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Pulmonary Solid / Sub Solid Nodule Classification in Thin Slice CT Images Using SVM

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Abstract: **- Machine learning techniques used in diagnosing cancerous lesions in medical images. The phenotype features of the pulmonary nodule in CT images are important cues for the malignancy prediction. This can improve radiologist make decisions which are difficult to identify, improving the accuracy with efficiency. Deep Learning or hierarchical learning as a major area of machine learning in the field of medical imaging hopefully faster and gives best results. Using parallel computing techniques speed up matrix operation with more parameters. Compared to the conventional machine learning methods deep learning has shown a superior performance in visual media. In this study, we develop EXHOG descriptor to characterize semantic features in deep convolutional Neural Network. An SVM classifier finds the nodule types with richer accuracy from LIDC lung medical image data set.**

Keywords: **Deep Learning, Convolutional Neural Network, Histogram of Oriented Gradients, Extended Histogram of Oriented Gradients, Support Vector Machine.**

I. INTRODUCTION

Lung Cancer is one of the dangerous malignancies among other cancers [1]. In USA 2, 21,200 is the lung cancer cased in 2015 and 13% of cancers diagnosed [2]. Lung cancer may come for smoker as well as non-smokers. Early diagnosis could improve 5 year survival period. Pulmonary nodules are small spherical sized, primary cause of cancer which leads to death in recent years. Computerized Tomography (CT) is one of the sensitive imaging Techniques with good image quality, superior to any other modality and widely used (Van Ginneken(2008)). In CT images the phenotype features of the pulmonary nodule is important. The level of detail and resolution of CT inside the lung parenchyma is comparatively better than other modalities [3]. Lung nodules, small mass of tissues in the lung, appears as round, white shadows in CT scan. Cancerous lung nodule requires treatment. The effective utilization of computer aided diagnosis in clinical procedures can support in making the decision of malignant nodule [4]. The Lung Image Database Consortium data is used in this study as resource. Each CAD system uses different steps to diagnose benign or malignant nodule. The various steps are: 1. The lung parenchyma extraction to segment the lung region 2.lung Solid nodule candidates feature extraction 3. Final Solid / Subsolid classification. In this CAD, the segmentation of the nodules is a complicated task aiming the entire region of the nodule. Normally, image processing algorithm has been used to extract features on images. Deep learning architecture convolutional neural network are capable of extracting nodule recognition in hierarchical manner by using multiple layers of convolution and maxpooling [5].Deep Learning has been proved in to detect pattern and classify lung nodules by modifying its architecture [6] .The heterogeneous features include deep learning CNN features as well as HOG features[8], score the radiologist ratings[7]. CNN convnet is highly suited for false positive reduction of a CAD system [11]. The low computation time of ConvNets-CAD is highly suited as decision aid in lung cancer screening [12]. We propose framework that leverages heterogeneous computational features derived from the deep learning models of convolutional neural network (CNN) as well as general low level histogram of oriented gradients (HoG) and Extended Histogram of Oriented Gradients (EXHoG) features diagnose the nodules in CT pulmonary images.

II. MATERIAL

2.1 Data set

The Lung Image Database Consortium (LIDC) and ANODE09 data base is a publicly available reference for the medical imaging research community [12]. LIDC dataset

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contains 1018 pulmanory CT images that originated from a total of 1010 patients , in total 2,43,958 images.This database was used by many over the years in many problems regarding pulmanory cancer diagnosis in nodule segmentation[13].

