Advances in Engineering Research (AER), volume 61
International Conference on Mechanical, Electronic, Control and Automation Engineering (MECAE 2017)

Comparison of Detection Methods based on Computer Vision and Machine Learning

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Keywords: Pathological image detection; Automatic diagnosis system; Feature extraction.

Abstract. Invisible diseases inside human's body even will lead the end of life. Hence, scientists put forward many computer-aided methods to detect the abnormalities in the body, which are proved to be beneficial for both doctors and patients. Nevertheless, how to select an accurate and convenient approach is a disturbing problem. In this paper, we will introduce some effective methods of image classification, and focus on the strength and weakness of them. Finally, we will present our future work on pathological image detection.

1. Introduction

Diseases inside the body are nearly invisible in the early stage, such as Alzheimer's disease [1-3], abnormal breast disease, multiple sclerosis [4, 5], microbleed [6], unilateral hearing loss [7], etc., so we must use other tools to find and treat it. Computer-aided methods, used to develop automatic diagnosis system, have been proved to be remarkable [8]. Different researchers proposed different methods to detect these diseases [9, 10].

Magnetic resonance imaging (MRI), as an imaging technique, can generates high quality images of the anatomical structures of the human body, especially in the brain. When detecting pathological brain, Yang (2017) [11] proposed a method via Hu moment invariants and machine learning. For abnormal breast, Grimm (2016) [12] introduced digital breast tomosynthesis (DBT), this method is a more innovative imaging technique, which reduces breast tissue superposition, in comparison to mammography. Imaging features and the diagnosis of tuberculosis of the breast can be learned from [13]. Hearing loss in children have been underestimate, but the effect on development and the potential pathophysiologic mechanism are now being noticed [14]. This paper tries to give a comparison of contemporary methods.

2. Methods and results

Chen (2017) [15] introduced the method of linear regression classifier, which is used to detect a feature-free 30-disease pathological brain. The accuracy of this method arrived at 97.51%.

Sun (2016) [16] put forward the method of extracting 12 fractional Fourier entropy (FRFE) features, then transporting those extracted features to an improved multi-layer perceptron (MLP) classifier. The average accuracy of the proposed method is 99.53%.

Lu (2016) [17] presented a novel pathological brain detection approach, which employed 2D discrete wavelet transform (DWT), and calculated the entropy as features. Then the pathological or healthy images are classified on radial basis function neural network (RBFNN). This method achieved a global accuracy of 95.44%.

Atangana (2016) [18] put forward an innovative method, stationary wavelet entropy (SWE), to extract features from image. The accuracy of the detected pathological brain images is 100%.

Zhou (2016) [19] selected wavelet entropy as features, a feed-forward neural network (FNN) as classifier to diagnosis the pathological or healthy brain image. The result of 64 images show that the average accuracy reached 100.00%.

Chen (2017) [20] combined wavelet packet Tsallis entropy (WPTE), feedforward neural network (FNN), and real-coded biogeography-based optimization (RCBBO) for pathological brain detection.

Under the background of existing methods for detection of Alzheimer's disease (AD), Wang (2016) [21] devoted to develop a better innovative system for computer-assisted AD detection, which based on following components: wavelet entropy, multilayer perceptron, and biogeography-base optimization. Moreover, this approach got an accuracy of 92.40 $\pm$0.83%. Atem (2017) [22] suggested that we can apply the linear regression with a randomly censored covariate to an Alzheimer's study.

Apart from pathological brain disease, breast cancer cannot diagnosis without any other tools. Nevertheless, we can detect the abnormalities of the breast before it become cancer with computer vision method. Chen (2016) [23] designed a program on account of wavelet energy entropy (WEE) and linear regression classifier (LRC) with 10-fold stratified cross validation.

In abnormal breast detection, Rao (2017) [24] also suggested a novel method. After segmenting the region-of-interest, the authors employed the weighted-type fractional Fourier transform (WFRFT) to get the unified time-frequency spectrum. Then author mentioned principal component analysis (PCA) for spectrum reduction. Next, feed-forward neural network (FNN) was used to generate the classifier, and Jaya was utilized to train the classifier.

Besides the diseases mentioned above, computer vision can analyze the etiology of hearing loss, which is helpful for us to prevent or cure it. In view of fractional Fourier transform (FRFT), Li (2016) [25] developed an approach to detect hearing loss which was proved to be efficient and accurate. The single-hidden-layer feed-forward neural network (SFN) classifier was trained by the Levenberg-Marquardt algorithm, and the accuracies are all higher than 95%.

