AN OPTIMIZED CONVOLUTIONAL NEURAL NETWORK FOR ARRHYTHMIA CLASSIFICATION

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ABSTRACT

Electrocardiogram (ECG) is a practical medical test to diagnose arrhythmia. As a crucial computational application in clinical practice, ECG automatic classification can effectively detect the possible occurrence of cardiovascular disease. At present, the main problems in the automated classification of ECG are due to (1) the complexity of algorithms to capture heartbeats, (2) the complex changes of irregular heartbeats in rhythm or morphology leading to difficulties in the ECG feature recognition, and (3) the needs of large training samples and training time for a machine learning to achieve the ideal recognition accuracy. Given the problems in ECG automatic classification, this study proposes an effective automated classification approach for arrhythmia based on a representative convolution neural network that can decode ECG source files and identify heartbeats accurately based on the detection of QRS waveform from the ECG records. A one-dimensional convolutional neural network (1D-CNN) is proposed to accurately classify different types of arrhythmias by automatically extracting the morphological features of ECG. The initial connection weights of 1D-CNN are optimized based on differential evolution to improve its ECG classification. The optimized 1D-CNN is evaluated against two arrhythmia databases, namely the MIT-BIH and SCDH arrhythmia databases. Besides, a comparison is made between the optimized and unoptimized 1D-CNN. The results show that the proposed model has higher accuracy in heartbeat classification. Compared to the unoptimized 1D-CNN, the accuracy improves by 0.6% and 3.1%, respectively. Besides, the optimized 1D-CNN requires less training time, 9.22 seconds less with MIT-BIH and 10.35 seconds less with SCDH based on ReLU active function and 10 epochs, as compared to the unoptimized 1D-CNN based on the same parameter settings. The training time of the optimized 1D-CNN decreased by 67.2% and 64.2% with MIT-BIH and SCDH, respectively.

RANGKAIAN NEURAL KONVOLUSIONAL YANG DIOPTIMUMKAN UNTUK KLASIFIKASI ARITMA

ABSTRAK

Elektrokardiogram (ECG) adalah ujian perubatan yang praktikal untuk mendiagnosis aritmia. Sebagai aplikasi pengkomputeran yang penting dalam amalan klinikal, klasifikasi automatik ECG dapat mengesan dengan berkesan kemungkinan berlakunya penyakit kardiovaskular. Pada masa ini, masalah utama dalam pengelasan automatik ECG adalah disebabkan oleh (1) kerumitan algoritma untuk mengesan degupan jantung, (2) perubahan kompleks degupan jantung yang tidak teratur dalam irama atau morfologi yang membawa kepada kesukaran dalam pengecaman ciri ECG, dan (3) keperluan sampel latihan yang besar dan masa latihan untuk pembelajaran mesin untuk mencapai ketepatan pengecaman yang ideal. Memandangkan masalah dalam pengelasan automatik ECG, kajian ini mencadangkan pendekatan pengelasan automatik yang berkesan untuk aritmia berdasarkan rangkaian neural konvolusi perwakilan yang boleh menyahkod fail sumber ECG dan mengenal pasti degupan jantung dengan tepat berdasarkan pengesanan bentuk gelombang QRS daripada rekod ECG. Rangkaian neural konvolusional satu dimensi (1D-CNN) dicadangkan untuk mengklasifikasikan jenis aritmia dengan tepat dengan mengekstrak ciri morfologi ECG secara automatik. Pemberat sambungan awal 1D-CNN dioptimumkan berdasarkan evolusi pembezaan untuk meningkatkan klasifikasi ECG. Prestasi 1D-CNN yang dioptimumkan dinilai berdasarkan dua pangkalan data aritmia, iaitu pangkalan data aritmia MIT-BIH dan SCDH. Selain itu, perbandingan dibuat di antara 1D-CNN yang dioptimumkan dan tidak dioptimumkan. Keputusan menunjukkan bahawa model yang dicadangkan mempunyai ketepatan pengelasan yang lebih tinggi dalam pengelasan degupan jantung. Berbanding dengan 1D-CNN yang tidak dioptimumkan, ketepatan dipertingkatkan masing-masing sebanyak 0.6% dan 3.1%. Selain itu, 1D-CNN yang dioptimumkan memerlukan masa latihan yang kurang, iaitu pengurangan sebanyak 9.22 saat dengan MIT-BIH dan pengurangan sebanyak 10.35 saat dengan SCDH berdasarkan fungsi aktif ReLU dan 10 kitaran, berbanding dengan 1D-CNN yang tidak dioptimumkan dengan menggunakan parameter yang sama . Masa latihan 1D-CNN yang dioptimumkan berkurangan sebanyak 67.2% dan 64.2% dengan MIT-BIH dan SCDH masing-masing.

