Research Article

The Research of Chronic Gastritis Diagnosis with Electronic Noses

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In order to solve the problem of existing diagnostic methods for chronic gastritis which are complex and traumatic, a novel noninvasive method for diagnosis of chronic gastric based on e-nose and deep convolutional neural network is proposed. Firstly, in order to collect samples, a respiratory gas sampling device was established and the response curve of respiratory gas is generated. Then, a deep convolutional neural network for the diagnosis of chronic gastritis is proposed to recognize and classify the respiratory gas response curve. The DCNN model attained good results with accuracy, sensitivity, and specificity of 85.00%, 90.00%, and 80.00%, respectively, for chronic gastric prediction. The proposed method provides a new way for the clinical auxiliary diagnoses of chronic gastric.

1. Introduction

Inspired by the principle of the biological olfactory, electronic nose is a new bionic detection equipment combined with modern sensor technology, electronics, and pattern recognition technology, with the ability to identify simple or complex odors [1–5]. Compared with the traditional gas detectors such as gas chromatography, mass spectrometry, and infrared spectroscopy, it has the advantages of small size, lightweight, low cost, and high accuracy [6, 7]. The e-nose system generally consists of two parts: sensor array and pattern recognition algorithms. The sensor array responds to different odors and generates response curves. This means that the signals from the sensor array contain a large amount of information about the sample, which plays an important role in the performance of the e-nose. There are many kinds of gas sensors; commonly used are as follows: solid electrolyte gas sensor, semiconductor gas sensor, electrochemical gas sensor, and polymer gas sensor. As the performance of various sensors is very different, it is selected according to different detection objects. Metal oxide semiconductor sensor plays a key role in the field of gas sensor researches and applications with the advantages of high sensitivity and

low cost [8, 9]. Based on these advantages, the e-nose with metal oxide semiconductor sensor contains a large amount of information from complex gas sample.

E-nose has been widely used in the field of food industry, tobacco industry, medical diagnosis, and environmental monitoring because of its character such as noninvasive and easy to operate [10–14]. The application of e-nose in medical diagnosis especially has attracted more and more interest of the researchers. Liu et al. developed an e-nose system for lung cancer detection via breath with a sparse group feature selection approach and attained better results with 94.2% accuracy, 97.8% sensitivity, and 90.2% sensitivity [15]. Raspagliesi et al. tested the feasibility of e-nose as a diagnostic tool for ovarian cancer, the performance tested in the prediction gave 98% of sensitivity and 95% of specificity [16]. Li et al. fabricated an e-nose based on 10 gas sensors of 4 types and attained mean classification accuracy of 86.42% using samples from 153 healthy participants and 115 lung cancer patients [17]. Hendrick et al. proposed a noninvasive method for tuberculosis-exhaled breath classification based on electronic nose [18]. There is a growing body of literature suggesting that e-nose could be considered a useful tool for the early detection of lung and head and

neck cancers [19–22]. In these applications, the original data acquired from the sensor array cannot be used directly due to noise and drift, and the signal processed, filtered, and dimension reduction should be carried out first, which greatly affected the performance of e-nose, and different methods are selected according to difference objects, which lead to a large waste of time and energy.