From Table 1 to

Table 3, we can learn the shortcomings of different methods. Hence, we can select suitable method in our experiment.

Table 1. Comparison of efficacy involved images in abnormal breast detection

Authors	Method	Accuracy	Weakness
Chen (2016) [23]	Wavelet energy entropy (WEE) + linear regression classifier (LRC)	Accuracy of 91.85 $\pm$ 2.21%, sensitivity of 92.00 $\pm$3.20%, specificity of 91.70 $\pm$3.27%	The e tissues only include three types
Rao (2017) [24]	The weighted-type fractional Fourier transform (WFRFT) + principal component analysis (PCA) + feed-forward neural network trained by Jaya (Jaya-FNN)	Accuracy of 92.27 $\pm$ 3.49%, sensitivity of 92.26 $\pm$3.44%, specificity of 92.28 $\pm$3.58%	The system is not robust enough to detect abnormal breast

Table 2. Comparison of efficacy involved images in hearing loss detection

Authors	Method	Accuracy	Weakness
Li (2016) [25]	The fractional Fourier transform (FRFT) - principal component analysis (PCA) - single-hidden-layer feed-forward neural network (SFN) - Levenberg-Marquardt (LM)	Higher than 95%	This method has lower accuracy on overall population
Nayak (2017) [26]	Stationary wavelet entropy (SWE) + single-hidden layer feedforward neural network (SLFNN)	Accuracies of HC, LHL and RHL are 96.94%, 97.14% and 97.35%	It takes about four minutes to train the network.
Gorriz (2016) [27]	Wavelet entropy (WE) +directed acyclic graph support vector machine (DAG-SVM)	95.10%	Cannot implicated the related brain area

Table 3. Comparison of efficacy involved images in pathological brain detection

Authors	Method	Accuracy	Weakness
Chen (2017) [15]	Linear Regression Classifier(LRC)	Accuracy=97.51%, sensitivity=96.71%, specificity=97.73%	Only 117 were classified correctly in 200 brains
Sun (2016) [16]	Fractional Fourier entropy (FRFE) +multi-layer perception improved by Kappa coefficient (KC-MLP) +adaptive real-coded biogeography-based optimization (ARCBBO)	99.53%	Dataset only contains 66 brain images
Lu (2016) [17]	Wavelet entropy (WE) + radial basis function neural network (RBFNN)	Accuracy of 95.44%, sensitivity of 95.89%, specificity of 92.78%	The dataset was small. This method cannot classify different types
Atangana (2016) [18]	Stationary wavelet entropy (SWE) + kernel support vector machine trained by biogeography-based optimization (BBO-KSVM) (SWE + feed-forward neural network trained by hybridized BBO and particle swarm optimization (PSO))	Higher than 97%	The number of features extracted by these methods is limited
Zhou (2016) [19]	Wavelet entropy (WE) +feed-forward neural network (FNN)	100%	The used brain images are only 64
Yang (2016) [28]	Dual-tree complex wavelet transform (DTCWT) +variance and entropy (VE) + twin support vector machine (TSVM)	99.57%	Dataset cannot reflect real-word scenario
Yang (2017) [11]	Hu moment invariants (HMI) + generalized eigenvalue proximal support vector machine (GEPSVM)	98.89%	The dataset only consists of 90 images
Chen (2017) [20]	Wavelet packet Tsallis entropy (WPTE) + feedforward neural network (FNN) + real-coded biogeography-based optimization (RCBBO)	99.49%	The types of pathological brain are only 8, and this method is not suitable for most diseases
Wang (2016) [21]	Wavelet entropy (WE) + multilayer perception (MLP) + biogeography-based optimization (BBO)	Accuracy=92.40%, sensitivity=92.14%, specificity=92.47%	Images from dataset only consist of AD and HC

3. Conclusion and future works

In this paper, we introduced many methods on pathological image detection, and these diseases include Alzheimer's disease, breast cancer, and hearing loss. We find that the accuracy of some methods reached to 100%, which inspires us. Nevertheless, each method has its own scope of application.

After the analysis of these methods, we learned that multi-classification is on the stage of starting. It means we still need to learn more methods about multi-classification, so as to improve the accuracy of classification. In addition, due to small data set used in many proposed methods, we should select more representative and more images in future work. Some preprocessing methods [29, 30] should be discussed.

Acknowledgements

This paper is supported by Open Program of Jiangsu Key Laboratory of 3D Printing Equipment and Manufacturing (3DL201602).

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