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Research on Lung Nodule Recognition Based on Stacking Algorithm

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Abstract:

In recent years, the incidence of cancer has been increasing year by year, and lung cancer has ranked the first place. In order to detect lung nodules quickly and accurately, since the lung CT images in the data set used in this experiment are original medical images, image preprocessing is first required, including noise reduction, segmentation and region of interest extraction, Therefore, this paper proposes a lung nodule recognition method based on Stacking algorithm to detect lung nodules quickly and accurately. Secondly, the three-dimensional gray co-occurrence matrix texture features of the region of interest are extracted. Finally, the Stacking evaluation model is used to identify and classify lung nodules.The experimental results show: Under ten-fold cross-validation, the training accuracy rate and the test accuracy rate can reach 90.9%,82.3%, respectively.This method is feasible for pulmonary nodule recognition and provides data reference value for doctors' auxiliary diagnosis

Keywords: *Medical image processing, CAD,Gray level co-occurrence matrix,Stacking evaluation mode*

I. INTRODUCTION

Cancer has become a major problem that seriously affects human health. In the article “Global Cancer Statistics 2018” published in the CA journal on September 12, 2018, the morbidity and mortality of 36 types of cancer in 185 countries around the world were counted, Among them, the prevalence of lung cancer, female breast cancer and colorectal cancer ranks in the top three, and the cancer mortality rate in Asia is much higher than that in other regions[1]. In recent years, the number of cancers in our country has also been increasing, and its morbidity and mortality rate of lung cancer ranks first [2]. The main reasons are: severe urban air pollution, high smoking population, aging population, difficulty in early detection and late It is difficult to cure. Therefore, cancer has issued warnings to human health problems, and early diagnosis and early treatment have become the main factors for reducing mortality [3].

At present, the main treatments for lung cancer include X-ray, low-dose spiral CT, nuclear magnetic resonance, and biopsy. Low-dose spiral CT is accessible to screen for lung cancer and

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reduce mortality effectively according to the 2012 National Cancer Screening Experiment in the United States.Although low-dose spiral CT can improve the survival rate, a large number of CT data and subtle nodules cause doctors' visual fatigue, resulting in misdiagnosis and missed diagnosis. In response to the above problems, computer-aided diagnosis and diagnosis technology [4] (CAD) has been continuously developed in the field of cancer.Arulmurugan R et al. [5] used wavelet feature descriptors in the classification research, combined with artificial neural networks to establish a lung nodule classification modelto raise the classification accuracy of lung nodules. Experiments verify that the accuracy, specificity and sensitivity of the classification model can reach 92.6%, 100%, 91.2%, respectively.Maria Jenifer L et al. [6] used the Gravity Search Algorithm (GSA) to build a lung nodule recognition model and filtered the image through low-frequency processing technology, Edge detection technology segments the region of interest, which provides a fast and accurate framework for feature extraction and feature selection. Kohei Arai et al. [7] used 2D LBP and 3D LBP probabilistic neural networks (PNN) to achieve lung image classification. Experimental results prove that, compared with 2D LBP, 3D LBP has higher accuracy performance,and the classification accuracy can reach 78%, while the classification accuracy of 2D LBP can only reach 43%.Wang Bin et al. [8] put forward a lung nodule detection algorithm based on the continuity of center points, to extract the ROI in the way of super pixel segmentation, and judge the false positive according to the degree of deviation of a series of center points of the ROI.

The main diagnosis of lung cancer is based on the benign and malignant lung nodules, but in the detection process, the existence of suspected nodules (vessels, pleura, etc.) similar to lung nodules will cause an increase in the false positive rate and reduce the accuracy. Therefore, in this paper, considering the characteristics of lung slices and lung nodules, combined with the three-dimensional gray level co-occurrence matrix, a stacking algorithm-based lung nodule recognition method is proposed, which more comprehensively considers its texture information, reduces the false positive rate, and improves the accuracy.

