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Deep Time Growing Neural Network vs Convolutional Neural Network for Intelligent Phonocardiography

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Abstract. This paper explores the capabilities of a sophisticated deep learning method, named Deep Time Growing Neural Network (DTGNN), and compares its possibilities against a generally well-known method, Convolutional Neural network (CNN). The comparison is performed by using time series of the heart sound signal, so-called Phonocardiography (PCG). The classification objective is to discriminate between healthy and patients with cardiac diseases by applying a deep machine learning method to PCGs. This approach which is called intelligent phonocardiography has received interest from the researchers toward the development of a smart stethoscope for decentralized diagnosis of heart disease. It is found that DTGNN associates further flexibility to the approach which enables the classifier to learn subtle contents of PCG, and meanwhile better copes with the complexities intrinsically that exist in the medical applications such as the imbalance training. The structural risk of the two methods is compared using the A-Test method.

Keywords. Deep time growing neural network, intelligent phonocardiography, A-Test method, heart sounds, deep learning

1. Introduction

The trend of the potential effectiveness of artificial intelligence in the healthcare domain has been noticeably increased by the creation of deep machine learning methods that can potentially enable machines to perform accurate classification of different health-related modalities. Such development has been directed towards creating smart electronic stethoscopes using heart sound signals as the input to a classifier, which was not widely successful to convince the medical users in terms of the reliability of the classifier. A recording of heart sound is named PhonoCardioGraph (PCG), and a system for recording and processing PCB which is supported by the machine learning methods for the decision making, is known as Intelligent PhonoCardioGram (IPCG). This system can be of special importance for screening children with heart disease since as many as 50% of healthy

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children have abnormal heart sounds, which imposes a huge burden on healthcare systems and also stress the families. Several machine learning methods such as Convolutional Neural Network (CNN) and Deep Time Growing Neural network have been introduced for the classification of PCG [1–3]. One of the bottlenecks in development of a reliable IPCG for the medical application lies in the interpretability of the machine learning methods employed for the classification. Most of the proposed methods for IPCG cannot fit well into an explainable artificial intelligent-based method. For example, CNN has been intrinsically proposed for image classification, while it is dominantly seen in IPCG in which the PCG is turned into images by using a mathematical transformation method prior to the classification. This will in turn bring further complexities and undesirable features to the methods. A consequence of such complexities is the incapability to detect subtle disease-related variations of PCG, due to the dominant class of harsh abnormal as well as the between-class similarities, especially considering the imbalance of training. DTGNN on the other hand is an explainable machine learning method, sophisticated for PCG classification [4–7]. Studies showed its capabilities for several case studies of IPCG along with its superiorities against hybrid methods [8–12]. This paper, studies and compares the capabilities of DTGG against CNN, which has been broadly employed for the development of IPCG. The structural risk and learning capacity of DGTNN will be explored and compared to CNN.

2. Materials

Heart sound recordings from the referrals to the Children Medical Centre of Tehran were invoked for this study due to the variety and well-described class labels of real data which cannot be found in the other datasets. An electronic stethoscope of WelchAllyn Meditron Analyzer in conjunction with a portable computer was used for data acquisition. All the referrals underwent echocardiography, and the study was approved by the appointed ethics committee and was conducted according to the Good Clinical Practice. All the referrals or their legal guardians gave their informed consent to participate in the study. The patient population is listed in Table 1.

Table 1. Patient population of the study.

Heart Condition	Number of Patients	Age Range (years)
Aortic Stenosis	15	1–8
Mitral Regurgitation	15	4–8
Normal without murmur	30	4–15
Pulmonary Stenosis	15	1–10
Ventricular Septal Defect	25	1–9

3. Methods

3.1 DTGNN Method

DTGNN is a multi-scale classifier that is composed of a multi-layer perceptron method in which the input layer adjusts itself for learning the deep contents of the training data. The input layer extracts spectral energies from a set of the temporal windows with growing length, where the growing scheme is forward, backward and bilateral manner. Details can be found in [2–3]. DTGNN employs discriminant analysis to learn the subtle contents of the signals by finding the frequency bands whose spectral energies provide optimal discrimination. Figure 1 illustrates a DTGNN with a C number of the features. The TGNN learns the contents of heart sound within the cycles and the inference part makes filtering to exclude noisy cycles and delivers the filtered feature vectors to a Support Vector Machine (SVM) for the ultimate classification.

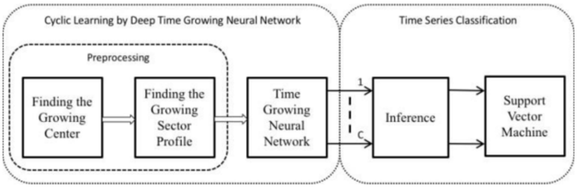

Figure 1. Architecture of Deep Time Growing Neural Network (DTGNN)

3.2 Evaluation Method

We employed the A-Test method for evaluation which is based on *k*-fold validation with different values of *k* (k=2,…,$k_{\max}$) , and the classification error is calculated foe each *k*-value.

$$\Gamma = \frac{\sum_{K=2}^{K_{max}} \Gamma_K}{K_{max}-1} \tag{1}$$

where Γ_k is the classification error of a classification, and k is the fold value for validation.

K_{max} is less than the minimum group size of the validation data. For a classification method, the difference between the minimum and maximum value of the classification error is an indication of the capacity of the classification method.

4. Results

In order to explore and compare the performance of the two classifiers, a DTGNN with six features. The baseline for comparison is a CNN with a kernel size of 5x5, 18 cells as defined by ResNet, the benchmark for comparison. The input to the CNN is composed of the Short-Time Fourier Transform of PCG. We employed A-Test for the comparison, taking the AS along with the PS classes as the pathological classes and the rest as the control group. The classification error obtained by A-Test is listed in Table 2.

Table 2. Descriptive statistics of the classification error for the two learning methods, the deep time growing neural network (DTGNN) and the Convolutional Neural Network (CNN).

Statistics	DTGNN	CNN
Average	10.51	11.17
Minimum	6.92	7.52
Maximum	18.46	19.20
Median	8.46	9.69

It is observed that the DTGNN provides a lower classification error, especially for higher k-values, implying further on learning capacity. The other descriptive statistics are better for DTGNN, confirming the superiority of the DTGNN.

5. Discussion

This study suggested to use DTGNN for IPCG. An important feature of DTGNN which makes it suitable for learning subtle contents of time series is its flexibility to choose various schemes of the growing time windows to preserve temporal contents of a time series. Such an elaboration cannot be seen in other deep learning methods where the learning process is a black box and unexplainable. It can therefore be customized for learning different segments of a cyclic time series which have similar behavior, in contrary with CNN in which the architecture cannot have such the flexibility. This justifies a better learning when it comes with the signals with high between-class similarities. Important feature of the classifiers were not discussed in many other studies.

6. Conclusions

Outperformance of the DTGNN in this case study, can be resulted from this feature of the classification method. In most of the other studies, signal with high between-class dissimilarities were used as the case study making reliability the resulting IPCG questionable.

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