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Image classification toward breast cancer

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ABSTRACT: *Image classification plays an important role in computer vision and its applications, such as scene cate-gorization, image retrieval. Convolutional neural network based methods have shown competitive per-formance in image classification, which aims to exploit deep feature of training images. In this paper, based on CNN methods and image quality assessment (IQA) algorithms, we propose a novel method for medical application, that is breast cancer classification. First, we leverage CNN architecture to calcu-late the number of pixels in the lesions, where maximum pooling layers are used. Then, large density of pixel regions will be assigned with large quality scores, which reflect more texture and grayscale features. Finally, we construct a multi-SVM based image kernel using obtained quality scores to achieve breast cancer classification. Experimental results show our proposed method outperforms single recognition based image classification methods such as pixel grayscale or gradient.*

Keywords:
Image classification
CNN
Quality score

I. INTRODUCTION

Cancer has always been a major threat to human health and wellness, putting tremendous pressure on families and society. As we age, the incidence of cancer increases. With the improve-ment of people's quality of life, the incidence of breast cancer is also rising. In the past ten years, the mortality rate of breast cancer in China has increased rapidly, and the mortality rate of breast can-cer in urban and rural areas has increased by 38.9% and 39.7% respectively. The first-tier cities such as Beijing and the developed coastal areas have become the high-incidence areas for breast can-cer in China. In addition, it is worth noting that the breast cancer patients in China are constantly becoming younger. Data show that the incidence of breast cancer in China there are two peak periods, which are between 45–55 years old and 70–74 years old. Western countries compared to the peak incidence of breast advance, tend to be younger of momentum, even 20–40 year-old woman has become a high risk of breast cancer. Breast cancer has become the fastest-growing disease in the past three decades.

