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## Comparison of Accuracy in Extreme Learning Machine Based on Hidden Node Structure Variation for Lung Cancer Classification

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# Comparison of Accuracy in Extreme Learning Machine Based on Hidden Node Structure Variation for Lung Cancer Classification

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**Abstract.** This paper present Extreme Learning Machine to classify lung cancer nodules. Lung cancer is a type of lung disease that requires fast and specified treatment. Skills, facilities and multidisciplinary approach are required for diagnosing lung cancer. The use of Computed Tomography (CT) to detect lung cancer can reduce the number of deaths from lung cancer, but it increases the workload of the radiologist because CT screening process produces many medical images. Computer systems become one of the potential solutions to help radiologists solve the problem. Extreme Learning Machine is an algorithm that able to provide good generalization at fast learning time which is essential to help radiologists in analyzing lung cancer nodules images. In this paper, there were 877 nodules extracted from LIDC-IDRI dataset. All nodules used in this experiment consist of lung cancer nodules that diagnosed to four different level of malignancy and annotated by up-to four different radiologists. The result shows Extreme Learning Machine achieve 85.17%, 85.58% and 84.87% in accuracy and Matthew Correlation Coefficient 0.755, 0.762 and 0.749 using Hardlimit, Radial basis Function and Triangular Basis function, respectively.

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## 1. Introduction

Cancer is one of the leading causes of death in the world. In 2012 the number of cancer deaths is 8.2 million. The biggest causes of death caused by cancer include lung cancer, liver, stomach, colorectal, and breast cancer. Lung cancer is a cancer with the highest number of deaths as many as 1.59 million people [1]. Lung cancer is a type of lung disease that requires fast and specified treatment. Skills, facilities and multidisciplinary approach are required for diagnosing lung cancer. Radiological examination is one of the tests performed to detect and diagnose lung cancer. Radiological examination to see the condition of the lungs can be done using X-rays and Computed Tomography (CT). Currently, CT is an excellent imaging technique for early detection of lung cancer [2, 3]. Many kinds of research have harness computer vision technology to develop system to assist medical practitioner in cancer diagnosis [4-7].

Computer-aided Detection and Diagnosis (CAD) is a computer system that aims to prove radiologist accuracy and reduce the time needed to analyze images. CAD system is divided into two namely Computer-aided Detection (CADe) and Computer-aided Diagnosis (CADx). CADe was built to locate pulmonary nodules in medical images. Several studies have shown that the use of CAD systems can improve radiologist performance in detecting pulmonary nodules in CT images [3]. Computer-aided Diagnosis System (CADx) takes the characteristic values contained in the image and



then uses the classification method to determine benign or malignant tumors. The use of CT to detect lung cancer can reduce the number of deaths from lung cancer. But it increases the workload of the radiologist because CT screening process produces many medical images. Computer systems become one of the potential solutions to help radiologists solve the problem [8].

In the lung cancer screening process using CT scan, radiologist should check or analyze the data in large quantities. In this paper we present Extreme Learning Machine performance as CADx to predict malignancy of lung cancer nodule from CT scan images. Several methods have been introduced whether to detect or classify lung cancer in CT images using different approaches. Firmino et al. developed a system to detect and diagnose pulmonary nodules in CT images. The system used Watershed and HOG to detect nodules and features that presented by McNitt-Gray et.al which is calcification, internal margin, shape, texture, lobulation, spiculation [9]. Zayed and Elnemr present analysis of Haralick feature to classify abnormal lung to cancerous or edema [10]. El-Baz et al. introduced the nodule diagnose method using three-dimension feature from spherical harmonic that represent the surface of nodule in three dimensional [11]. J. Yuan et al. use the combination of Fisher Vector based on the SIFT algorithm to classify six types of nodules based on the intensity distribution and position [12]. Zhu et al. classified the malignancy of lung cancer using CT image data using GBM and 3D Dual Path Network which achieve a comparable result with human level [13]. Lee et al. [14] use two step approaches by combining genetic algorithm with random Subspace Method for feature selection and LDA as the classifier and show possibility to predict the malignancy for solitary pulmonary nodules. Han et al. [15] compared 2D and 3D texture feature of Haralick, Gabor and LBP on CADx system for lung nodule using SVM to classify benign and malignant nodules.