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LIST OF ABBREVIATIONS

AF	Atrial Fibrillation
AI	Artificial Intelligence
BP	Back Propagation
CHF	Congestive Heart Failure
CNN	Convolutional Neural Network
CVD	Cardiovascular Diseases
DBN	Deep Belief Network
DCNN	Deep Convolutional Neural Network
DNN	Deep Neural Network
ECG	Electrocardiogram
GA	Genetic Algorithm
LSTM	Long Short-Term Memory
MCNN	Multi-Scale Convolutional Neural Network
OSAH	Obstructive Sleep Apnea and Hypopnea
RAN	Region Aggregation Network
SCDH	Sudden Cardiac Death Holter
SDE	Standard Differential Evolution
SVM	Support Vector Machine

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LIST OF PAPERS PUBLISHED

[1] **Review of ECG detection and classification based on deep learning: Coherent taxonomy, motivation, open challenges and recommendations.** SW Chen, SL Wang, XZ Qi, SM Samuri, C Yang. *Biomedical Signal Processing and Control*. Volume 74, April 2022, 103493. ISSN: 1746-8094 SCI (IF: 5.076) SCOPUS-Q2.

[2] **A CNN based Handwritten Numeral Recognition Model for Four Arithmetic Operations.** C ShanWei, S LiWang, NT Foo, DA Ramli. *Procedia computer science*. ISSN: 1877-0509 SCOPUS.

[3] **Differential Evolution Optimized One-Dimensional Convolutional Neural Network for Classification of Electrocardiogram (submitted in 2021).** SW Chen, SL Wang*, XZ Qi, Theam Foo Ng, Haidi Ibrahim

[4] **Artificial Intelligence in Cardiovascular Imaging (accepted in 2022).** SW Chen, SL Wang*, TF Ng, Haidi Ibrahim. *Cardiovascular and Coronary Artery Imaging Volume 2, Elsevier*

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter mainly describes the research background, problem statement, research questions, research objects, the significance of the research, research scope, and thesis organization.

Cardiovascular disease is a perilous disease with high mortality. The electrocardiogram (ECG) analysis is helpful for the early detection of cardiovascular diseases such as arrhythmia, and its clinical value is widely recognized. However, the disadvantage of traditional ECG detection is that the processing of electrocardiogram images is time-consuming, which is easily affected by the personal ability of doctors and subjective factors, resulting in inconsistent disease detection or disease severity judgment. The advancement of computational technology and machine learning such as combining deep neural networks and electrocardiogram detection, can shorten the image processing time and make the diagnosis results more reliable based on the objective analysis of big data. Besides, using advanced computer technology improves the accuracy of cardiovascular disease diagnosis and helps to alleviate the contradiction between medical resources and patient needs.

1.2 Research background

Recently, as people's daily rhythms have accelerated and their life and work pressures have increased, cardiovascular disease deaths have increased. Cardiovascular diseases have become one of the most critical diseases threatening human health (Shortliffe et al., 2014). The electrocardiogram, abbreviated as ECG, is one of the most common methods for diagnosing cardiac problems (Bernstam et al., 2010). The ECG, a non-invasive procedure, is a visual representation of possible variations in the surface of the human body while the heart beats.

ECG conveys much information related to electrical conduction and heart rhythm. It has become one of the crucial bases for evaluating heart function and diagnosing heart diseases due to its low cost, reliable diagnosis, simple method, and non-invasive characteristics (Lesk, 2019). In ECG diagnosis, about 90% of the common types of clinical arrhythmia can be diagnosed by analyzing the surface electrocardiogram (Shiyovich et al., 2010). An arrhythmia, for example, is a heart rhythm that deviates from the normal rhythmic activity of the heart. It may occur occasionally or continuously (Grau et al., 2006). It is commonly associated with a variety of organic heart diseases. Arrhythmias may also occur under anesthesia, during surgery, and with electrolyte disturbances, hypothermia, and medication. Arrhythmias make the process of atrial and ventricular contraction disordered, and cardiac output decline leads to abnormal blood circulation, resulting in physical discomfort or even death (Uhlen et al., 2010). Thus, the early prevention of arrhythmia and accurate diagnosis is vital.

