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Lung Cancer Detection from Images of Computer Tomography Scan

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Abstract: Computer–aided detection (CAD) can help the radiologists to detect pulmonary nodules at an early stage. In this paper we propose a CAD system to detect the pulmonary nodules from the segmented lungs from Computer Tomography images and classify the abnormalities. First the lung is segmented from the CT images using Watershed Transform then the nodules are extracted. Here for detection of lung nodules some features is considered such as 1) Shape features: Shape based feature descriptor are used. The shape of the nodules is considered for detection of nodules. 2) Texture features: 2D Haar Wavelet Transformation is used which is used to obtain the texture information in different levels of decomposition. 3) Intensity features: The intensity of the nodules is taken as a feature which helps us in putting a threshold which is taken on trial and error manner which help us in detecting the nodules. 4) Context features: Specifies the location of nodule. Classification is done using three different classifiers like SVM, ANN & KNN to increase the efficiency and decrease the error rate. Finally a comparative study is made with respect to error rate, efficiency and training ratio.

Keywords: Lung cancer, Image pre-processing, Image segmentation, Feature Extraction, Classification.

1. INTRODUCTION

Lung cancer is a major reason of cancer related casualty in the world. So early detection of lung cancer has become important. The patient's survival rate can be increased if the abnormal nodules are detected at early phase. Pulmonary nodule detection at early stage is significant in the curing of lung cancer; every scan contains 100 of image samples that must be evaluated by a radiologist. Seeing this, the use of a computer-aided detection (CAD) system can provide an effective result by incrementing the efficiency of scanning and improving potentially nodule recognition.

The growth of abnormal cell in lung is referred as Lung cancer. Computer tomography [1] is the most sensitive method used in detection of lung knobs and their nearby structures from the thorax. CT examine is used as the most painless, non-invasive diagnostic imaging procedure which can be used to create several images (slices) of the body organ, such as lungs.

A pulmonary nodule (Lung nodule) is a small round or oval-shaped growth in the lung. A spot on the lung or a coin lesion is called as a pulmonary nodule. These nodules are generally smaller than 3 centimetres in diameter. If the nodule size is larger than 3 centimetres than, it is known as a pulmonary mass. A mass is more likely to represent a cancer than is a nodule.

The pulmonary nodules are described as round opacities, well or poorly defined, measuring up to 3 cm in diameter. The pulmonary nodules can be differentiated into subsolid and solid nodules. Solid nodules [2] have homogeneous soft-tissue attenuation on Computer Tomography scans.

Subsolid nodules can be further differentiated into non-solid nodules and part solid nodules. Non-solid nodules manifest as focal areas of hazy increased attenuation that do not obliterate the bronchial or vascular margins.

In ELCAP, 81% of all positive finding at baseline were solid nodules and 19% were a subsolid nodule, which indicates that subsolid nodules are less common in screening. However, this study published a larger malignancy rate of 34% for subsolid nodules, compared to 11% of solid nodules. Consequently half of the lung cancer found originated from subsolid nodules. Therefore early detection of subsolid nodules with solid nodules is of major importance.

2. PREVIOUS WORK

Colin Jacobs et al. [6] designed a CAD system which detected sub solid nodules by extracting context features from the nodules and classification was done by LDC and GentleBoost10. The sensitivity of 80% was achieved with average of 1.0 FP per scan.

The author [7] introduced a CADe system named as ISI-CAD, where CT images of lungs were segmented using region growing technique and morphological smoothing. The candidate nodules were determined and false positive rate was reduced using Geometric filters and the KNN classifier. The CAD system had achieved a sensitivity of 84% and reduced the false positive rate to 8.2 FP per case with 268 pleural and non-pleural knobs (nodules) with nodule sizes around 2mm and 14mm.