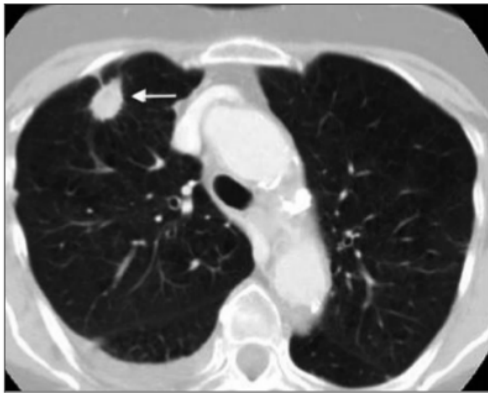
The result showed a 3D extension of Haralick feature show potential gain in accuracy if optimal direction can be found. Madero Orozo et al. [16] use Daubechies and Wavelet Sub-band to extract feature from lung images and classify to contain cancer or not using Support Vector Machine. The system able to reduce the complexity of CADx by not using the segmentation process like others CADx system. Kumar et al. [17] diagnose lung cancer using autoencoder as the feature extraction algorithm and L-BFG optimization. In this paper, Extreme Learning Machine (ELM) performance for classification of lung nodules level of malignancy was presented. The experiment conducted with different hidden node number and activation function and measured using Accuracy, Matthew Correlation Coefficient, Sensitivity and Specificity.

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## 2. Materials and Methods

### 2.1. Datasets

The Dataset used in this paper obtained from Lung Image Database Consortium (LIDC) consist of 1010 patients with one or more lung cancer nodules that have been annotated and diagnosed by up-to four radiologists [18]. For malignancy diagnosis from radiologists, the nodules are labelled with different level of malignancy, which is "1", "2", "3", "4", and "5". Figure 1 shows sample images of patient lung cancer. There were 877 cases extracted for this study which consist of 439 cases labelled as "1" or highly unlikely malignant appearance, 98 cases labelled as "2" or moderately unlikely malignant appearance, 99 cases labelled as "4" or moderately suspicious malignant appearance and 241 cases labelled as "5" or highly suspicious malignant appearance. Nodules with label "3" was not included because it's diagnosed as uncertain malignancy by the radiologists. Each nodule is segmented using annotation from radiologists. Figure 2 shows segmented nodules with different malignancy levels. Each nodules images size is set to 64 x 64 and then will be used as inputs for Extreme Learning Machine (ELM).



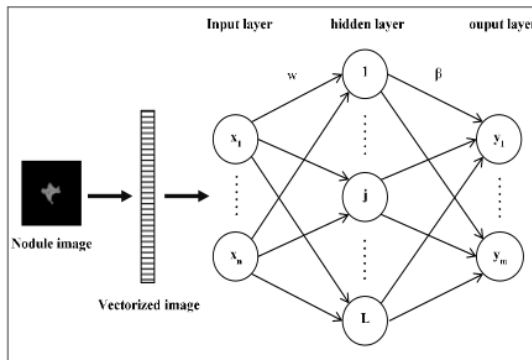
**Figure 1.** CT Lung image that diagnosed have cancer  
 Source: The Lung Image Database Consortium



**Figure 2.** Extracted lung cancer nodules based on annotation from radiologists. From left to right is nodule with malignancy level 1, 2, 4, and 5

## 2.2. Classification

This study employs Extreme Learning Machine (ELM) as lung cancer nodule classification method. ELM was introduced by Huang et al. [14] based on single hidden layer feedforward neural networks (SLFNs). ELM algorithm tends to provide performance with good generalization and fast learning time. There are two important steps in ELM, which are calculate the output weights and to determine the number of nodes to optimize the networks. The process of ELM algorithm for lung cancer nodule classification is shown in Figure 3.