The traditional ECG analysis is performed by an electro-cardiographer, who makes the diagnosis based on the patient's ECG waveform and other supporting data (Arel et al., 2010). Although this traditional diagnostic method can improve the accuracy of diagnosis, the conclusion depends on the subjective factors of doctors, coupled with the uncertainty of some heart diseases, which may lead to different doctors getting different diagnosis results for the same patient(Lipman & Pearson, 1985). Or to dynamic ECG of the patients who need extended time monitoring, 24 hours available up to 2.16 km, including more than a thousand times of cardiac and hundreds of times of the cardiac cycle. In this case, on the one hand, artificial diagnosis and analysis are time-consuming and laborious. On the other hand, diagnosis of physician due to factors such as fatigue, may ignore some abnormal ECG waveform, missed diagnosis and misdiagnosis and accuracy also decreases; In addition, for patients undergoing surgery, it is impossible for medical staff to record the patient's every cardiac cycle data.

Under this background, the use of computer-aided diagnosis systems is useful. Computer-aided diagnosis system uses intelligent computing and other technologies to process and analyze ECG data. It combines wireless communication, big data processing, and other technologies to realize the data storage and analysis and ultimately learn early prediction, prevention, and accurate diagnosis of diseases. Scholars at home and abroad have made good progress in ECG diagnosis and processing. However, ECG signals are easily affected by different motion states, individual differences, noise interference, and other factors. The waveform is easy to change, which brings difficulties to the accurate diagnosis of arrhythmia. In the conventional computer-aided diagnosis, the existing methods of arrhythmia diagnosis and classification still have significant progress in effectiveness, real-time and other aspects. Therefore, it is of great theoretical significance and practical value to further improve the performance of analysis and classification of arrhythmia in ECG monitoring equipment to protect people's physical health and develop medical health in society.

ECG acquisition conditions include internal and external environments with individual differences (Bengio, 2013). Compared with other signals, the ECG signals have the following salient features:

1. Strong randomness

ECG signals are collected in complex internal and external environments, making the signals have strong randomness and often difficult to describe and quantify with certain mathematical functions. For example, the strong randomness of the distribution of features around the heart sounds in the ECG units makes the distribution of signals in the abnormal feature areas very irregular in different directions, which presents a series of challenges for follow-up diagnosis and treatment. Therefore, it is often necessary to improve the general signal processing method according to the specific problem in ECG signal-based modeling to obtain a more effective signal description and analysis results.

2. Low frequency

Except for the relatively high frequency of sound signals, the spectrum range of other biomedical signals is concentrated in the lower numerical range. For example, the ECG distribution is predominantly 0.01 Hz - 35 Hz. External instruments and analysis methods should consider the characteristics of signal frequency in the process of signal acquisition, amplification, and processing

3. Strong noise

As a complex organism, the human body or other living things will constantly produce physiological signals with various characteristics. There are other signals from different sources in the environment where the signal collection object is located. In acquiring an ECG signal, the other physiological signals are often noise that interferes with its standard processing and analysis.

4. The signal is weak

The ECG signal generated by the human body itself is generally of small amplitude, which is often between 0.1mV and 2mV. Therefore, the ECG signal is amplified by a high-performance amplifier, which determines the signal's quality.

The main features of the above ECG signals determine the particularity of the ECG processing methods, their complexity, and the challenge of processing tasks. Aiming at different kinds, sources, and modes of ECG signals, designing effective signal processing and analysis methods is the key and difficult point of ECG signal processing (Burbidge et al., 2001). With the rapid development of modern machine learning methods represented by deep neural networks and the tremendous increase in computer hardware, it is becoming increasingly viable to successfully process and analyze multi-type, cross-modal, and large ECG signals. Machine learning, specifically deep learning, shows promising potential in modeling the complexity of ECG classification.