In order to obtain more information from e-nose data, new effective pattern recognition algorithms and prediction models are urgently needed. A deep convolutional neural network (DCNN) shows powerful features in image classification and recognition applications [23]. The DCNN is an efficient recognition algorithm developed in recent years, which mainly includes feature extraction layers and mapping layers. The input samples can be used directly without any preprocessing. And the DCNN can learn independent characteristics, with the stronger discriminant power than traditional manual selected characteristics. It has been widely used in the fields of traffic, remote sensing, agriculture, and medicine and biology and mainly application in image classification and recognition [24–27]. Wei et al. proposed a new LeNet-5 convolutional neural network structure for electronic noses [28]. The final gas identification accuracy rate reached 98.67%. Galanty et al. presented a tool that can facilitate the recognition of cladonia lichen species with deep convolutional neural network, and the trained model achieved 60.94% accuracy [29]. Their final experimental result has an accuracy of 95.2%, which is higher than SVM and MLP. Wang et al. used a flow modulation method to exploit transient sensor information [30]. The proposed method uses fewer steps to achieve higher recognition accuracy and improve the recognition speed and to reduce the training and testing costs. Jiang et al. proposed an active learning (AL) algorithm based on improved query by committee (QBC) for RBFNN is to distinguish three indoor pollutant gases, and the classification accuracy has been improved when using unlabeled samples in an application process [31]. Yang et al. developed an ANN model for analysis of benzoic acid in cola-type-carbonated beverages [32]. The model generated accuracy rates of 90.0% in category identification for test samples. Peng et al. proposed a novel deep convolutional neural network with 38 layers for gas classification [33]. Experimental results show that the DCNN method is an effective technique for classifying electronic nose data. All these works show good prospective applications of deep learning methods in gas identification fields.

Chronic gastritis is a common digestive disease caused by different reasons. Clinical trials have found the patients with chronic gastritis with varying degrees of oral off-odors [34]. Zhenqin verified that e-nose can help distinguish benign and malignant gastric cancer, and the analysis of respiratory gas offers a new way to research methods in the early diagnosis of gastric cancer [35]. Xuejuan et al. analyzed the odor fingerprint map of respiratory gas from patients with chronic gastritis used e-nose and concluded that the odor fingerprint map of respiratory gas can be accurately identified and chronic gastritis differences of cold and hot syndromes can be discerned by e-nose [36]. At present, research on chronic gastritis using e-nose is still in the begin-

ning and exploratory phase. The above researches are proved to be effective in the diagnosis of chronic gastric with respiratory gas response curve.

This paper studied the detection and classification of chronic gastritis, combining e-nose and DCNN, and proposed a new diagnosis method of chronic gastritis. The raw data of the e-nose is directly input in the form of gray value image without any operations such as data processing and feature extraction, which greatly simplifies the data processing of traditional methods. In this paper, a new model that can identify chronic gastritis has been established based on DCNN, which can effectively distinguish patients with chronic gastritis from healthy people, and further verified the feasibility of chronic gastritis detection used e-nose.

The main contributions of this paper are as follows: (1) a novel noninvasive method for diagnosis of chronic gastric based on breath analysis is proposed to solved the problem of vivo trauma detection. (2) It was proved that diagnosis of chronic gastritis through breath analysis is feasible, by comparing the responses of chronic gastritis patients and healthy volunteers and PCA analysis. (3) The experiments are designed and executed to prove the effectiveness of the improved DCNN model by comparing with the PCA+BP.

The paper is organized as follows. In Section 2, the respiratory gas acquisition system is presented and introduced in detail. Section 3 describe the improved DCNN model for detection of chronic gastritis. Section 4 discusses and evaluates the performance of the proposed model by experiment and analysis. Finally, the inclusion and future works are summarized in Section 5.

2. The Respiratory Gas Acquisition System

Medical electronic nose with SnO_2 thin-film gas sensor arrays of EN0111103-A developed by professor Wu is used in this paper [37]. Figure 1 shows the overall structure of the sensor; the sensor consists of 4 SnO_2 thin-films, heater, and temperature measurement circuit. Figure 2 shows the structure of SnO_2 film, the oxide semiconductor film materials mixed with different substances which provides gas selectivity. The respiratory gas acquisition system is shown in Figure 3. The system consists of two parts: the control computer and the sampling device. The control computer is composed of signal processing, power source, and the data sampling circuit. The sampling device is composed of a gas chamber, a injector port, and flow control equipment. The chamber size is $100 \times 50 \times 100$ mm, with 10 built-in thin-film gas sensor arrays installed in the chamber. The operating temperature of the sensor is 200 degrees. The gas flow rate is controlled by a flow controller; when patients breathe into the sampling device, the respiratory gas attached to the semiconductor film and the resistance of the semiconductor film changes.