**Figure 3.** Lung Cancer Nodules classification with ELM

Given  $N$  training data  $(x_i, y_i)$ , for  $i = 1, \dots, N$ , where  $x_i$  consist of input data with  $n$  dimensions, and  $y_i$  is target data with  $m$  dimensions. The number of hidden nodes in hidden layer is denoted as  $L$ . Training process in Extreme Learning Machine Algorithm is conducted as follows:

1. Randomly generate hidden neuron parameter (e.g. input weight vector  $w$  and bias  $b$ ) based on uniform distribution.
2. Calculate matrix  $g(w, x, b) = w * x + b$ .
3. Calculate  $\beta = H^+ * Y$ .
4. Calculate the result decision function,  $Y = H * \beta$ .

Where  $H$ ,  $\beta$ , and  $Y$  are defined as follows.

$$H = \begin{bmatrix} g(w_1, x_1, b_1) & \dots & g(w_L, x_1, b_L) \\ \dots & \dots & \dots \\ g(w_1, x_N, b_1) & \dots & g(w_L, x_N, b_L) \end{bmatrix}_{N \times L} \quad (1)$$

$$\beta = \begin{bmatrix} H_1^\dagger * y_1 \\ \dots \\ H_L^\dagger * y_m \end{bmatrix}_{L \times m} \quad (2)$$

$$Y = \begin{bmatrix} y_1 \\ \dots \\ y_m \end{bmatrix}_{N \times m} \quad (3)$$

$H^\dagger$  is the Moore-Penrose inverse matrix of  $H$ ,  $\beta$  is the output weight vector, and  $g$  is activation function. This study applied Sigmoid, Hardlimit, Radial basis function, Triangular Basis function and tanh as activation function and various hidden node number to find the best configuration. All the activation function used in this experiment shown in equation (4)-(8).

$$g(n) = \frac{1}{1 + e^{-n}} \quad (4)$$

$$g(n) = \begin{cases} 1, & \text{if } n \geq 0 \\ 0, & \text{if } n < 0 \end{cases} \quad (5)$$

$$g(n) = \exp(-n^2) \quad (6)$$

$$g(n) = \begin{cases} 1 - \text{abs}(n), & \text{if } -1 \leq n \leq 1 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

$$\tanh(x) = \frac{2}{1 + e^{-2x}} - 1 \quad (8)$$

### 2.3. Evaluation

ELM performance on lung cancer nodule classification is measured using confusion matrix and time needed for training and testing process. Accuracy, sensitivity, specificity, F1 score and Matthew Correlation Coefficient (MCC) are calculated from confusion matrix to see ELM performance., which defined in equation (9)-(13).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (10)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (11)$$

$$F_1 = \frac{2TP}{2TP + FP + FN} \quad (12)$$

$$MCC = \frac{\#TP \times \#TN - \#FP \times \#FN}{\sqrt{(\#TP + \#FP)(\#TP + \#FN)(\#TN + \#FP)(\#TN + \#FN)}} \quad (13)$$

where True Positive (TP) is the number of outcomes where the model predicts positive class correctly. False Positive (FP) is the number of outcomes where the model predicts negative class as positive class. False Negative (FN) is the number of outcomes where the model predicts positive class as negative class. True Negative (TN) is the number of outcomes where the model predicts negative class correctly.

### 3. Result and Discussion

Experiment on lung cancer classification was performed in Matlab Ver 9.3 that running on PC Intel Core i7 with RAM 8 GB. There were 877 data use in this experiment that consist of 614 training data and 263 testing data. ELM was trained and tested for 10 times and the result presented as the highest averages performances at different configurations on activation function and number of hidden neurons. The average accuracy and computation time from each activation function are shown in Table 1.