Deep learning is a type of machine learning, and a deep neural network is a deep learning technique (Dhawan, 2011). In many cases, machine learning is almost an alternative concept to artificial intelligence. In short, machine learning allows a computer to learn potential patterns and characteristics from a massive quantity of current data using machine learning algorithms, which can intelligently recognize new samples or predict the likelihood of something happening in the future. Since the 1980s, the development process of machine learning has gone through two stages: shallow learning and deep learning, according to the hierarchical structure of the algorithm model of machine learning.

Shallow learning is the first stage of growth:

The introduction of the Back Propagation algorithm (BP) and its use in the learning process of artificial neural networks in the late 1980s accelerated the development of machine learning. It ushered in a new era of statistical machine learning models(Rajpurkar et al., 2017).

The researchers discovered that using the back propagation algorithm can cause the artificial neural network model to automatically modify its parameters during the training process, allowing the network model to fit the training data to a greater degree, resulting in many training samples. By training neural networks, we can make them learn mathematical laws and predict unknown events. Compared to prior systems based on artificial rules, this machine learning model based on statistical principles has several advantages. Although the artificial neural network in this period is referred to as a Multilayer Perceptron (Joseph, 2012), it is essentially a shallow model with only one layer of hidden layer nodes.

Since the 1990s, various shallow machine learning models have successively appeared, such as the maximum entropy method (Logistic Regression, Boosting, Support Vector Machines, etc.). These machine learning model architectures have no hidden layer nodes (logistic regression) or only one hidden layer node (Boosting and SVM) (Zipser & Andersen, 1988). This model type has achieved great success in both theoretical research and practical application. However, due to the challenges in theoretical analysis, the network model requires particular skills and a great deal of empirical information throughout the training process. Thus, the development of shallow artificial neural networks seems to be somewhat behind schedule.

Deep learning is the second stage of growth:

In 2006, Geoffrey Hinton, a master of machine learning and professor at the University of Toronto, and his student Ruslan published a paper in the world's top academic journal *Science*, which triggered a boom in the development of deep learning in the research field and application field (Azimi-Sadjadi et al., 1990). This paper makes two main points:

1. The multi-layer artificial neural network model has a strong feature learning capacity. The feature data collected by deep learning models have an essential representation of the original data, making classification and visualization issues much easier to solve.

2. The layered training approach is used to overcome the problem of challenging deep neural networks to obtain optimal performance through training. The result of the upper training is taken as the initialization parameter of the lower training. In this paper, layer-by-layer initialization in-depth model training begins to adopt unsupervised learning.

Since 2006, the research on deep learning in academic circles has been heating up. The University of Toronto, University of Montreal, New York University, and Stanford University in the United States have become research centers of deep learning. In 2010, the deep learning project received its first funding from DARPA, the U.S. Department of Defense, with NEC Research, New York University, and Stanford University. The brain nervous system is composed of rich hierarchical structures, which is an essential theoretical basis for supporting deep learning. Hubel and Wiesel won the 1981 Nobel Prize in Physiology or Medicine for their extensive experiments on the visual system of cats, which revealed how the visual nervous system works. In addition to the bionic perspective, due to the difficulty of mathematical demonstration and complexity of the depth model, the research on deep learning theory is still at the initial stage. Still, the deep learning model has shown great potential in engineering applications.

Nowadays, Google, Microsoft, Baidu, and other well-known high-tech companies with big data resources have increased their investment in deep learning, striving to seize the commanding heights of this technology field and seize the opportunity in future competition. They see that more advanced and powerful deep learning models can expose the potentially complex, massive, and rich data and make a more precise prediction about the possibility of some upcoming activities in the era of big data they have developed.

In summary, deep learning is a machine learning architecture model with multiple hidden layers, and obtaining more representative feature information through large-scale data training (Wooff, 2004), intends to improve sample classification and prediction accuracy. The goal of this technique is to use a deep learning model to achieve the purpose of feature learning. The following are the differences between a deep learning model and a standard shallow learning model:

1. There are more layers in a deep learning model's structure. The number of layers with hidden layer nodes is frequently greater than 5, in certain cases, greater than 10 layers.