3. The Proposed Model

Inspired by the traditional Alexnet and application of other typical models [38–40], we proposed a deep convolutional neural network model for detection and identification of

FIGURE 3: Respiratory gas acquisition system.

FIGURE 4: The architect of the proposed DCNN.

TABLE 1: Description of proposed twenty layer DCNN architecture.

Layers	Layer name	Maps and neurons	Kernel	params	ops
0	Image input	3@56x56	—		
1	Convolution	96@14x14	11x11	12 K	2.3 M
2	Batch normalization	Batch normalization	—		
3	ReLU	ReLU	—		
4	Max-pooling	96@7x7	3x3		
5	Convolution	256@7x7	5x5	6 K	0.3 M
6	Batch normalization	Batch normalization	—		
7	ReLU	ReLU	—		
8	Max-pooling	256@4x4	3x3		
9	Convolution	384@4x4	3x3	4 K	0.06 M
12	Batch normalization	Batch normalization	—		
13	ReLU	ReLU	—		
14	Max-pooling	384@2x2	3x3		
16	Fully connected	256	—	393 K	0.4 M
17	Dropout	Dropout	—		
18	Fully connected	256	—	65 K	0.07 M
19	Dropout	Dropout	—		
20	Classification output	2	—	512	512

response value at 180 seconds was selected and analyzed in the experiment. The contributing rate of each principal component is shown in Table 2. It can be seen from the table that the contribution rate of the first principal component (PC1) is 83.6% and the contribution rate of the second principal component (PC2) is 10.1%. The first and second principal components were selected in this paper, and their additive contribution rate came up to 93.7%. It contains almost all

the information of the sensors. The correlation coefficients of 10 sensors are shown in Table 3.

Figure 7 is the analysis diagram of PCA for chronic gastritis. From the diagram, we can see that there are apparent differences between chronic gastritis and healthy volunteers, and they can be distinguished. The samples were forecasted using the BP network, input layer with 2 neurons, and output layer with 2 neurons corresponding

FIGURE 5: Response curves of 10 sensors obtained from respiratory gas.

FIGURE 6: The gray value images of the response curve.

to the chronic gastritis and healthy volunteers; the number of iterations is 2000.

To evaluate the performance of the method, the root mean squared error (RMSE) and correlation coefficients (R^2) are adopted. RSME and R^2 are defined as Equations (1) and (2), respectively.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y^{\wedge}_i)^2}, \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y^{\wedge}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (2)$$

where $\hat{y}_i$ is the output value of the model, y_i is actual value, $\bar{y}$ is the mean of actual values, and n is the total number of samples.

The experimental results on the test data are shown in Figure 8. The experiment results showed that the proposed DCNN of $R^2 = 0.9787$ and $\text{RSME} = 0.8513$ better than the BP of $R^2 = 0.97377$ and $\text{RSME} = 1.7649$. It shows that the proposed DCNN has higher precision of detection and identification for chronic gastritis, and the processing of the data is easier.

TABLE 2: Variance of each component by PCA.

Number	Characteristic value	Contribution (%)	Total contribution (%)
1	9.32157	83.636	83.636
2	1.12992	10.138	93.774
3	0.35453	3.181	96.955
4	0.16974	1.523	98.478
5	0.10621	0.953	99.431
6	0.05929	0.532	99.963
7	0.00278	0.025	99.988
8	0.00066	0.006	99.994
9	0.00044	0.004	99.998
10	0.00022	0.002	100