In response to the increasing rate and incidence of breast can-cer, many research teams have begun to study the pathogenesis, performance characteristics, clinical treatment and postoperative recovery of breast cancer in different directions, and achieved good results [35-41]. Wen Min [1] and others found that the tumor microenvironment affects tumorigenesis, proliferation, angiogene-sis and apoptosis, especially in the occurrence, development and metastasis of breast cancer. Xu Bin [2] and other studies showed that the risk of recurrence in the pregnant group after breast cancer treatment was not statistically different from that in the non-pregnant group; the risk of death was significantly lower than that in the non-pregnant group. Pregnancy in patients with breast can-cer may have no adverse effects on disease-free survival, but may be a protective factor for overall survival. Lu Yao [3] said that the application of artificial intelligence in the screening and diagnosis of breast cancer is essentially the analysis of the application of neu-ral network in the field of breast imaging and pathology. At pre-sent, artificial intelligence screening can be used as a doctor's aid, and it is an objective diagnostic reference assistant for improving the diagnosis time of breast ultrasound diseases. With the develop-ment of medical imaging omics and neural networks, the applica-tion of artificial intelligence in the medical field can be extended to surgical design, efficacy evaluation, and prognosis analysis. Sun Wei [4] and others found that the novel photosensitizer 5-ALA for PDT has a significant inhibitory effect on HER2-positive breast cancer cell line SKBR3, and the inhibitory effect of PDT combined with LAP is stronger, and its mechanism reduces the mitochondrial membrane potential of tumor cells. There is a certain relationship between HER2 expression levels. Therefore, PDT combined with LAP is expected to improve the quality of life and improve the sur-vival rate of HER2-positive breast cancer patients, and has a good application prospect. Qu Chunan [5] found that FOXL2 gene is highly expressed in breast cancer and can inhibit the proliferation of breast cancer cells, which may be a new tumor suppressor, but further research is needed. Ding Huajie [6] et al. compared the screening of breast cancer tissue with normal tissue based on gene expression profile, providing new ideas for anti-tumor drug discov-ery and providing important information for later relevant clinical research. Gao Qiang [7] found 25 lesions in 23 cases, including clusters of heterogeneous calcification in 19 cases of 21 lesions, and branching calcification in 4 cases of 4 lesions. Conclusion: Molybdenum and bismuth dual-target digital radiography can improve the detection rate of early breast cancer and improve the clinical treatment of breast cancer. Bu Jingting [8] finally achieved the goal of improving the accuracy of non-tumor type breast cancer by summarizing the characteristics of non-tumor type breast cancer under various ultrasound techniques. Cai Cun-wei [9] used immunohistochemical staining and Western blotting to detect the expression of SIAH1 in breast cancer cells to investi-gate the molecular mechanism of nuclear ectopic expression of SIAH1 in inhibiting apoptosis of breast cancer cells. GSNO induces ectopic expression of SIAH1 and may inhibit apoptosis of breast cancer cells by down-regulating the expression of E2F1/Bim. Liao Sifan [10] used bioinformatics methods to analyze the target genes of breast cancer candidate therapeutic drugs and studied the molecular mechanism of drug treatment of breast cancer. The anti-tumor drugs represented by resveratrol, apigenin and gossy-pol, as well as candidate therapeutic drugs such as hormones and antibacterials were screened. Han Mingli [11] found that the detec-tion rate of MRI in preoperative breast cancer was higher than that of mammography, and the case classification was also accurate. The evaluation of tumor volume was consistent with pathological results. Liu Hong [12] and other people discussed the application of targeted nursing in breast cancer MRI. It was found that targeted nursing can improve the patient’s bad mood in breast cancer MRI, and promote the examination smoothly. It is worthy of populariza-tion and application. Wu Xiaohong [13] and others found that the TPB-based health education model can effectively change the unhealthy lifestyle of breast cancer patients during rehabilitation, establish a healthy lifestyle, improve treatment outcomes, and improve quality of life. Fang Yi [14] and others found that PAK4 can promote the proliferation and metastasis of breast cancer cell MDA-MB-231 by regulating PI3K/AKT signal transduction path-way. Yang Wei [15] found through experiments that compared with FEC chemotherapy, the recent effect of TC chemotherapy on breast cancer patients is better. Qu Fangfang [16] explored the clin-ical effects of mind mapping in the treatment of complications after breast cancer surgery. The postoperative satisfaction and complications of the two groups were compared. Breast cancer patients can effectively reduce the incidence of complications and improve patient satisfaction through mind mapping mode, which is worthy of clinical promotion. Shin HC and Miao S [17,18] selected two sections before and after the largest section of the tumor, so that each sequence utilized 5 images, and then three tumor ROI boxes were taken at 1, 1.5, and 2 times, respec-tively, re-adjust them to a uniform size. The ROI extracted from the three enhancement sequences was adjusted to a uniform scale (64 64) to compare the discrimination ability of different sequences for breast cancer, and to adjust the influence of network structure and parameter analysis on the classification diagnosis results.

Although experts and scholars at home and abroad have achieved fruitful results in breast cancer research, these studies have drawbacks. First, some research teams have adopted a rela-tively simple method. Although the detection speed is faster, it does not have comprehensive characteristics. Secondly, the image feature analysis and algorithm adopted have low accuracy. The classification model of breast cancer requires that the recognition process be fast and accurate, and that the image features can be analyzed accurately and quickly.