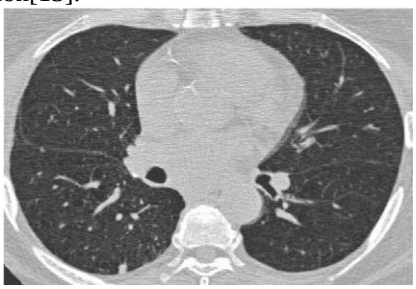

Fig 1. Sample Input image and its threshold image

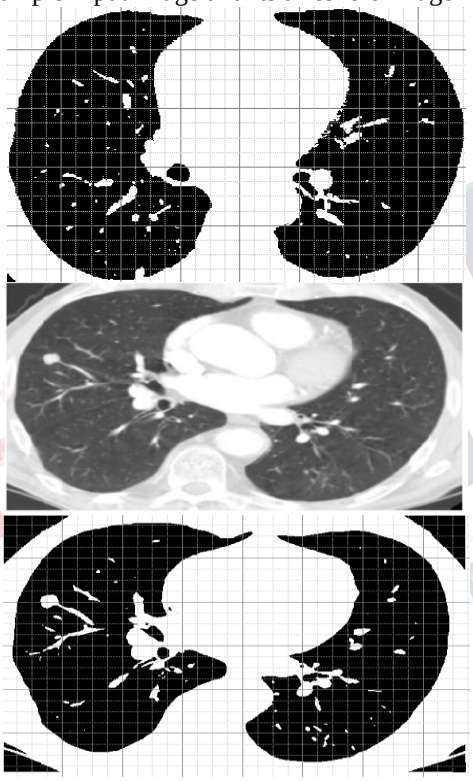

Fig1. Sample Input image and its threshold image

Fig.2. Input image of lung CT nodule case from left to right, (a) solid; (b) part solid; and (c) non solid.

2.2 Feature Extraction

Feature extraction is the major role of object learning in medical images. Low Level and high level features of an image is important to detect the exact pixel region in an image [15]. Low level features are color, texture, shape and spatial location. HOG supports low level features and translation of high level features. ExHOG supports the strongest corner detection in pulmanory images. CNN convnet supports translation, scaling and rotation which is termed as high level features.When hybridize both descriptors, the result image shows excellent extraction which matches the train nodule features. In this heterogenious scheme the result improves the accuracy.

2.3 Blocks of Convolutional Neural Network as Feature Descriptor

Convolutional Neural Network (CNN) is a type of feedforward neural network and inspired by modern biological and visual system. Convolution means trying every possible match. It is a function to map input data to an output. Generally it consists of convolutional layer,max or sum pooling layers, activation layers and sofmax layer. Mathematically a CNN can be represented as a function f, which is the composition of a function f, where f = fL f L-1 …….f1. Each function represents a layer. The first convolutional layer of CNN extracts edges and subsequent convolutional layers act as high level feature extractors [14].The architecture of the CNN in this paper is showed in fig 1. It is composed of multiple maps in each layer , each map is composed of many neural units. Each neural units in the same map share one kernel or weight. Each kernel represents a feature, such as access to the edge of image features. The input data has a strong robustness on the distortion. The multiscale convolution image feature is formed by kernel size and parameter.

2.4 HOG (Histogram of Oriented Gradients)

The image is divided into small connected regions called cells. The pixel within each cell, a histogram of gradient directions is compiled. The descriptor is the concatenation of these histograms. For improved accuracy the local histograms can be contrast normalized. In block larger region of image calculate the intensity measurement. In normalization image get good intensity and shadowing in normalization. This operated on local cells. HOG is suitable in tumor detection in images. To filter color or intensity of the image gradient computation in horizontal and vertical directions , [-1 0 1] and [-1 0 1]T are necessary.Steps followed in Hog,

1. Set the number of HOG windows nwinx, nwiny per bound box
2. Set the number of histogram bins b

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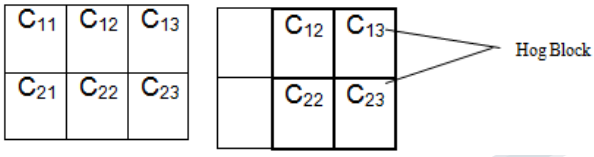
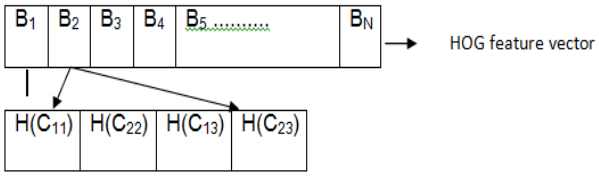
3. [L , C] = size(Image) here L - No of lines , C - No of Columns
4. If (num of columns ==1) verify the size of the image
5. End
6. Hx=[-1 0 1]
7. Hy = -Hx
8. Find grad-xr,grad-yr
9. Angle = tan-1(grad-xr,grad-yr)
10. magnitude= sqr(grad-yr 2 +grad-xr 2)
11. for n = 0 to y-1
12. for m = 0 to x-1
13. calculate angle and magnitude
14. k = max(size(angles))
15. assembling the histogram with 9 bins range of 20 degrees per bin
16. end



The Hog feature vector is arranged by HOG blocks. The cell Histogram H(Cyx) is 1 by numbins.