**Table 1.** ELM classification average accuracy on different activation function

Activation Function	Number of Hidden Nodes	Training		Testing	
		Acc (%)	Time(sec)	Acc (%)	Time(sec)
Hardlim	4900	100.00	3.42	85.17	0.59
Radbas	4900	100.00	3.80	85.59	0.67
Sigmoid	100	74.41	0.08	77.07	0.03
Tanh	4900	100.00	3.45	79.96	0.65
Tribas	5000	100.00	3.75	84.87	0.61

The best results for training accuracy in Table 1 are for all the activation function except sigmoid function. In testing process, Radial basis Function achieved highest accuracy but compared with other activation function, Hardlimit (Hardlim) showed a less computational complexity. Table 2 shows ELM performance in terms of Matthew Correlation Coefficient (MCC). For multiclass case, generalized MCC presented in [19] was used. MCC values is in range [-1, 1], with 1 demonstrate perfect classification. MCC considered more useful for evaluating classifier, because it's the only measurement to consider the unbalanced condition occurs in dataset [20] which is also occurs in this experiment. The result of average MCC values was presented in Table 2. The average MCC values were similar among Radial basis, Hardlim and Triangular basis function.

**Table 2.** MCC measurement for training and testing

Activation Function	Number of Hidden Nodes	Training	Testing
Hardlim	4900	1	0.755
Radbas	4900	1	0.762
Sigmoid	100	0.53	0.541
Tanh	4900	1	0.675
Tribas	5000	1	0.749

For more in-depth result, the average sensitivity and specificity of Hardlimit, Radial basis function and Triangular basis function for each class used in the testing process are presented in Table 2. Hardlimit, Radial basis and Triangular basis function have good ability to correctly identified nodule that have level 1 malignancy or highly unlikely malignant characteristic which proven with high

Sensitivity values. High Specificity values at level 2 and 4 means that Hardlimit, Radial basis and Triangular basis function have good ability to ignore lung nodule without the characteristic of nodule level 2 and 4 malignancy. For level 5 malignancy, Hardlimit, Radial basis and Triangular function have high Sensitivity and Specificity which means that the activation functions have good ability to recognize lung nodules with level 5 malignancy characteristic and ignore lung nodules without the characteristic of nodules with level 5 malignancy.

**Table 3.** Sensitivity and specificity measurement for each level of malignancy

Level of Malignancy	Sensitivity			Specificity		
	Hardlim	Radbas	Tribas	Hardlim	Radbas	Tribas
1	0.951	0.949	0.947	0.820	0.818	0.817
2	0.538	0.517	0.490	0.983	0.987	0.991
4	0.514	0.576	0.467	0.978	0.979	0.983
5	0.882	0.892	0.913	0.959	0.961	0.941

#### 4. Conclusion

The ELM performance in classification of lung cancer nodules has been presented. ELM algorithm was implemented with various activation function and number of hidden nodes to find the best configuration to predict malignancy level of lung cancer nodules. The ELM algorithm was trained and tested using LIDC-IDRI dataset. All the activation function used in this study achieved highest average accuracy for training process except Sigmoid function. Meanwhile, Hardlimit, Radial basis function and Triangular basis function show good testing performance in lung nodule malignancy classification but Hardlimit function show less computational complexity compared with other Radial basis and Triangular function. ELM with Hardlimit, Radial basis and Triangular basis function have good ability to recognize lung nodules with the characteristic of level 1 malignancy or highly unlikely malignant and level 5 malignancy or highly likely malignant. The algorithm also shows good ability to ignore lung nodules without the characteristic of level, 2, 4 and 5 malignancy. However, there was still improvement needed in the ability to ignore lung nodules without the characteristic of level 1 malignancy and to recognize lung nodules that classify as level 2 and 4 malignancy.

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