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The author [8] introduced a new methodology in detection of knobs (nodules) with GGO (non-solid knob). This improved the sensitivity of CADe systems. For selection of candidate knobs, knob segmentation and elimination of FP rate respectively the methods used were fuzzy thresholding, feature maps, adaptive thresholding and rule-based classifiers and SVM to segment the images of the lungs. The system targeted 90.2% sensitivity and FP of 8.2 per case which was validated against 220 knobs of sizes between 2mm to 20mm.
A CADe system [9] was presented to segment, detect candidate knobs (nodules) and eliminate the FP using thresholding, morphological processing and Fisher Discriminant. The system targeted the sensitivity of 82.66% with 3 FP per case validating 143 knobs of size 3mm to 30mm. Liu et al proposed a system where the images were divided in 3 planes to improve sensitivity. They used technique like thresholding and rolling ball algorithm with dot-enhancement filter to segment images and detect knobs. They targeted 97% sensitivity and FP reduced to 4.3 per case. The drawback of this system was they validated their system with less amount of knobs (nodules) i.e., 32 knobs, being 31 solitary knobs. So it was not sure that the system will perform well with wide range of nodules.
The author [10] designed a system which achieved efficiency of 76.9% and 122 FP which was validated with a 13 knobs and 8 knobs of size less than 2 mm. They used image processing techniques like Fuzzy C-Mean algorithm and neural classifier for pre-processing, segmentation and detection of knobs.
The author [11] designed a CADe system which targeted a sensitivity of 86% and reduced FP rate to 2.17 per case which was validated with 538 knobs. This system used region growing, Biorthogonal Wavelet Transform and fuzzy inference system in pre-processing, segmentation and detection of knobs. This system not only detected nodules but also classified them into malignant nodules and benign nodules.
The author [12], presented a system which achieved the sensitivity of 89.47% with 11.9 FP per case which were tested on 44 solitary pulmonary knobs (nodules). They used different techniques like Wiener and morphological filters with thresholding in the pre-processing and segmentation stages. Candidate detection was done by adaptive thresholding and false positives were eliminated using SVM. The drawback of this approach was, it was restricted to solitary pulmonary knobs (nodules).
The author [13] presented a system which achieved the sensitivity of 80% with FP rate 4.2 per case which validated with 103 nodules with diameter range from 5mm to 20mm. This system used the detection method that prioritizes quick response. This system showed a detection speed of 25.34 seconds per case using a personal computer with 28 GHz processor. This system used SVM and cylindrical filters to reduce false positives.
The author [14] proposed a method to classify a lung tumor for CT-Scan images using different classification methods like SVM, decision trees approach with feature selection methods to develop a model for tumor classifications. The overall results indicate that the both 2D and 3D features is possible to recognize tumor classes with accurately. In this method the diagnosis of lung cancer via tumor detection has done successfully.
The author [15] presented a system to detect and classify lung knobs (nodules) from chest Computer tomography scan images. The system achieved a accuracy of 84% with sensitivity of 97.14% and specificity of 53.33. They used gray level characteristics and optimal thresholding for segmentation of lung knobs. They used simple filtering and morphological operations on CT images. The result of projected methodology detects and provides earlier classification of knobs.
The author [16] displayed a voxel arrangement strategy, where the positions of voxels in the lung and with respect to the crevices are utilized as elements. At long last, every flap is subdivided in its aspiratory portions by applying another voxel grouping that utilizes highlights taking into account the distinguished crevices and the relative position of voxels in the projection. The technique was assessed on 100 low-measurement CT filters acquired from a lung disease screening trial and contrasted with appraisals of both interobserver and intraobserver understanding. The strategy could portion the pneumonic sections with high exactness (77%), equivalent to both interobserver and intraobserver precision (74% and 80%, individually).

3. DATA

The dataset was collected from online database ELCAP. This database was made possible by collaboration between the ELCAP and VIA research groups. It was created to make available a common dataset that may be used for the performance evaluation of different computer aided detection systems. This database was first released in December 2003 and is a prototype for web-based image data archives. The database currently consists of an image set of 50 low-dose documented whole-lung CT scans for detection. The CT scans were obtained in a single breath hold with a 1.25 mm slice thickness. The locations of nodules detected by the radiologist are also provided.

4. PROPOSED METHOD

The stages of the proposed methodology to design a CAD system are: 1)Image Preprocessing 2)Lung Segmentation 3)Nodule Segmentation 4)Feature Extraction 5)Classificaiton.

4.1 Image Pre-processing
Pre-processing is done in CT lung images to removal of noise. MATLAB software is used to do most of the pre-processing of images. Every image test is stored to 512 X 512 pixels of size. Due to, variations, shift, non-uniform intensity, motions and noise the quality of image is affected by different artifacts. Thus, the initial pre-processing of input image sample aims at selectively removing the redundancy present in scanned images

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without affecting the details which that play a key role in the diagnostic process. Hence, Histogram Equalization becomes the important step in pre-processing. Therefore each image is pre-processed to improve its quality.
Morphological operations are influencing the structure, structure or state of an article. Connected on double pictures (dark and white pictures – Images with just 2 hues: highly contrasting). They are utilized as a part of pre or post preparing (sifting, diminishing, and pruning) or for getting a representation or depiction of the state of articles/areas (limits, skeletons raised structures).