2. The importance of feature learning for the depth model is clearly emphasized. That is, the feature of the data sample in the original space is transformed into a new feature space to represent the initial data through the feature extraction layer by layer, which makes the classification or prediction more easily realized.

The data features acquired by deep model learning are more representative of the rich internal information of large data than the manually created feature extraction method. As a result, ECG signals can be detected and classified using deep learning technology, which will be the future trend of ECG-aided diagnostic systems.

1.3 Problem statement

Deep learning is an effective tool for mining medical data, which uses machine learning algorithms to generate relevant models from physiological signals to guide medical decision-making, reduce medical costs, improve resource utilization and benefit society. Based on the classification of ECG signals, this study uses deep learning to investigate the automatic identification and optimization of heart-related diseases.

As for the classification of ECG heart types, although obtaining ECG data is relatively simple, there are still many challenges in extracting the features of the signals. Each heartbeat in an ECG represents the electrical activity of the heart over time. For

ECG specialists, irregular heartbeats can be easily identified by changes in heartbeat, rhythm, or morphology. However, automatic recognition of computers is still a challenge, mainly for the following reasons:

1. The heartbeat can be captured through the location and detection of the QRS wave. By detecting the QRS wave's location, the heartbeat's location can be roughly located. At present, the primary location method is wavelet transform. This method is complex to complement, the processing efficiency is not high enough, and the accuracy is not ideal (Pal & Mitra, 2012). Therefore, it is challenging in the field of ECG recognition to find a QRS waveform detection algorithm with a simple implementation method and good operation effect based on ensuring the practical value of accuracy.

2. In addition to the simplicity of obtaining the ECG data, there are many challenges to classifying ECG heartbeat types. Each heartbeat in an ECG represents the heart's electrical activity over time. For ECG specialists, irregular heartbeats can be easily identified by changes in heartbeat, rhythm, or morphology. For the current machine learning, the ECG features to be extracted mainly include morphological features and transform coefficient features. The main problem of extracting morphological features is accurately locating each heartbeat waveform. Extracting transform coefficient features depends on complex mathematical transformations, such as wavelet transform and polynomial fitting. The above work is complex, and the threshold is very high, which is not conducive to promoting computer-aided medical

treatment. Therefore, computers' automatic recognition and feature extraction is still a challenge (Sahoo et al., 2017).

3. Through literature review, we find that Convolutional Neural Network (CNN) is suitable for image processing, and traditional machine learning may not be able to perform the task. Its operation focuses on optimizing weights and biases for the training of a convolutional neural network (Zubair et al., 2016). First, the network will initialize weights and biases with specific strategies, essentially a set of random values assignments. Then, using the BP algorithm and stochastic gradient descent, all weights and biases are iteratively optimized, and finally, the expected recognition rate gradually or approximately is achieved. However, another problem is how to optimize the weights and the initial values of the bias to shorten the training time of CNN (Salloum & Kuo, 2017) and further improve the recognition accuracy (Mathews et al., 2018).

1.4 Research questions

The research questions are shown as follows:

1. How to capture and extract heartbeat from the ECG signals' recording automatically?

2. How to design a one-dimensional CNN (1D-CNN) that can classify the types of Arrhythmia?

3. How optimize the performance of 1D-CNN by improving accuracy and shortening the training time?

1.5 Research objectives

This study selected ECG signals, which represent biomedical signals, as the research object. Combined with CNN, the most representative neural network model in deep learning, a series of studies were conducted on the classification and optimization of ECG signals and the identification and application of common heart-related diseases. The main research objectives are as follows according to the problem statement and research questions:

1. To capture and extract heartbeat from the ECG signals' recording automatically.

2. To design a one-dimensional CNN (1D-CNN) that can classify the types of Arrhythmia.

3. To optimize the performance of 1D-CNN by improving accuracy and shortening

the training time.

1.6 Significance of research

This study summarizes the development process and the latest research results of deep learning. Besides, it details the concepts and algorithms involved in artificial neural networks and classical CNN. Another focus of this study is to apply the improved classical CNN algorithm to ECG classification and disease judgment. The architecture and performance of the convolutional neural network based on theory and application are analyzed in this study. The main significance of this study is as follows:

1. Applying CNN based on deep learning technology to ECG classification solves the shortage of traditional machine learning methods requiring manual feature extraction.

