree of the equipment needs to be improved. Different algorithm models are applied to the corresponding wearable devices, which can be "denoise" through data processing, provide truly useful data information to expert reference, greatly reduce misdiagnosis and predict the pathological process of patients as accurately as possible, and reduce the fatality rate of patients. Therefore, continuously improving the operating system of the equipment and finding the acquisition model with stronger performance and higher information resolution have become the main goals in the field of intelligent monitoring.

2.3 Traditional noise reduction processing which relies on mathematical model and signal processing algorithm

At present, the mainstream noise reduction treatment can be roughly divided into three categories: the traditional denoising methods based on the denoising filter, the wavelet-based denoising and hybrid denoising methods [5]. The basic principle of the filter is to screen the noise before the incoming prediction model according to the frequency band difference between the useful signal and noise in the ECG. The disadvantage is that it cannot distinguish the noise similar to the true ECG signal frequency, that is, the ability of signal screening is limited. Some literature also mentioned that some equipment systems apply the combination of different types of denoising methods to process signals, which is better than using a certain method alone, but the disadvantage is that the resolution speed is slow, and there will be a certain delay in data upload. In 2020, A wearable arm with ECG recorder developed by Hossain et al. is equipped with a frequency conversion plural demodulation algorithm [6-7], By sub-band splitting of the normal cardiac cycle to eliminate the more subtle EMG artifacts mixed with the ECG, the accuracy of predicting the ECG abnormality type was significantly increased in the test of MITDB.

But it is worth noting that the above currently published more cardiovascular function monitoring system has a common technical bottleneck: different from artificial intelligence algorithms such as machine learning, the algorithm in the noise reduction system are affiliated to digital signal processing, they have no weight iterative update ability, once the parameters are set, the ability to resolve information to ascend. Therefore, by expanding the scope of keyword access, we found the application of artificial intelligence algorithms in health monitoring systems, including machine learning, perceptron, support vector machine and deep learning, which opened up another research field to continuously improve the performance of monitoring systems.

2.4 Attempts and superiority of artificial intelligence in ECG signal differentiation

Machine learning is a major branch of the field of artificial intelligence algorithms, including supervised learning, unsupervised learning, weakly supervised learning, reinforcement learning, etc. Logic regression is a form of algorithm used for classification in supervised learning. Support vector machine is an algorithm proposed in 1963 to solve the two-classification problem. At present, it is mainly divided into three categories: hard interval, soft interval and nuclear support vector machine. The SVM has been successfully applied in multiple areas, such as mail information processing, you can judge whether a message is spam. In medicine, AI can also be used to classify bioelectrical signals.

In recent years, the incidence of arrhythmia is increasing, and shows a trend of younger age, it is also one of the main causes of sudden cardiac death. Arrhythmias are classified as electroshock able and non-electroshock types. Usually, stable arrhythmias can be terminated by devices such as defibrillator using shock therapy. In contrast, non-electroshock arrhythmias do not respond or worsen after electroshock therapy. Although the automatic defibrillator is equipped with a detection algorithm based on ECG morphological characteristics, it is difficult to distinguish the two weak signal differences of the two types of arrhythmias, resulting in its low detection success rate. A new automatic function based on wavelet has been developed by the Manish team [8]. The classification algorithm of artificial intelligence was added to the previous architecture of the signal input system. The support vector machine, logistic regression and decision tree algorithms used enable the wavelet filtered electrical signals to be further classified in the device, providing more accurate information for the judgment of arrhythmia types in later stages. The resolution accuracy of the arrhythmia types obtained by the MITDB test was as high as 98.9%.

2.5 Application of artificial intelligence in blood pressure measurement

Hypertension is the third leading cause of death and the most common chronic disease in the world. It is estimated that more than one billion people worldwide have varying degrees of hypertension, and it is expected to grow to 1.5 billion by 2025 [9]. At present, the international hypertension index is not the same. The published standards in China are systolic blood pressure > 140mmHg and diastolic blood pressure> 90mmHg, which can be judged as hypertension. The new type of blood pressure measurement transmits various signals, such as acoustic signals, mechanical vibration signals or electrical signals, to the computing equipment, and then conducts signal conversion and processing to obtain blood pressure. But similar to the ECG signals measured above, these methods have common drawbacks: loss or deterioration of signals in the process of conduction and transformation, and interference with chaotic signals. Some in the industry also believe that the new measure of blood pressure is generally less accurate than the traditional mercury column pressure method.