Regular Morphological Operations:
- Shrinking of the forefront ("disintegration")
- Expanding the forefront ("expansion")
- Removing openings in the frontal area ("shutting")
- Removing stray forefront pixels in background("opening")
- Finding the framework of the forefront
- Finding the skeleton of the forefront

4.2 Lung Segmentation
Lung volume segmentation is an essential stride for distinguishing knob (nodule) hopefuls. In our proposed system we have used watershed transform for lung segmentation. The fundamental motivation behind lung division is to split the voxels relating to the lung hole in axial CT examine cuts from the encompassing lung life systems. It is an competent strategy for knob competitor discovery, on the grounds that there are numerous confounding items outside the lung district in chest CTs. We can isolate the CT check into two sorts of voxels, described by the thickness contrast between the two anatomical structures. The low-thickness areas contain the air encompassing the body, the lung depression and other low-force districts. Conversely, the high-thickness locales consist of the body encompassing the lung cavity. We should segment the low-thickness districts in the underlying stage to separate the lung volume. An ideal edge quality is connected to every scan, enabling the low-thickness lung parenchyma to be split from the encompassing lung life structures on account of the various scanning conventions and anatomical contrasts among scans. The beginning segmentation results can be achieved by applying this ideal edge.

4.3 Nodule Detection
The phase for knob (nodule) identification goes for deciding the nearness of pneumonic knobs in the picture, and on the off chance that this nearness is distinguished, to advise the area of the knobs. At present, the important trouble for Computer Aided Detection frameworks is to recognize genuine knobs from other pulmonary parenchymatous wounds or distinctive organs and tissues. Accurate knob division is vital for different symptomatic and treatment strategies for lung disease, for example, checking tumor reaction to treatment and diagnosing tumor development and danger. The primary wellsprings of blunders in the location are little knobs, ground-glass opacity knobs, knobs connected to vessels (juxtavascular), and knobs joined to arenchymal divider and diaphragm (juxtapleural). In our system we have used different image processing tools from matlab toolbox to detect the nodule.

4.4 Feature Extraction
After the segmentation is performed, the portioned lung knob (nodule) is utilized for highlight extraction. An element is a noteworthy bit of data removed from an image which gives more itemized comprehension of the image. The elements like geometric and intensity based measurable components are extricated. Shape estimations are physical dimensional measures that portray the presence of an article. The CT image texture can offer a critical wellspring of data on the condition of the strength of an inspected organ. Infected tissue more often than not has more harsh or riotous structure than the solid partners, which can be portrayed quantitatively for a robotized symptomatic emotionally supportive network. The nature of the extricated composition measures is of huge significance for a right classification of lung nodules. In our system the below given techniques are used for feature extraction.

4.4.1 Shape features
Shape features are computed from the candidate segmentation. Division on different structures than knobs can make odd shapes and in this way, shape is a critical component to segregate genuine positive from false positive examples. To begin with, the accompanying elements are figured: sphericity, compactness1, compactness2 and guessRadius. All together to compute the sphericity, a circle S is characterized at the focal point of mass of the hopeful locale with the same volume as the competitor division.

At that point, sphericity is characterized as the proportion between the volume of the voxels of the hopeful division inside circle S and the aggregate volume of circle S. At that point, with a specific end goal to ascertain [6] compactness1, compactness2 and guessRadius, the jumping box around the competitor division is utilized and the measurements are named dimx, dimy and dimz. To ascertain compactness1, the number of voxels of the competitor group is isolated by the aggregate number of voxels inside the bouncing box.

Compactness2 is computed by isolating the quantity of voxels in the hopeful bunch by the number of voxels in a 3D square for which the size is characterized by the biggest measurement of the jumping box (max dimx; dimy; dimz). The element guessRadius is figured by separating the volume of the bouncing box by 6. In the event of a flawless circular knob, this will create the careful range of the circle. Besides, the quantity of voxels and the bunch size in mm3 are processed to portray the extent of the competitor. These two components are verging on indistinguishable, yet the group size considers the determination of the CT check.