II. LUNG NODULE TEXTURE FEATURE EXTRACTION BASED ON 3D-GLCM

The detection of lung nodules is mainly analyzed by some features. Common feature analysis methods include texture feature extraction method, shape feature extraction method, gray feature method and so on. This paper mainly analyzes the texture features, and the two-dimensional texture features cannot fully reflect all the texture information of the nodules, and combined with the continuity of CT slices and other characteristics, this paper uses the 3D-GLCM method to conduct experiments in the process of texture features extraction.

2.1 Pretreatment of Lung CT Images

Medical CT images are affected by many factors during their imaging and transmission: 1. The artifacts caused by the patient's self-occupancy and involuntary movement during the filming process; 2. The quality problems of the imaging device itself; 3. The interference caused by the external environment; 4. The noise carried during the image transmission process, etc. Medical CT processing becomes a challenge. Therefore, lung CT images must be pre-processed

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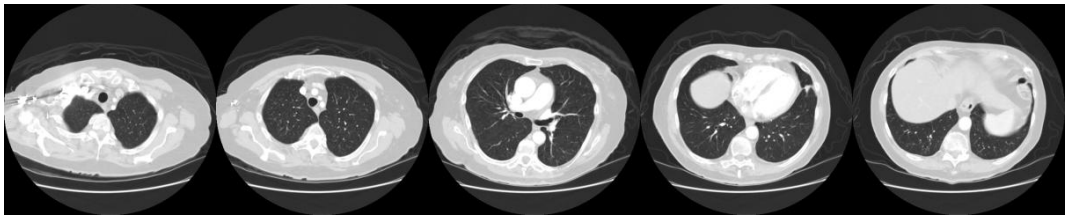
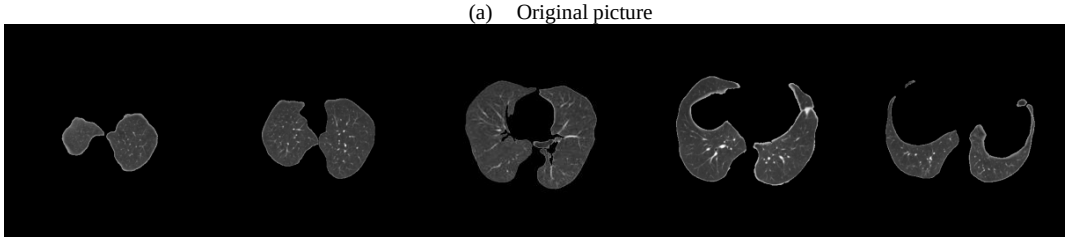
before feature extraction, including image normalization, reasonable denoising, accurate boundary segmentation, and accurate ROI extraction.

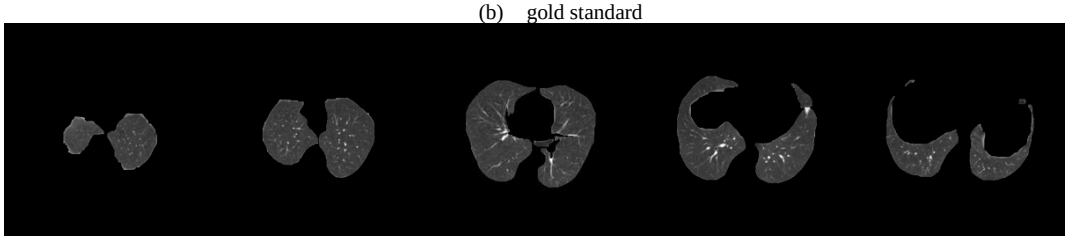
In this paper, the Sant DicomViewe software is used to normalize the CT image, the size is 512 × 512, and the median filter is used to denoise, and then the random walk algorithm is used to segment the lung parenchyma [9,10].Fig. 1 is the comparison results of the gold standard image segmented by four radiologists and the image segmented using the random walk segmentation algorithm.