In order to further verify the model's effectiveness and reliability, 60 samples (healthy: 30, chronic gastritis: 30) were selected for the experiment. For both approaches, the criteria such as accuracy, corresponding to the probability of doing a correct classification; sensitivity, corresponding to the probability to classify a subject as a case when this is true; and specificity, corresponding to the probability of classifying a subject as control when this is true have been utilized. The equations are given as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{n} \times 100\%, \quad (3)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%, \quad (4)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} \times 100\%, \quad (5)$$

where TP is the number of chronic gastritis correctly

TABLE 3: The correlation of 10 sensors.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	1	0.85698	0.32548	0.75421	0.26802	0.65751	0.86591	0.54695	0.32157	0.26985
S2	0.85698	1	0.26587	0.41257	0.32685	0.14573	0.86544	0.68472	0.21965	0.32548
S3	0.32548	0.26587	1	0.68663	0.57862	0.6752	0.88522	0.58562	0.87662	0.85632
S4	0.75421	0.41257	0.68663	1	0.85531	0.79953	0.60218	0.86521	0.35851	0.43651
S5	0.21546	0.32685	0.57862	0.85531	1	0.86201	0.6592	0.21546	0.89751	0.77853
S6	0.65751	0.14573	0.6752	0.79953	0.86201	1	0.80359	0.68845	0.25486	0.85631
S7	0.86591	0.86544	0.88522	0.60218	0.6592	0.80359	1	0.88713	0.68626	0.36681
S8	0.54695	0.68472	0.58562	0.86521	0.21546	0.68845	0.88713	1	0.80031	0.8587
S9	0.32157	0.21965	0.87662	0.35851	0.89751	0.25486	0.68626	0.80031	1	0.30354
S10	0.26985	0.32548	0.85632	0.43651	0.77853	0.85631	0.36681	0.8587	0.30354	1

FIGURE 7: PCA for gastritis patients and healthy volunteers.

FIGURE 8: BP and proposed DCNN results for the test sets.

classified, TN is the number of healthy volunteers correctly classified, FN is the number of chronic gastritis misclassified, FP is the number of healthy volunteers misclassified, and n is the total number of samples.

The experiment results are shown in Table 4. As shown in Table 4, it can be seen that the DCNN has nearly the same accuracy compared with BP. But the DCNN has a higher recall rate. This is due to the salient features can be

TABLE 4: Comparison of performances with PCA+BP and DCNN.

Model	Accuracy	Sensitivity	Specificity
PCA+BP	0.77	0.77	0.77
DCNN	0.85	0.90	0.80

automatically extracted by the DCNN model, while the success of most other traditional classifiers relies largely on the retrieval of good hand-designed features which is a laborious and time consuming task.

The sensor responses gradually increased during sampling, reaching a peak after 180 s. The BP model only takes the peak values as a characteristic for distinguishing between chronic gastritis patients and healthy volunteers; the sensor's response procedure and sensibility are ignored, which leads to problems later during classification. During the experiment, we found the characteristics of peak values changed due to drifting problem of sensors, which is difficult to obtain good classification results. The proposed DCNN model extracts features from the pattern of sensor responses. The results obtained in the experimental study indicate that e-nose is quite a promising method in the chronic gastritis diagnosis field.

5. Conclusions

In this paper, a novel nondestructive diagnostic method for chronic gastritis is proposed by combining e-nose and DCNN. A respiratory gas acquisition system was established to collect respiratory gas samples from patients with gastritis and healthy volunteers. The experimental results show that the proposed method has higher accuracy than the BP method in the detection and identification of chronic gastritis. But the research on the DCNN model to diagnosis chronic gastritis is in its early stage. We hope that this can provide a new thought for a noninvasive detective method for chronic gastritis. The proposed approach can be applied for many sensing application with the help of appropriate sensors. In the future, accuracy and efficiency of the proposed model can be further improved by the fine tuning of its structure and parameters. Some optimizing techniques can also be investigated to boost the classification performance.

Data Availability

The [sensor data] data used to support the findings of this study have been deposited in the [e-nose] repository (<https://github.com/Chenyif/enose>).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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