H(C11) refers cell histogram

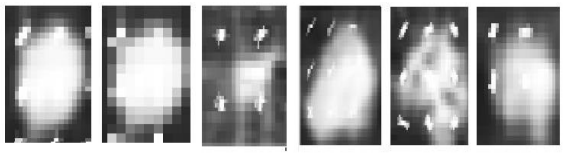


Fig.4 Sample hog shape feature of nodules

2.5 ExHOG (Extended HOG) Feature Descriptor

In this paper we used a method for whole lung nodule detection using our extended histogram of gradients (EXHOG) feature proposed in []. This descriptor resolves the larger intra class variation of image by the brightness reversal of image and background. ExHOG represents the image contour more discriminatively than HOG and has less intraclass variation than HG. The Number of bins taken is 18 and window size 6X6. To calculate feature of lung images the contributes n fold , first is CNN second is HOG and the third one is ExHOG. Given an image window I , first order gradients are computed using mask of [1 0 -1] T convolved in the x and y directions of the window. The gradient magnitude(M) of each pixel (x,y) and its direction , theta are computed as follows:

$M(x,y) = \sqrt{Ix2 + Iy2}$

M(x,y) is the magnitude of pixel.

We can calculate pixel direction (x,y) , $\theta = \tan^{-1}(Iy/Ix)$, where the theta intervals between o to 2π. Where Ix and Iy are gradients in the x and y directions. The image window is divided into nonoverlapping cells of ξ x ξ pixels. Histograms of gradients of directions are computed for each cell in an overlapping block of ξ x ξ cells.HG considers the directions from 0 to 2π, in which bright object is against a dark background or vice versa. This makes the object larger.Denote i as the bin of quantized gradient direction theta, hy(i) as the bin value of HG and L as number of bins of HG which is even. HOG is computed from HG by adding hy(i) and hy(i+L/2). To solve the problem of HOG , we consider the absolute difference between hy(i) and hy(i+L/2) of HG of each cell to form a histogram of difference gradients which is referred as DiffHG.We concatenate DiffHG and HOG of L/2 bins each to form a histogram of L bins for each cell in the image window called Extended histogram of gradients (EXHOG) . The feature concatenated and normalized.

3. Classification with SVM Classifier

The LIDC benchmark dataset consists the details of patientid, nodule, noduleid, slicenumber, zposition and diameter. The Trained and shape extracted nodules are classified by hyperplane distance equation from SVM classifier. Here TN and TP values are classified and performance analysed. Support Vector Machine is supervised learning model, suited for extreme cases, effective in high dimensional LIDC dataset space and memory efficient. Also it used different kernel functions for various decision functions. SVM analyzed lung images and classified nodule and nonnodule where nodule equal to 1 else zero in matlab 2017b.

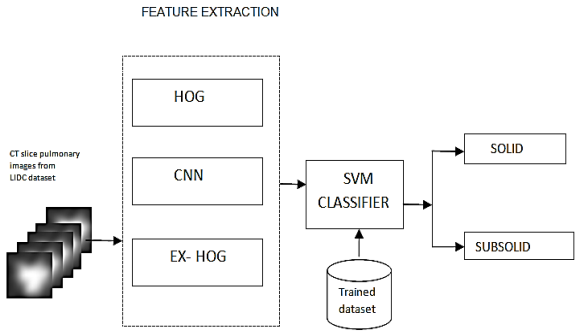


Fig.5 Block diagram of proposed work

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In support vector machines are supervised learning model that anayze data used for classification and regression analysis. Maximum margin hyperplane and margins for an svm trained with samples from two classes. Samples on the margin are called the support vectors. The equations of two hyperplanes,

$$\overline{w}.\overline{x} - b = 1$$
$$\overline{w}.\overline{x} - b = -1$$

The distance between 2 hyperplanes is $\frac{2}{\overline{w}}$. So to maximize the distance between the planes we want to minimize $\overline{w}$. To prevent data points from falling in to the margin, we add the following constraint for i,

$\overline{w}.\overline{x} - b \geq 1$ if yi =1 or $\overline{w}.\overline{x} - b \leq -1$ if yi =-1

These constraints state that each data point must lie on the correct side of the margin.Optimal separating hyperplane will obtain maximize the distance of closest point to hyperplane.. Given training examples labeled either "yes" or "no", a maximum-margin hyperplane splits "yes" and "no" training examples, such that the distance from the closest examples to the hyperplane is maximized.

IV. RESULT AND DISCUSSION

In this study, the Solid and Subsolid are classified from the CT lung pulmanory images using SVM classifier implemented in matlab 2017b. The performance of SVM classifier calculated using various metrics such as Accuracy , Sensitivity, Specificity, Cohen's Kappa, Fscore , Precision and Recall.