In theory, the most accurate measurement method is to directly insert a pressure measurement device into the arterial blood for pressure measurement, but this invasive measurement method is often abandoned because of its great harm to human body. In recent years, improved methods for blood pressure measurement have increasingly tended to record the true blood flow pressure on the vessel wall as much as possible non-invasively. The new non-invasive blood pressure monitoring technology machine encourages the combination of artificial intelligence and information collection system. Machine learning, deep learning and other models can be updated through the parameters within the algorithm to play the role of signal fitting, which is of great use value in improving the accuracy of blood pressure measurement. DeepCNAP, a novel deep learning model containing deep convolutional networks, was applied to real-time estimation of continuous arterial blood pressure waveforms from non-invasively measured signals of photoplethysmography (PPG) [10]. The model predicted more than 900 blood pressure samples in the MIMIC database, and tested its performance from both the classification of blood pressure and the average absolute error of systolic blood pressure estimates, with an accuracy of more than 90%.

Another two-step algorithm with a single-channel PPG also showed more accurate prediction results in the assessment of blood pressure [11]. Compared to the complex deep learning algorithm above, this concise model is more robust in practice. Machine learning is also used to analyze PPG signals, and decision tree, support vector machine and random forest can effectively solve the problem of nonlinearity of data collected in blood pressure monitoring.

The ultra-high monitoring accuracy achieved by AI is built on strict conditions —— BP training dataset. Therefore, the signal is generally preprocessed before entering the algorithm, such as noise filtering, baseline correction, and accurate extraction of effective features from the original waveform information [11], improve the generalization and reduce the risk of overfitting of the algorithm. Nowadays, many blood pressure monitoring systems in smart watches or mobile phones collect blood pressure information through PPG. If the above learning algorithms can be applied to the monitoring system, accurate blood pressure measurement will no longer be limited to hospitals or during medical treatment.

1. **Cardiovascular Disease Risk Prediction**

Cardiovascular disease has a long latency period and early symptoms are mild and difficult to detect. By the time a patient is diagnosed with CVD, the disease is usually already in critical condition. Effective assessment and early prevention of potential patients with CVD can significantly reduce its prevalence and adverse consequences, so it is very important to predict the risk of CVD through artificial intelligence techniques. Machine learning plays an important role in predictive modeling of CVD, of which supervised learning is again the most important [12]. Supervised learning refers to the use of known specific feature samples as a training set to build a model, and then mapping new unknown samples, which can be used for the construction of CVD risk prediction models, usually including Logistic Regression, K-Nearest Neighbors, Decision Trees, SVMs, RFs, and Artificial Neural Network models [13]. Unsupervised learning, on the other hand, can be used to discover new subtypes of the disease and decompose them into more precise independent subtypes [14].

3.1 Disease risk prediction model based on physiological data of CVD patients

The occurrence of cardiovascular diseases can often be diagnosed and predicted by various physiological indicators of the human cardiovascular system, while machine learning can make intelligent predictions based on sample data learning, which helps doctors make clinical decisions. Machine learning, as an important branch of artificial intelligence technology, plays an important role in the prediction of CVD. Hypertension is a cardiovascular disease characterized by elevated pressure in the arteries of the body circulation and is also the most important risk factor for many cardiovascular diseases, leading to thickening of the arterial wall and reduced elasticity which increases the risk of blockage, stenosis and rupture.

Kanegae[15] et al. developed and validated a prediction model for the risk of new-onset hypertension based on conventional machine learning. The study included a total of 18,258 patients' health examination data from 2005-2016, mainly BMI, age, CAVI, and triglyceride levels. Then 75% of the data were randomly selected as a training set for model construction and development, and another 25% of the data set was used as a test set for model validation. By calculating the error generated by the model using the test set and using it as an approximation of the generalization error, the effect of the final model can be tested by simply minimizing the error of training the model on the test set. By using scalable end-to-end tree boosting system, i.e., XGBoost model, as well as integrated modeling and logistic regression algorithms in supervised learning, for combine multiple weak methods to preduce a strong model, and a logistic regression model, and validated by comparing the relative importance of the predictor variables to conclude that the best predictor of the XGBoost model is systolic blood pressure at the time of cardiac and ankle vascular index measurements. This model can be used to predict the risk of hypertension in the general population, identify high-risk individuals, and provide early non-pharmacological intervention through individual data.Baker et al[16] proposed a hybrid neural network-based approach to analyze the electrocardiogram (ECG) and photoplethysmogram (PPG) waveform data of 110 patients. waveform data of 110 patients, and realized the continuous non-invasive assessment of blood pressure. The results showed that this method has high accuracy and efficiency in continuous non-invasive blood pressure estimation, and can provide a valuable reference for clinicians and researchers.