(a) Original picture



(b) gold standard



(c) Random walk

Fig 1:Comparison of segmentation method results

ROI extraction is an important process for processing medical images, which is to extract the region of interest in the lung parenchyma,the extraction results are divided into two categories: lung nodules and suspected nodules.Fig. 2 is the result marked by four radiologists through an XML file. The left picture shows the lung nodules and the right picture shows the suspected nodules.

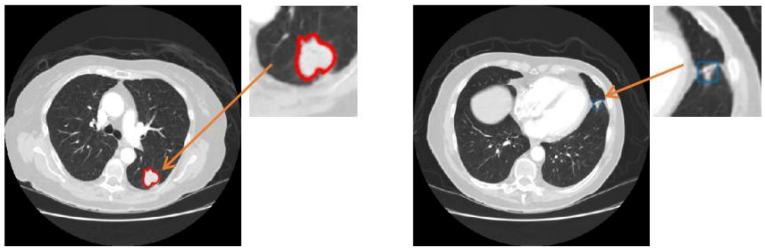


Fig 2: ROI annotation

2.2 2D-GLCM Texture Feature Extraction

Haralik et al. put forward the gray-level co-occurrence matrix method in the early 1970s.[11], which considered the spatial distribution relationship of each pixel in the figure, including the direction, local area and change range. The definition of the gray level

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co-occurrence matrix is: The probability of pixels with gray values g_1 and g_2 appearing in the direction θ and the difference distance d is denoted $P(g_1, g_2 \mid d, \theta)$. The schematic diagram of the direction of the gray level co-occurrence matrix is shown in Fig. 3.

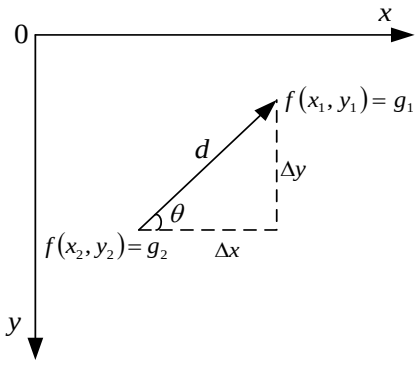

Fig 3: Schematic diagram of the gray level co-occurrence matrix

$$P(g_1, g_2 \mid d, \theta) = \#\left\{\left[(x_1, y_1), (x_2, y_2)\right] \in S \times S \mid f(x_1, y_1) = g_1 \,\&\, f(x_2, y_2) = g_2\right\} \quad (1)$$

g_1, g_2 represent gray value; # representsthe total number of pixel pairs in the formula.It can be seen from the above formula that the main factors affecting the computational complexity are the image size, the image grey level, the image distance, the image direction. In the middle of the two-dimensional gray level symbiotic moment, the four most commonly used directions are $0^\circ, 45^\circ, 90^\circ, 135^\circ$.

2.3 3D-GLCM TextureFeature Extraction

The three-dimensional gray-scale matrix is derived from the two-dimensional gray-scale matrix and has similar characteristics to the two-dimensional gray-scale co-occurrence matrix. According to its direction, distance and pixel value, the definition of the three-dimensional gray-scale co-occurrence matrix is[12-15]:

$$P(g_1, g_2 \mid d, \theta) = \#\left\{\left[(x_1, y_1, z_1), (x_2, y_2, z_2)\right] \in S \times S \mid f(x_1, y_1, z_1) = g_1 \,\&\, f(x_2, y_2, z_2) = g_2\right\} \quad (2)$$

The three-dimensional gray-level symbiotic moment is positively compared with the two-dimensional gray-level symbiotic moment. Increased from the commonly used 4 directions to 13 directions, not only considering the neighborhood, but also considering the information in the spatial domain.

