Machine Learning Methods for Intelligent Abnormal Brain Identification

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Abstract—**This survey paper describes a focused literature survey of machine learning methods in order to detect pathological brain. Based on the published time and emerging methods, this paper introduces in details the methods used in each documents. Because of the requirement to select a good approach in the process of pathological brain analysis, we compare the classification results of different methods and present a promising future.**

Keywords-pathological brain detection; machine learning; intelligent algorithm; category recognition

I. INTRODUCTION

With the change of people's lifestyle and the rapid arrival of the population aging, brain disease now becomes a major disease that has endangered the health of the elderly [1-3]. In this case, the medical diagnostic personnel need to identify the abnormal brain timely and effectively. There are several machine-learning methods to solve the problem.

Machine learning (ML) is a significant technology that allows computers to discover hidden areas where they are not explicitly programmed [4-8]. ML can produce models faster and automatically, used to reproduce known patterns and knowledge. ML methods focus on achieving high-value predictive results and apply these results to decisions and actions. Therefore, ML is widely used in computer vision [9], biometric identification [10], medical diagnosis [11], and so on [12].

The ML methods are summarized in this paper is useful to solve the normal and abnormal brain detection problems. At the same time, we compare the evaluation results of each approach.

II. METHODS

Yang (2016) [13] presented a new approach respond to wavelet energy because WN shows excellent performance in practical application. The weights of SVM are optimized using BBO before classification. After that, WN and SVM are combined to classify magnetic resonance brain images automatically.

Nayak, Dash and Majhi (2016) [14] used a smart computer aided diagnosis system (CADS) to identify disease brain images. This system includes three aspects, applying 2D DWT to extract features, using PPCA to reduce features and using ADBRF to identify normal and disease brain.

Yang and Sun (2016) [15] suggested BPSO-MT to select only two features from both approximation and detail sub-bands. BPSO-MT includes two improvements, one is adding mutation operator and the other is combining with time-varying acceleration coefficient technique. To ensure the classification performance of BPSO-MT, which is compared with BPSO-M and BPSO-T in the literature.

Sun (2016) [16] used an attractive method of assisting to recognize the patterns, types and conditions of the brain. In "WE + QPSO-KSVM", after the outstanding feature extraction, the weights of the classifier are optimized effectively.

Atangana (2016) [17] proposed a novel method, stationary wavelet entropy (SWE), to extract features. Compared with the following three approaches: (i) WE; (ii) WN; (iii) DWT, the performance of SWE is best. The experimental results are 98.82 %, 96.00 %, 99.76 % 98.67 % for sensitivity, specificity, precision and accuracy, respectively.

Sun (2016) [18] provided a system to detect pathological brain better. The most important thing is to make two improvements to MLP. On the one hand, the best pruning technique is chosen to determine the number of hidden neurons by comparing three pruning techniques. On the other, the authors apply ARCBBO to train the biases and weights of MLP by comparing it to BBO and RCBBO. The accuracy of the experiment achieved 99.53%.

Yang (2016) [19] described three classifiers and a comparative study on them is reported. At the first stage, applying DTCWT to transform wavelets in order to improve the weakness of DWT. Then, feature extraction is performed by VE. Meanwhile, this paper testify "DTCWT + VE + TSVM" achieved the highest accuracy compared with "DTCWT + VE + SVM" and "DTCWT + VE + TSVM".

Chen (2016) [20] developed contemporary PBDS based on single slice is the highlight in this paper. Firstly, they focus on the changes of fractal pattern and extract features using FD. Then, an improved PSO algorithm is put forward to avoid to plunging into local minimum in training phase. SLFN is applied to distinguish normal and abnormal brain images. The prospect of the overall approach is bright.

Chen, Yang and Phillips (2015) [21] proposed the following methods to identify pathological and healthy brain images: (i) WFRFT + PCA + GEPSVM; (ii) WFRFT + PCA + TSVM; (iii) WFRFT + PCA + SVM and the first one has the

best test results. The novelty of this paper is that they create the possibility of WFRFT to extract more effective features.

Chen and Du (2017) [22] introduced a detection system based on disease brain images that includes three parts. Using WPTE to extract global features at first, using RCBBO to train the classifier in the next step and using FNN to categorize at last.

Yang (2017) [6] approved Hu moment invariants (HMI) to describe features which take the place of traditional DWT. Although the performance measure is 98.89%, there are only 90 images used in this work.

Wang and Lv (2016) [23] improved particle swarm optimization (PSO) by embed predator-prey operator to train weights and biases of SLN. The experiment prediction achieved $97.02 \pm 0.33\%$.

Jiang and Zhu (2017) [24] found pseudo Zernike moment (PZM) that represent a feature is effective to categorize. According to the paper, they not only analyzed the reason that KSVM performs better than SVM and also contrast "PZM + KSVM" with eleven previous approaches.

III. RESULTS

In the above approaches of this survey paper, we analyze and research the performance and disadvantages of each method in **Table 1**.

TABLE I. COMPARISON OF SEVERAL CONTEMPORARY METHODS

Author	Method	Vulnerability	Accuracy
Yang (2016) [13]	WE + BBO-KSVM	Wavelet entropy has lower performance than other ways.	97.78%
Nayak, Dash and Majhi (2016) [14]	2D-DWT + PPCA + ADBRF	Using PPCA to reduce features are able to improve.	99.53%
Yang and Sun (2016) [15]	WE + BPSO-MT + PNN	Comparatively time-consuming in the experiment.	99.53%
Sun (2016) [16]	WE + QPSO-KSVM	not fully capture the focus and deformed region	98.22%
Atangana (2016) [17]	SWE + RBF-KSVM	low validity during parameter optimization	100%
Sun (2016) [18]	FRFE + KC-MLP + ARCBBO	Compared with other approaches, the sensitivity and specificity are lower.	99.53%
Yang (2016) [19]	DTCWT + VE + TSVM	Computation time is not optimal.	99.57%
Chen (2016) [20]	MBD + SLFN + PSO-TTC	Other algorithm can optimize SLFN better	98.08%
Chen, Yang and Phillips (2015) [21]	WFRFT + PCA + GEPSVM	Only applied to specific T2-weighted images	99.11%
Chen and Du (2017) [22]	WPTE + FNN + RCBBO	The number of running times is inconsistent slightly.	99.49%
Yang (2017) [6]	HMI + GEPSVM and HMI + TSVM	The dataset only includes 90 specific images.	98.89%
Wang and Lv (2016) [23]	HMI + SLN + PP-PSO	The test results are unstable.	$97.02 \pm 0.33\%$
Jiang and Zhu (2017) [24]	PZM + KSVM	There are other better SVM improvements to classify.	$99.45 \pm 0.38\%$

IV. CONCLUSION

This study compared the latest machine-learning methods for abnormal brain identification. Furthermore, we look forward to make a comparison of the algorithms for detecting other human brain-related diseases, such as sickle cell disease [25], HIV disease [26], etc. Some image preprocessing methods [27-34] may be added to check the performance.

ACKNOWLEDGEMENT

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