3.2 Disease risk prediction model based on facial information of CVD patients

As cardiovascular disease is the most prevalent disease in the world, in addition to conventional prediction models based on clinical physiological indicators for risk factor analysis, prediction tools with the advantages of accuracy, practicality and low cost are necessary. Coronary artery disease (CAD) is a heart disease in which coronary arteries undergo atherosclerosis causing narrowing of the lumen, which in turn leads to myocardial ischemia and hypoxia, and is the leading cause of cardiovascular deaths and chronic disability in all regions of the world, and patients' facial features are associated with an increased risk of CAD such as alopecia, graying, and facial wrinkles, which could provide a basis for potential disease screening [17]. Zhen et al. through a deep learning algorithm to develop an artificial intelligence model that integrates facial features based on facial photographs of Chinese populations to predict the risk of developing coronary artery disease, which provides early screening for people at high risk of cardiovascular disease [18]. First the model first binary classified the test data based on coronary angiography and then used to train the CAD risk prediction model by deep convolutional neural network. The patient's facial photographs were superimposed to integrate the facial features, which in turn was used to train the CAD risk prediction model bygiven an integrated photo of the training set, to extract the useful features and perform the output with the ground truth for the model.The prediction error is then calculated by comparing the output with the actual results and the corresponding parameters are adjusted to minimize the error so that the model achieves the level of accurate assessment of CAD. The model divides the face into nine regions, due to the different correlations between facial features and disease risk in different regions, the model classifies the regions by highlighting them through the algorithm, then masks them and retrains and validates the algorithm, and conducts a secondary test based on the decrease in the accuracy of the algorithm's performance after the masking, and visualizes the positive regions classified according to the CAD by outputting the heatmap of each photo. The output heatmap of each photo is used to visualize the positive facial regions classified according to the CAD predictive correlation and to adjust the relevant parameters. Compared with the prediction model that collects individual physiological data from patients for the purpose of predicting the risk of CVD, this model is simpler and more convenient to recognize and analyze facial information directly, and has higher performance and generalizability.

**4. Summary and outlook**

In this review, we provide an overview of the application of AI in cardiovascular disease monitoring and prevention. In the process of collecting information data such as ECG and blood pressure from patients, AI algorithmic models such as machine learning and deep learning are equipped on the traditional information collection system to accurately differentiate, extract as well as fit the information, so that the information obtained is a more realistic representation of the patient's general physiological condition. The purified and converted information is also integrated and analyzed using AI, such as convolutional neural networks, to improve the system's performance in predicting the course of cardiovascular disease. According to current reports, in the field of cardiovascular diseases, most intelligent monitoring systems equipped with AI algorithms can demonstrate more than 90% accuracy in analyzing a patient's disease type in the real clinic after being trained on a large number of samples. The biggest challenge in the use of AI in cardiovascular disease monitoring and prediction systems is the selection and training of models. For cardiovascular diseases, data information tends to show small continuous fluctuations. Therefore, an ideal model design should be able to be robust to small-amplitude signal fluctuations, i.e., it will not seriously interfere with the prediction results due to such deviations, and also have high feature extraction performance and high sensitivity to small changes in the really useful information. In addition, a good model needs a large number of real samples to be trained to realize it. At present, most of the new monitoring systems use information from several major cardiovascular disease databases recognized worldwide for testing and training, but these data are only the tip of the iceberg that can reflect the whole field of cardiovascular disease. In the future, using big data and the Internet of Things to collect and share patient information from around the world may be a fast way to achieve the sample size needed for AI algorithm models. Cardiovascular disease has always been a common problem for all mankind. As the privacy of patients, it has always been an acute issue whether information such as ECG and blood pressure is public or not. For AI to truly serve humanity, clearer answers to ethical questions such as these are also needed. Developing standard monitoring and judging processes and algorithmic interpretability so that healthcare professionals and the general public recognize the usability and applicability of AI in health monitoring and disease prediction may be the only way to get more people to overcome the barriers to disclosure of information and allow for the expansion of the use of AI in cardiovascular disease monitoring and prediction.

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