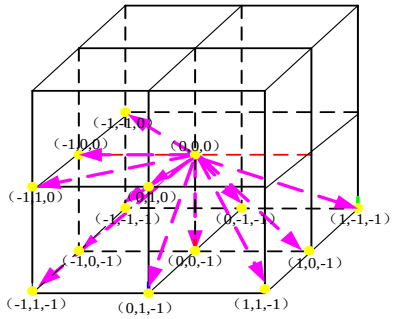

Fig 4: 3D-GLCM direction diagram

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Therefore, the calculation formula of the three-dimensional gray level co-occurrence matrix in the a direction [14,15]:

$$P\left(g_1,g_2\,|\,d,0^{\circ}\right)=\#\left\{\begin{array}{l}\left[\left(x_1,y_1,z_1\right),\left(x_2,y_2,z_2\right)\right]\in S\times S\,|\left(x_1-x_2=d,y_1-y_2=d,z_1-z_2=0\right)\\ \text{or}\left(x_1-x_2=-d,y_1-y_2=d,z_1-z_2=0\right)\text{or}\left(x_1-x_2=-d,y_1-y_2=0,z_1-z_2=0\right),\\ \text{f}\left(x_1,y_1,z_1\right)=g_1\ \&\ \text{f}\left(x_2,y_2,z_2\right)=g_2\end{array}\right\} \quad (3)$$

(1)Angle second-order moment W_1:

$$W_1=\sum_{g_1}\sum_{g_2}\left[P\left(g_1,g_2;d,\theta\right)\right]^2 \quad (4)$$

Both the uniformity and smoothness of the image distribution require angular second moment (energy) to measure. When all $P\left(g_1,g_2;d,\theta\right)$ are equal or concentrated near the main diagonal,W_1 reaches the minimum value and the image is the smoothest.

(2) Moment of inertia W_2:

$$W_2=\sum_{g1}\sum_{g2}\left(g_1-g_2\right)^2P\left(g_1,g_2;d,\theta\right) \quad (5)$$

The amount of change between the local gray levels in the image, that is, the clarity of the image, can be reflected in the moment of inertia.When the small value in $P\left(g_1,g_2;d,\theta\right)$ is mainly concentrated near the main diagonal of the matrix, ethe larger the value of W_2 ,it reflects that the contrast of adjacent pixels in the image is very large.

(3)Inverse differential moment W_3:

$$W_3=\sum_{g_1}\sum_{g_2}\frac{P\left(g_1,g_2;d,\theta\right)}{1+\left(g_1-g_2\right)^2} \quad (6)$$

To a certain extent, uniformity can be regarded as the reciprocal of the moment of inertia. When the elements in the co-occurrence matrix $P\left(g_1,g_2;d,\theta\right)$ are closer to each other and more similar, the value of W_3 becomes larger and larger.

(4) Entropy W_4:

$$W_4=-\sum_{g_1}\sum_{g_2}P\left(g_1,g_2;d,\theta\right)\lg P\left(g_1,g_2;d,\theta\right) \quad (7)$$

The unevenness of texture is reflected by entropy. If in the co-occurrence matrix, the gray-level probability between the pixel pairs is the same, then the entropy reaches the maximum value.

(5)Relevance W_5:

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$$W_5 = \frac{\sum_{g_1}\sum_{g_2} g_1 g_2 P(g_1, g_2; d, \theta) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (8)$$

In the formula, μ_x, μ_y, σ_x, σ_y are defined as:

$$\mu_x = \sum_{g_1} g_1 \sum_{g_2} P(g_1, g_2 : d, \theta) \quad (9)$$

$$\mu_y = \sum_{g_2} g_2 \sum_{g_1} P(g_1, g_2 : d, \theta) \quad (10)$$

$$\sigma_x^2 = \sum_{g_1} (g_1 - \mu_x)^2 \sum_{g_2} P(g_1, g_2 : d, \theta) \quad (11)$$

$$\sigma_y^2 = \sum_{g_2} (g_2 - \mu_y)^2 \sum_{g_1} P(g_1, g_2 : d, \theta) \quad (12)$$

The correlation coefficient reflects the linear correlation between the rows and columns of the matrix to a certain extent. When the correlation coefficient becomes larger and larger, the gray distribution in the image area will be more uniform.