Based on the advantages and forward-looking nature of deep learning, many research teams have conducted in-depth research on deep learning [37,42-45]. Shen Xiangxiang [19] and others applied deep learning in game graphics extraction, and proposed a state-focused A3C algorithm by adopting a more simplified net-work structure and combining attention mechanisms with rewards in reinforcement learning. The resulting agent uses the fewer fea-ture layers in individual interstellar mini-games to achieve higher scores than Deepmind’s baseline agent. Jixiang Ling [20] applied deep learning to area detection, and proposed a feature fusion tar-get detection algorithm for image sub-area detection. The algo-rithm can accurately detect the controlled items in the security image in real time, especially for the small target detection in large pictures. Huang Gang [21] applied deep learning to road markings and verified the method based on experimental data. The results show that the accuracy and Fscore of automatic extraction and classification using this method are 92.59% and 90.15%, respec-tively. The automatic extraction of the line provides a new idea, which makes the road marking extraction work more accurate and efficient, and improves the intelligence level of road marking acquisition and classification. Wu Mengdie [22] applied deep learning in face recognition, and used the two-dimensional face image extracted by two DCNNs and the high-level abstract features of the face depth map as the input of an artificial neural network (ANN). The output is used as the final feature of the extraction. Yan Hao [23] applied deep learning to emotion detection, and pro-posed an emotional state detection method based on integrated deep learning model. Four kinds of representation emotions were extracted from the time domain, frequency domain and time-frequency domain of EEG signals. The initial characteristics of the state significant information. Yang Tingting [24] applied deep learning to food identification, and introduced food recognition and food composition identification methods based on deep learn-ing methods. It analyzes the challenging problems faced by food identification and points out the future research direction. Zhang Lihua [25] applied deep learning to fingerprint recognition, and proposed a big data fingerprint recognition system based on ARM and deep learning. Firstly, the schematic diagram of fingerprint recognition system is described. Establish a general-purpose multi-layer deep neural network that can automatically identify fingerprints. In summary, deep learning has a more thorough research and more specific advantages, so it can be used for image analysis of cancerous tissues and to establish a classification model for breast cancer.

The research work of this thesis is mainly based on image fea-ture analysis and deep learning methods, exploring research based on deep learning methods, and using different modal image data to analyze breast cancer classification models. Based on image feature analysis and RBM learning method for breast cancer feature extrac-tion and classification, pre-processing experimental data, extract ROI and PCA whitening. A three-dimensional convolutional neural network was proposed based on three-dimensional convolutional neural network for breast cancer, and two-dimensional and three-dimensional convolutional networks were used to predict disease classification. The recognition and classification of early breast cancer is realized by using three-dimensional enhanced image sequence and enhanced rate image.

II. METHOD

2.1. Cancer recognition tissue image recognition principle

The principle of image recognition of medical lesions is to establish a clear pixel model of the pixel features of the lesion, and to describe the difference characteristics of the pixels through the model, and to determine whether the difference belongs to the lesion by accurately identifying and identifying the difference fea-tures. Computation and iterative classification calculations, based on the classification results, update the lesion tissue pixel model parameters. Complete the identification of the diseased tissue.

(1) Image preprocessing

Image preprocessing. In some areas of special organs, depend-ing on the shape of the organ, the quality of the images that may be acquired is not very good, so much information is lost. Let the gray value of a pixel in the image of the diseased tissue be m(x, y), its neighborhood S is N N, the total number of point sets is Q, and the gray value of this point after preprocessing is:

mðx; yÞ ¼ Q 1 X mði; jÞ

i;j2S

By replacing the gray value with the repair, the image prepro-cessing can be completed, and most of the features of the image are maintained, so that the image is more clear.

(2) Pixel feature extraction

After the acquired image is obtained, it is necessary to calculate the pixel-specific features of the image.

vffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffiffi

u n

ðf 1 . . . f=ðn2

g ¼ 0Þ2 Þ

uX

t ¼

i 1

where f represents the characteristic of the determined single pixel, n is the number of features, and g is the determined pixel feature.

(3) Determining the threshold of the morphological feature to complete the diseased tissue recognition

0 g 2 G

s ¼ 1 g R G

where g is the characteristic of the pixel of the diseased tissue, G is the threshold of the characteristic of the lesioned pixel, and is the result of the judgment. By properly setting the image pixel thresh-old, it is possible to accurately distinguish the lesion pixels. If the threshold value is set unreasonably, the segmentation effect may be deteriorated. Using this method, the judgment and recognition of the diseased tissue is completed.