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4.4.2 Texture features

For Texture analysis, [6] 2D Haar wavelets are utilized. It is generally utilized texture descriptors to portray restricted spatial composition data what's more, have been utilized for parenchymal surface examination as a part of CT pictures. These elements for instance avoid false positive hopefuls in locales of homogeneous ground glass mistiness created by movement relics. A VOI is made from the bounding box around the candidate segmentation and this volume is resampled 32 x 32 voxels, separately. Moreover, 2D Haar wavelets are connected on the 32X 32 resampled volumes. Every cut of the resampled volume is decayed into four groups. Four volumes are built from the four groups from each cut. Three standardized histograms are registered from the three volumes worked from the high-recurrence groups. The volume worked from the low-recurrence band is not utilized. Once more, the same histogram measurements are utilized as texture descriptors.

4.4.3 Intensity features:

Intensity components [6] are computed on three diverse arrangements of voxels, division, voxels inside the hopeful division, Bounding Box, voxels inside a bounding box characterized around the competitor division, surrounding3, voxels inside the encompassing of the applicant division, made by expanding the competitor division with a rectangular organizing component of size 3 x 3 x 3 voxels, surrounding5, voxels inside the encompassing of the hopeful division, made by widening the competitor division with a rectangular organizing component of size 5x 5 x 5 voxels.The intensity profiles of the inward and the encompassing of a hopeful are characterized by the three locales to concentrate highlights. For every arrangement of voxels, a standardized histogram is registered utilizing a bin size of 50 HU. The canister size has been exactly decided such that the histograms are not excessively scanty, but rather still contain the fundamental data to portray the fundamental power appropriation. For each standardized histogram, the accompanying measurements are processed: entropy, mean, standard deviation, least, most extreme quality and the initial 7 moments are processed for voxel set division. The Hu minutes are interpretation, scale and turn invariant and used to portray the hidden power profile. At last, the greatest vesselness is processed and the base, most extreme, mean and standard deviation of the most extreme vesselness in voxel set division are utilized as elements. Fractional volume impacts can make ranges of ground glass darkness near vessels or on vessel dividers and by counting these elements; we catch data whether the hopeful is in region to or at a vessel divider.

4.4.4 Context features

At long last, [6] a novel gathering of context features is characterized, which depict the area of the hopeful district in appreciation to the lung limit, the aviation route tree, the vessels and other subsolid knob (nodule) hopefuls. The area of the hopeful as for the lungs, vessels and aviation routes is imperative for numerous reasons. For instance, bigger ranges of ground glass opacity can be seen at the gravity subordinate bits of the lung (base of the lung when CT is performed recumbent) because of microatelectasis. This will bring about an applicant which has a stretched shape along the limit of the lung. A mix of shape and setting elements can catch this. Another case is aviation routes loaded with bodily fluid, which can show in the power scope of ground glass opacities. These candidates will demonstrate a cover with the aviation route division and this can be utilized to arrange them as false positive. Besides, the connection of contender to different applicants is significant relevant data. For instance, a little applicant which is encompassed by numerous different applicants will probably be starting from a territory of microatelectasis than to be a subsolid knob. Initial, two separation changes are computed inside the lung locales; the principal utilizing the lung division and the second utilizing the aviation route tree. The separation to the lung limit and separation to the nearest aviation route is separated from the separation changes for all voxels inside the competitor division. The mean, standard deviation, least and greatest separation to the lung limit and aviation routes are registered and utilized as setting components. Also, a bounding box is characterized around the lungs and this is used to register relative position highlights; relative X, Y and Z position, furthermore, separation to left base corner of the bounding box are figured. Moreover, the separation to the focal point of mass of both lungs is figured.

4.5 Image Classification

Classification is the final step of determination of disease stages to have lung cancer nodule or not of the patient lung. Artificial neural network (ANN) is one of the classification methods commonly used in image processing techniques.ANN is collections of mathematical models that emulate the real neural structure of the brain[16]. ANN has three layers. They are input layer, hidden layer and output layer. For classification we have applied 3 different algorithms like ANN, KNN and SVM classify the nodules.