2.4Lung CT Image Texture Feature Analysis and Extraction

As described above, there are four main variables that affect the calculation complexity in the GLCM algorithm, which are the image size N, gray level L, distance d, and direction θ. When the algorithm analyzes the texture features of lung nodules in the lung CT image, the following four parameters are analyzed.

(1) The choice of image size N (window): If the pixels are too small, some texture information will be lost. If the pixels are too large, the storage and calculation will be too large.

(2) The choice of gray level L: The gray level of the image determines the complexity of the calculation. In this paper, the gray level is reduced from 256 to 16, and the main purpose is to increase the experimental calculation speed.

(3) The choice of distance d: In rough textures, the GLCM algorithm changes slowly under the influence of distance;in fine textures, the GLCM algorithm changes faster under the influence of distance. Experiments prove that when the distance $d = 1$, better experimental results will be achieved, so d is 1 in this paper.

(4) Choice of direction: The image has certain directionality in terms of texture characteristics, and the amount of texture information in different co-occurrence matrices generated by different images is also different. After a lot of experiments, it was found that some texture information is incomplete, mainly because the texture information in a certain direction is lost or discarded, so the 13 directions mentioned above can be used for feature extraction.

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TABLE I.Lung Nodule Texture Feature Extraction Algorithm Based on 3D-GLCM

Step	Process
1	Input lung nodule slices to form a three-dimensional three-dimensional nodule;
2	Quantify the nodules in gray scale from 256 to 16;
3	Extract the texture information feature of the gray level co-occurrence matrix from thirteen directions;
4	Average the extracted texture feature information in thirteen directions;
5	Output a 5-dimensional texture feature vector and return to step one.

III. LUNG NODULE RECOGNITION BASED ON STACKING ALGORITHM

Stacking algorithm [16,17] is a kind of integrated learning method. It is a non-linear combination of multiple learners to build a multi-layer network to achieve sample prediction and classification to achieve better learning results. In this paper, combined with the characteristics of texture feature extraction, a lung nodule assisted diagnosis model based on Stacking algorithm is constructed. First divide the unbalanced samples to form independent disjoint sets;then through the classifier SVM, RF, ELM sample training and testing to form a basic learner; second, the output of the basic learner is used as the input of the meta-learner, and the KNN is used for sample training and testing. Finally, the evaluation index and receiver characteristic curve are used to evaluate the model.

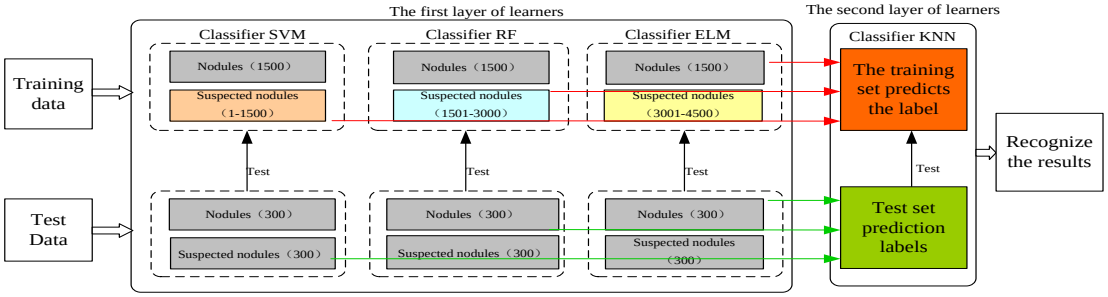

Fig 5: Lung nodule assisted diagnosis model based on Stacking algorithm

Although there are many integration methods, the Stacking algorithm is to achieve heterogeneous integration, and the effect is better than any single model. Therefore, this paper proposes a lung nodule assisted diagnosis model based on the Stacking algorithm, as shown in Fig.5, the diagnosis process of this model for lung nodules is as follows:

(1)Aiming at the imbalance problem of samples, this paper achieves sample balance by changing the distribution of training set samples (that is, training set division), and combines the stacking algorithm idea to divide the disjoint subsets of training samples and test samples;

(2)Use support vector machine, nearest neighbor classification, extreme learning machine to form a primary learner, and perform label prediction oftraining samples and test samples;

(3)Use the labels obtained by the primary learner in process (2) as the input of the secondary learner, and use random forest [18] to learn to obtain the final classification result;

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(4)The final classification results are analyzed with evaluation indicators and subject characteristic curves to obtain the final evaluation of the model.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

3.1Experimental Environment and Data

(1)Experimental environment:

CPU: Intel Core i5-4200, memory: 16G, simulation platform: Matlab R2016b, system type: 64-bit operating system.

(2)Experimental data: This article uses the lung image database (LIDC-IDRI) [19] collected by the National Cancer Institute (NCI) to conduct experiments. The database has a total of 1010 subjects, 1018 research examples and 244527 images, and 500 of them are selected for experiments, 1884 samples of lung nodules and 6503 samples of suspected nodules were obtained.

3.2 Evaluation Criteria

In the computer-aided diagnosis system, the evaluation index [20] mainly uses Accuracy, Sensitivity, Specificity, Matthews Correlation Coefficient (MCC) and F1 score (F1)etc Evaluation, In order to show the classifier performance and diagnosis results more intuitively, the ROC curve is also used as the evaluation standard. The subject characteristic curve is the area under the curve (AUC) as a measure of the performance of the classifier,the abscissa is the false positive rate (1-specificity), and the ordinate is the true positive rate (sensitivity), which combines sensitivity and specificity to accurately reflect the relationship between the two of the classifiers. When the area under the curve is closer to 1, it means that the classifier performance is better, when the area under the curve is 0.5, it means that the classifier fails; the degree to which the curve is close to the upper left indicates the accuracy of the classifier, and the two are directly proportional.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{13}$$

$$Sensitivity = TPR = \frac{TP}{TP + FN} \times 100\% \tag{14}$$

$$Specificity = TNR = \frac{TN}{TN + FP} \times 100\% \tag{15}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{16}$$

$$F_1 = 2\frac{Sensitivity \times \Pr ecision}{Sensitivity + \Pr ecision} \tag{17}$$

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3.3 Results and Analysis

In this paper, 3000 samples are selected to verify the effectiveness of the texture feature extraction method, including 1500 lung nodules and 1500 suspected nodules, and use 10-fold cross-validation to fully explain the effective performance of the verification model, that is, divide the sample into 10 parts, take one of them as the training set for each model training, conduct 10 trainings, and find the average value as the performance of the classification model Evaluation value. In this paper, four kinds of classifiers are used: SVM, KNN, RF and ELM to verify the extracted texture features.

(1). Correlation analysis and selection of base classifier

In the parameter selection of the classifier, the SVMselects Gaussian RBF, for the nearest neighbor classification, the number of neighbors is 1, and the distance is the Euclidean parameter, 100 decision trees are used in the random forest, the number of hidden layers of the extreme learning machine is 900, and the activation function is Sigm. The above parameters have been verified by experiments to obtain the best results.Evaluation indicators of computer-aided diagnosis system, namely accuracy rate, sensitivity, specificity, Matthews correlation coefficient (MCC), F1 score (F1), classifier SVM, KNN, RF, and ELM for comparative analysis, The classifier evaluation indicators of the training set and test set are shown in TABLE II and TABLE III below.