2.2. RBM learning method

RBM is an energy-based model. The energy model first defines the energy function of the entire model, and the energy function is used to achieve the learning purpose. Assuming that both the visible and hidden layer variables obey the Bernoulli distribution, the energy function is defined as:

I J I J
X X X X
Eðv; h; hÞ ¼ wijvihj bivi ajhj
i 1 j 1 i 1 j 1
¼ ¼ ¼ ¼

where h is the RBM parameter, wij is the connection weight between the visible layer and the hidden layer unit, and bi and aj represent the offsets of the visible layer and the hidden layer, respectively.

Then by maximizing the likelihood function of the visible layer data:

1
Z
$p_h$ðvÞ ¼ h exp v^TWh þ a^Th þ b^Tv
X

h

Use Stochastic Gradient Descent (SGD) to maximize i(h)

simplification:

@‘ðh
Þ
E h E h
p_{dxa} p_h vi
@w_{ij} ¼ vi j j

The former is easier to calculate, and the latter is a very large combination of v and h.

2.3. Softmax classifier and convolutional neural network

(1) Softmax classifier

The Softmax classifier implements classification by fitting the data classification boundaries, using optimization methods such as gradient descent to determine the best regression coefficients. One of the more important formulas in logistic regression is the step function:

1
$h_h$ðxÞ ¼ 1 þ e hT x

The waveform diagram is shown in Fig. 1, between the value range [0, 1];

The negative log-likelihood loss function at this time is:

1 2 m k $e^{h_j^T x^{ðiÞ}}$ 3
JðhÞ ¼ 6 i 1j 1 I $y^{ðiÞ}$ ¼ j 7

m log $^{k}{}_{h}T_{x}$ i
ð
X X þ
6 ¼ ¼ e l 7
6 7
4 P 5
l¼1

where I {.} means that when the value is true, the result of the func-tion is 1, and vice versa is 0; then the gradient function is used to optimize the objective function.

(2) Convolutional neural network

Convolutional neural network (CNN) is inspired by biological neurology and refers to its hierarchical structure principle. The innovative research results that are derived from the advantages of neural networks are deep learning skills with deep learning abil-ity. The internet.

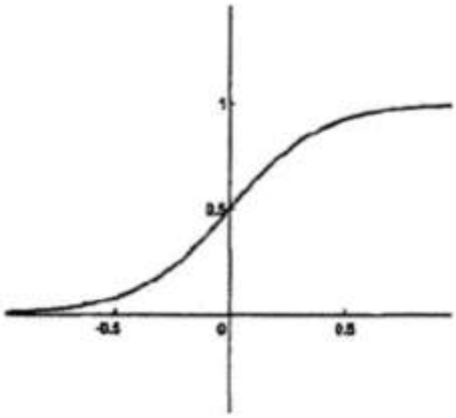

Fig. 1. Logical regression step function formula.

Weight sharing. Each filter in the convolutional layer in CNN changes the sliding cover to the entire image, convolves the input image, and extracts some local features in the image, such as direc-ted edges and corners, by convolution. Each Kernel is shared by a feature extractor, with each Kernel parameter, with the same weight and offset.

Convolution layer. The same feature may appear in different locations in an image, and these features should be extracted. At this time, a convolution operation is required, that is, the convolu-tion kernel is moved in different regions of the image, and the region covered by the convolution kernel is weighted and summed to obtain the output of the group of neurons through the nonlinear activation function. The original signal is enhanced by convolution to suppress noise.

Pooling layer. The CNN convolution layer is usually connected to the downsampling layer, that is, the pooling layer (Pooling). Downsampling is a method of nonlinear dimensionality reduction. According to the local correlation of the pixel space, a point is sam-pled in a fixed size region on the feature map of the convolution layer as an input of the next layer node. The methods of downsam-pling are maximum sampling, mean sampling, and probability sampling. Downsampling not only reduces the data dimension, reduces the training parameters, but also effectively preserves the coarse position of the feature points, making the convolutional neural network have certain translation, rotation and scaling invariance. Fig. 2 shows a maximum sample of 3 * 3.