2. Using a differential evolution algorithm (DE) to optimize the parameters of 1D-CNN helps improve the performance of CNN and enrich the theoretical research of CNN.

3. Using the 1D-CNN and its optimized version to classify arrhythmia in the MIT-BIH and SCDH databases. The MIT-BIH database consists of the normal beat, left

bundle branch block beat, right bundle branch block beat, and premature ventricular contract. On the other hand, the SDCH database consists of the normal beat, premature ventricular contraction, premature or ectopic supraventricular beat, and left or right bundle branch block. The classification accuracy is further improved, the classification time is further shortened, and the early detection of cardiovascular diseases is improved.

4. Improving the performance of arrhythmia analysis and classification of ECG monitoring equipment encourages advanced intelligent diagnosis systems in healthcare.

1.7 Scope of the study

This research belongs to the applied study of computer science in medicine, which involves three categories of medicine, artificial intelligence, and optimization algorithm, respectively. Specific research areas are as follows:

1. Medical field involving ECG physiological signal principles, characteristics, acquisition, recognition, and classification.

2. Artificial intelligence field by analyzing and comparing the mainstream neural networks in deep learning, the CNN suitable for image classification and prediction is

selected as the basic deep neural model for ECG classification. Its advantages, principles, framework, application, and implementation are mainly studied.

3. Optimization algorithm field by determining the appropriate optimization algorithms to use. After comparing three optimization algorithms, including genetic algorithm, particle swarm optimization algorithm, and differential evolution algorithm, we decided to use the differential evolution algorithm. The reason is the structure of the differential evolution algorithm is simple, the control parameters are few, the real coding is easy to implement, the convergence speed is fast, and its convergence has been proved theoretically. Therefore, DE is used to optimize CNN weight and threshold. Thus, the network's performance is improved by accelerating training time and improving classification prediction accuracy.

1.8 Thesis organization

The study focuses on the design of a 1D-CNN to classify ECG signals. The designed 1D-CNN is evaluated using two arrhythmia databases: MIT-BIH arrhythmia and SCDH arrhythmia. The MIT-BIH arrhythmia involves the classification of normal beat, left bundle branch block, right bundle branch block, and premature ventricular contraction based. In contrast, SCDH consists of the classification of normal beat, premature ventricular contraction, premature or ectopic supraventricular beat, and left or right bundle branch block. At the same time, the weights and thresholds of the whole connection layer of the 1D-CNN are optimized by using a differential evolutionary algorithm. Through experimental analysis, the effectiveness of the optimization is verified, and the network's training speed and classification accuracy are improved. The dissertation contains into five chapters, which are as follows:

The first chapter describes the research background and significance, research content, research scope, and the whole thesis organization. This chapter begins with the characteristics of ECG signals. First, it briefly describes the application and importance of ECG signals in today's society, analyzes the shortcomings of traditional artificial ECG detection and diagnosis, reviews the development process of deep learning, and finally describes the advantages of the combination of deep neural network and ECG detection. Based on a review of the research background, this chapter further presents the challenges and difficulties faced in the ECG classification field and provides a brief overview of the work planned for the thesis.

The second chapter summarizes the main contents of this thesis, including the basic concepts of physiological signals represented by ECG and methods for classified detection, the principle of CNN, features, and the essential framework. The chapter also introduces the genetic algorithm, differential evolution algorithm, and particle swarm optimization algorithm, which prepares for the subsequent optimization of the CNN network. Finally, the chapter describes the evaluation criteria of the ECG classification method based on CNN.

The third chapter presents a flow chart of the ECG classification optimization network model based on 1D-CNN. Based on the flow chart, the theory and function of each module are described in details. It mainly includes:

1. ECG binary data decoding and reading
2. The acquisition of heartbeats in ECG records
3. The implementation of CNN in ECG heartbeat recognition
4. Optimization of CNN by differential evolution algorithm
5. Testing and evaluation

The fourth chapter implements ECG classifications based on optimized and unoptimized 1D-CNN. The optimized and unoptimized 1D-CNN are tested separately, and then the test results are compared and analyzed.

The fifth chapter summarizes this thesis's research work, explains the areas that still need improvement, and looks forward to future research.