TABLE II. Evaluation indexes of each classifier in the training set

	Accuracy	Sensitivity	Specificity	(MCC)	(F1)
SVM	0.779	0.771	0.775	0.551	0.776
KNN	0.680	0.837	0.759	0.524	0.738
RF	0.807	0.793	0.800	0.600	0.801
ELM	0.707	0.624	0.665	0.333	0.678

TABLE III. Evaluation indexes of each classifier in the test set

	Accuracy	Sensitivity	Specificity	MCC	F1
SVM	0.742	0.739	0.741	0.482	0.741
KNN	0.648	0.820	0.734	0.476	0.709
RF	0.810	0.787	0.798	0.597	0.801
ELM	0.751	0.643	0.697	0.397	0.712

In order to visually analyze the performance of the classifier, it is represented by the receiver characteristic curve (ROC).Fig. 6 shows the lung nodule classification results. The abscissa is the false positive rate (1-specificity), and the ordinate is the true positive rate (sensitivity). The area under the curve represents the performance of the classifier.

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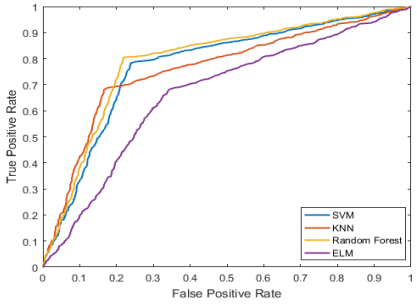
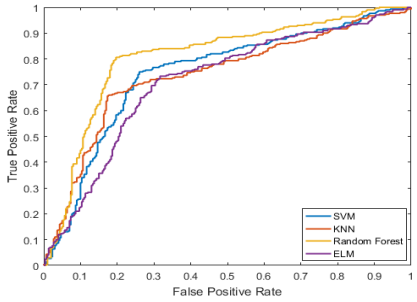


(a)Comparison of various classifiers in the training set



(b)Comparison of various classifiers in the test set

Fig 6: ROC curves of texture features of lung nodules under different classifiers

(2)Lung nodule recognition results based on Stacking algorithm

During the identification of lung nodules, the differences between the auxiliary diagnostic models will produce different results. This subject uses a lung nodule assisted diagnosis model based on the Stacking algorithm to classify lung nodules. The model is composed of two layers of learners, the first layer: Leve1-SVM, Leve1-RF, Leve1-ELM, the second layer: Leve2-KNN. TABLE IV and TABLE V. are the training results and test results under the base classifier and meta classifier, respectively.

TABLE IV. Training results under base classifier and meta classifier

	Accuracy	Sensitivity	Specificity	MCC	F1
Leve1-SVM	0.785	0.768	0.777	0.554	0.779
Leve1-RF	0.809	0.787	0.798	0.597	0.800
Leve1-ELM	0.704	0.608	0.656	0.315	0.671
Leve2-KNN	**0.909**	**0.885**	**0.897**	**0.794**	**0.898**

TABLE V. Test results under base classifier and meta classifier

	Accuracy	Sensitivity	Specificity	MCC	F1
Leve1-SVM	0.746	0.732	0.739	0.478	0.741
Leve1-RF	0.813	0.762	0.788	0.576	0.793
Leve1-ELM	0.743	0.640	0.692	0.387	0.706
Leve2-KNN	**0.819**	**0.811**	**0.805**	**0.610**	**0.806**

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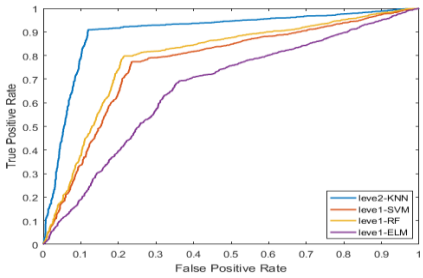
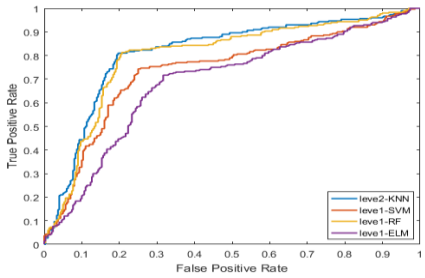