III. EXPERIMENT

3.1. Data source

Through the analysis of a large number of case pathologies, 143 patients' image data were screened for the study of this experi-ment. Of the 143 patient imaging data, all patients underwent mammary DCE-MRI and were diagnosed by histopathology after radiologist diagnosis. The data set was then divided into two groups: the malignant breast cancer patient group (Malignant) and the benign breast cancer patient group (Benign). In the image data, 77 patients with malignant tumor lesions, the average age of patients was 48 ± 8; 66 patients with benign breast cancer, the average age of patients was 43 ± 9. In the malignant group, the lesions were mainly invasive ductal carcinoma, and the benign patients included breast disease such as breast hyperplasia, fibroadenomas, ductal papilloma, and ductal dilatation.

3.2. Evaluation criteria

In order to objectively and quantitatively evaluate the classifi-cation results, we mainly evaluate the performance of the classifier

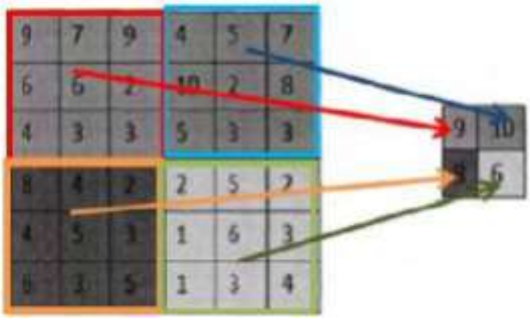

Fig. 2. Maximum downsampling.

from the following aspects. When evaluating the classification effect of a classifier, the indicators that are often used have sensi-tivity, specificity, and classification accuracy. A set of sensitivities and specificities will vary with decision thresholds, so only Sn and Sp can only be used to evaluate the classification effect of a particular threshold. The Receiver Opteration Characteristic Curve (ROC curve) can obtain the sensitivity and specificity of continuous change at different thresholds. It can be used to plot the curve with 1-Sp as the abscissa and Sn as the ordinate. In order to be able to simply compare ROC curves, Area Under ROC Curves can be used to quantitatively measure the distribution of sample data in two categories within the characteristic domain. In other words, the AUC value of the ROC curve can be used to characterize the classi-fication of the classifier. Capability, the closer the AUC is to 1, the better the performance of the classifier.

IV. RESULTS

4.1. Feature extraction and breast cancer classification

Intravenous injection of paramagnetic contrast agent gadopen-tetate (Gd-DTPA) is required. According to the diffusion rate of con-trast agent in blood circulation and tissue, a scan sequence of 4 time phases is generally set. The first scan sequence is Mongolian. The sheet (denoted as S0), the contrast agent is injected immediately after the end of the sequence scan, and two image scans (denoted as S1 and S2) are performed after 1 min 20 s and 2 min 25 s, and are performed once in 5 min and 30 s. The scanning of high resolu-tion sequences, the experimental results are shown in Fig. 3.

As shown in the figure, the S2 effect is better than S1, which is better than S0. This is because in a two-dimensional image, the correlation of adjacent pixels is very high, and the input data is mostly redundant information. PCA achieves high dimensionality. The linear change of the input vector to the low-dimensional vec-tor, that is, the dimensionality reduction. Whitening is a prepro-cessing process associated with PCA. The whitening process reduces the correlation between pixels, and the eigenvalues of all dimensions have the same variance.

4.2. Breast MRI sequence image ROI extraction

In order to reduce the area of interest and reduce the amount of computation in the process of extracting features using the cascad-ing self-encoder, this paper extracts the ROI region containing the tumor target in the preprocessing. A combination of interactive and automatic extraction is used to extract the ROI. First, an expe-rienced doctor is required to mark the location of the lesion initia-tion and termination layers in each breast MRI sequence image, the maximum cross-sectional contour of the tumor and the center position of the tumor, and then construct three rectangular boxes with initial termination and maximum section respectively. Maxi-mize the outer rectangle, then move the rectangle up and down by 5 pixels to get the final ROI box.