4.1 Accuracy

It is noted that SVM classifier is improved with ExHOG feature descriptor.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN}$$

Method	Overall
SVM _shape_texture%	89.73
Han et.al%	89.35
Automated Han et.al%	89.73
Region growing%	76.5
K-Means%	79.2
Local shape analysis%	82.9
PSO-SCNN%	88.9
OCPS_RF%	81.09
OCPS_SVM%	74.1
Da silva%	82.3
QingZeng CNN%	84.15
QingZeng DNN%	82.37
QingZeng SAE%	82.59
Proposed%	92.97

Fig.6 Accuracy of various classifiers

4.2 Specificity

It is the ability of the classifier predict the true negatives which is given by the equation.

$$\text{Specificity} = \frac{TN}{FP+TN}$$

Specificity of SVM classifier from ExHOG descriptor is good since true negatives are mostly identified. Specificity value of ExHOG is 80.09%. Because true negative rate is good.

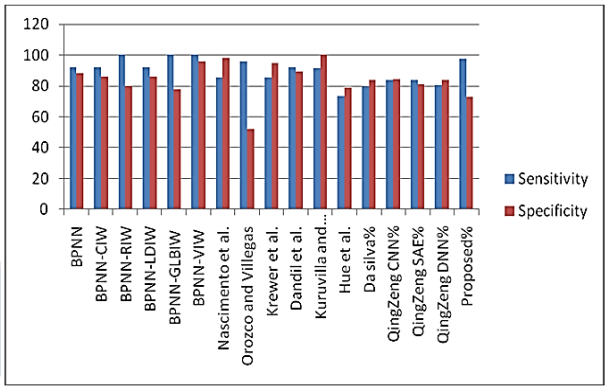

Fig.7 Sensitivity and Specificity comparison with other Papers

4.3 Sensitivity

Sensitivity is one that improve by .01% in SVM_EXHOG than SVM_CNN.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

4.4 Cohen's Kappa

The value of Cohen's Kappa in SVM_CNN is 58.36 and SVM_EXHOG is 78.71.This metric improves 20.35% in SVM_EXHOG%.

$$\text{Kappa Coefficient (K)} = \frac{P0 - Pe}{1-Pe}$$

$$\text{Here} \quad \text{Accuracy Expected (Pe)} = \sum_{i=1}^{c} \frac{x1x2}{n}$$

$$\text{Overall accuracy P0} = \sum_{i=1}^{c} \frac{xii}{n}$$

4.5 FScore

Fscore is a benchmark metric, which measures accuracy by considering both the recall and the precision.This is a measure of relative to sensitivity. The SVM_CNN is lower than SVM_EXHOG. The difference value is 4.39.

$$\text{F Score} = 2 \text{ X } \frac{\text{Precision X Recall}}{\text{Precision+ Recall}}$$

$$\text{Precision} = \frac{Total\ number\ of\ positive\ samples - false\ negative}{(Total\ number\ of\ positive\ smaples - false\ negative) + false\ positive}$$

$$\text{Recall} = \frac{Total\ number\ of\ positive\ samples - false\ negative}{(Total\ number\ of\ positive\ smaples - false\ negative) + false\ negative}$$

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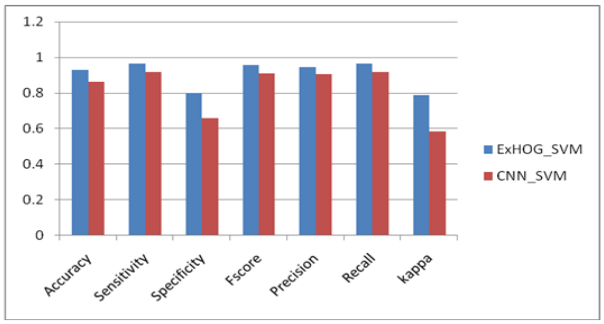
Where TP (cancer pixels) is true positive that counts classified foreground pixels.
FP counts the background pixels incorrectly classified as foreground.
FN counts false negative that counts foreground pixels incorrectly classified as background.
TN counts correctly classified background pixels.



V. CONCLUSION

The Proposed feature descriptor Extented Hog method with classifier SVM in deep learning shows an improved accuracy and specificity, a reduced FPR with reduced computation time.This SVM classifier classify the solid , part solid and non solid. The Challenge is to decrease the false positive rate and the method should be generalized with other medical images which leads to Content Based Retrieval in web search machine.

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