(a)Comparison of the results of various network levels in the training set



(b)Comparison of results at various network levels in the test set

Fig 7: ROC curve of lung nodule recognition based on Stacking algorithm

Fig. 7 is a comparison of the performance of the two-layer learner. Fig. 7(a) is a comparison of the ROC characteristic curve of each classifier under the base classifier and the ROC characteristic curve of the meta-classifier under the training set. According to the ROC curve results, we observe that the meta-classifier has better results. Fig. 7(b) is a comparison of the ROC characteristic curve of each classifier under the base classifier and the ROC characteristic curve of the meta-classifier under the test set.According to the ROC curve results, we observe that the meta-classifier also has better results. Therefore, it is understood from the above results and analysis: the classification results of lung nodules are improved based on the Stacking algorithm, which proves the effectiveness of the algorithm.

TABLE VI.Comparison of results of different test sets

	Accuracy	Sensitivity	Specificity	MCC	F1
200	0.817	0.763	0.790	0.581	0.796
400	**0.823**	**0.815**	**0.819**	**0.637**	**0.819**
600	0.819	0.811	0.805	0.610	0.806

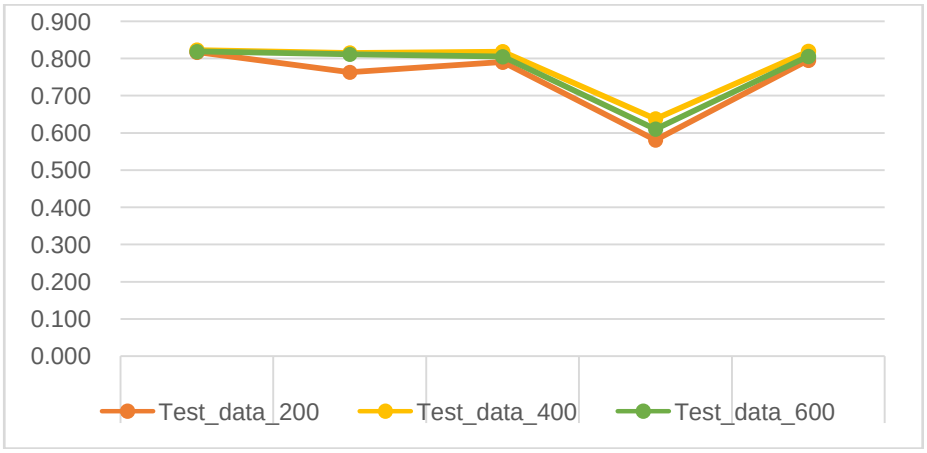


Fig 8: Comparison of results from different test sets

Different test sets have different generalization performance. Fig.8 shows the experimental results of different test sets. The comparison is made from the test set data 200, 400 and 600. It

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can be seen from the figure that when the test data is 400, the obtained experimental results are better, the test accuracy and sensitivity, Specificity, Matthews correlation coefficient and F1 score are the highest, so they have good generalization performance.

IV. CONCLUSION

This paper proposes a method of lung nodule recognition based on the Stacking algorithm. This method trains and tests the Stacking evaluation model by extracting the texture features of the three-dimensional gray level co-occurrence matrix, and finally realizes the classification and classification of lung nodules, Its training accuracy, specificity, sensitivity, Matthews correlation coefficient, and F1 score are 81.9%, 81.1%, 80.5%, 61.0%, and 80.6%, which are improved compared with other model evaluation indicators, so this method can be effective Identify lung nodules. Despite this, the method is still in a semi-supervised learning state and is still limited to the accurate segmentation of lung nodules, so future work will mainly consider how to allow accurate segmentation of medical images to improve diagnostic results.

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