Because the number of sections across different lesions is incon-sistent, in order to make the number of tumor sections provided by each patient consistent, we selected two sections before and after the largest section of the tumor, so that each sequence utilized 5 pictures, and then again Divide the three tumor ROI boxes on a scale of 1, 1.5, 2 and re-adjust them to a uniform size (see Fig. 4).

4.3. Enhanced image 2D CNN and 3D CNN experimental results and analysis
The results of Table 2 show that the AUC value of the 3DCNN experiment is about 9% higher than that of the 2DCNN experiment,

Table 1
Various series of image data.

	S0 sequence	S1 sequence	S2 sequence	S3 sequence
Scan time	0 min 0 sec	1 min 20 sec	2 min 25 sec	7 min 55 sec
Number of tomographic layers	88 slice	88 slice	88 slice	160 slice
Image resolution	512 512	512 512	512 512	512 512

Fig. 3. Experimental image.

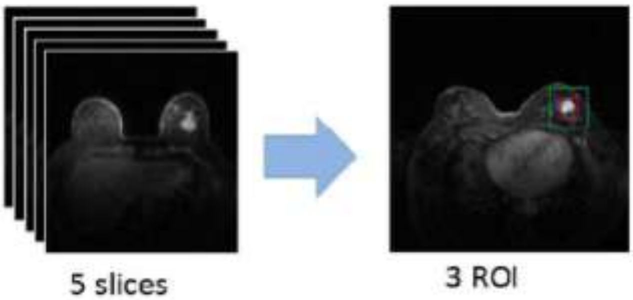

Fig. 4. ROI image extraction.

Table 2 CNN experiment results.

Network model	AUC	Sens	Spec	Acc
2DCNN	0.677	0.701	0.580	0.644
3DCNN	0.763	0.805	0.618	0.705

and the sensitivity is also improved by nearly 10%. This shows that compared to the traditional 2DCNN, it only uses the structural information of the two-dimensional plane of the image, ignoring the three-dimensional structure of the breast MRI image. 3DCNN combines the slice of different levels of lesion ROI, not only retains the ability of general CNN to extract two-dimensional planar fea-tures, but also makes full use of the three-dimensional spatial information of MRI images to extract the structural features of lesions in three-dimensional space, indicating the spatial structure information of breast tumors. It plays a certain role in distinguish-ing the benign and malignant early breast cancer. The two experi-mental methods ROC curve is shown in Fig. 5.

The enhancement rate three-dimensional image reflects the dif-ferent enhancement characteristics of the lesion in the spatial extent. For breast tumors of different nature, the internal space of the tumor is unlikely to be homosexual, and their response to the enhancer is also different. 3DCNN is able to extract spatial dynamic features of enhanced-rate imaging tumors. Using this fea-ture can significantly improve the ability of the model to distin-guish between benign and malignant tumors.

The experimental results show that with the increase of the self-encoding network level, the higher the AUC value, the deeper the level is, the more representative and distinguishing the fea-tures are. At the same time, due to the different modal data, the AUC value of the network experiment with the candidate layer is higher than the AUC value of the deep network. It can be seen that the quality of the data will also affect the differentiation of breast cancer.

V. DISCUSSIONS

The results of the study showed that the accuracy of early diag-nosis of breast cancer by a single image sequence can reach 0.82. Through the adjusted self-encoding network level, noise figure, and dropout sparse coefficient, the effects of their classification on the classification performance are analyzed. The results of the study indicate that early diagnosis of breast MRI images based on SAE has certain application value. The AUC of stacking self-coding for early breast cancer diagnosis is 0.85, which is 8 percent-age points higher than the shallow network AUC value of 0.77.

Since breast MRI can acquire the three-dimensional structure of the tumor, 3DCNN uses the breast MRI to obtain the three-dimensional spatial information of the tumor, and sequentially processes a single MRI image than the traditional CNN, and can extract the tumor features from multiple angles. In the single-sequence enhanced image, the 3DCNN classification result AUC value, accuracy and sensitivity are more than 5 percentage points higher than 2DCNN. Using the multiple sequences of DCE-MRI images to calculate the absorption state of the contrast agent at different times of the tumor, indirectly reflects the difference in the dynamic changes of the tumor space. We calculated the ROI of the enhancement rate image extraction lesions and combined the 3DCNN network model to identify the early stages of benign and malignant breast cancer. From the experimental results, the dynamic characteristics of the enhancement rate image are more distinguishable than the single enhancement sequence. This gives a certain reference value for the design of breast MRI assisted diag-nosis system and feature extraction. By combining the spatial fea-tures extracted by 3DCNN and the spatial dynamic change information, the diagnostic accuracy of the CAD system can be improved.

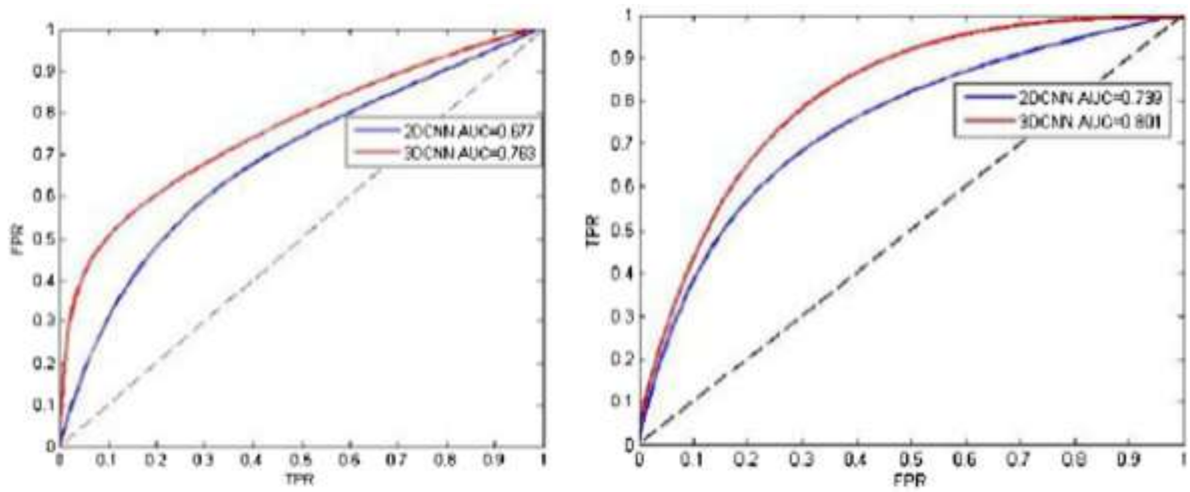

Fig. 5. ROC curve.

VI. CONCLUSIONS

Image feature extraction based on deep learning and breast can-cer classification, using RBM learning method, constructing layer-by-layer features of deep learning network to classify breast can-cer. The experimental results show that different parameter set-tings have a certain impact on the classification results.

Setting the appropriate network level, feature extraction can be identified and classified in breast cancer diagnosis.

CNN is a method for supervised extraction of features in image classification problems. The traditional 2D-CNN only focuses on the information of the two-dimensional neighborhood of the input image. In view of the three-dimensional characteris-tics of breast MRI images, a 3D convolutional neural network was constructed to effectively utilize the different three-dimensional spatial correlation information of breast tumors. Comparative analysis the 2D and 3D networks performed breast cancer results on grayscale ROI and enhancement rate ROI image data, respectively.

The breast cancer classification model established by deep learning and image feature analysis in many existing breast cancer imaging diagnosis methods has higher tissue resolution and can be used for mammary gland than mammography and ultrasound imaging. Organizing for more high-definition 3D imaging, doctors have higher accuracy for early diagnosis of breast cancer patients with mild symptoms, combined with computer-aided diagnostic techniques, with doctors for daily diagnosis and the development of precise personalized medical solutions.

Declaration of Competing Interest
There is no conflict of interest.

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