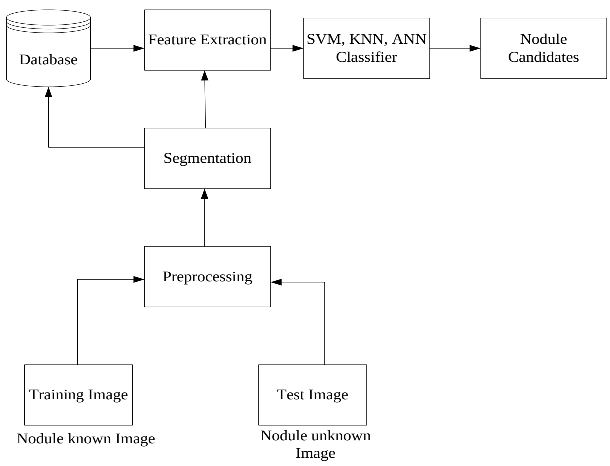

Fig.4.1. General Block diagram of proposed method

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5. RESULTS AND ANALYSIS

ELCAP provides the clinical data set which is used for experiments. For the training stage CT images are used which are having cancerous and noncancerous lung nodules. Initially the database is selected and loading all the images along with pause time. Then we have visualized all the images.

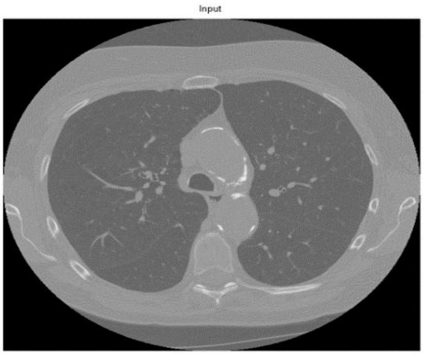

Fig.5.1 Input image

Fig.5.2 Segmented Lung

Figure 5.1 shows the input CT image taken for simulation purpose. In this presented system, we took DICOM image for the analysis of three different algorithms. The first step is to collection of input image and store in a database. From this database all the images are trained and all the features like texture, shape, intensity and context of all the images and stored in a vector. After training is done, the test image is taken for the analysis purposes.

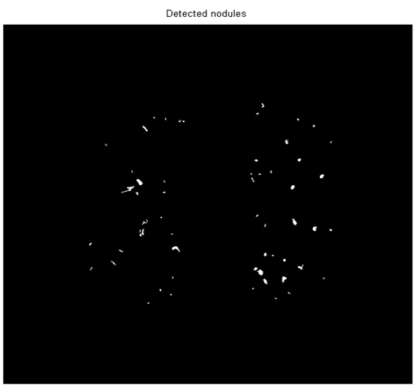

Fig.5.3 Detection of nodules

Figure 5.2 represents the segmented lung image. Then in figure 5.3 we can find the nodules detected in this image. Similarly, in figure 5.4 filtering of nodules also done using filtering techniques.

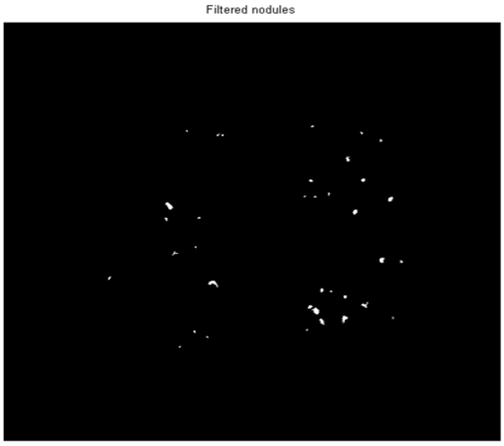

Fig.5.4 Filtered nodules

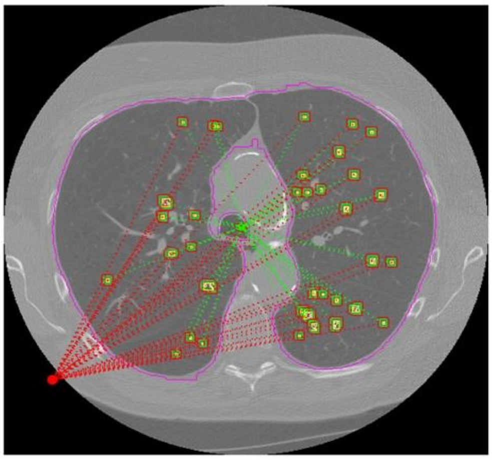

Fig.5.5 Feature extraction of lung nodules

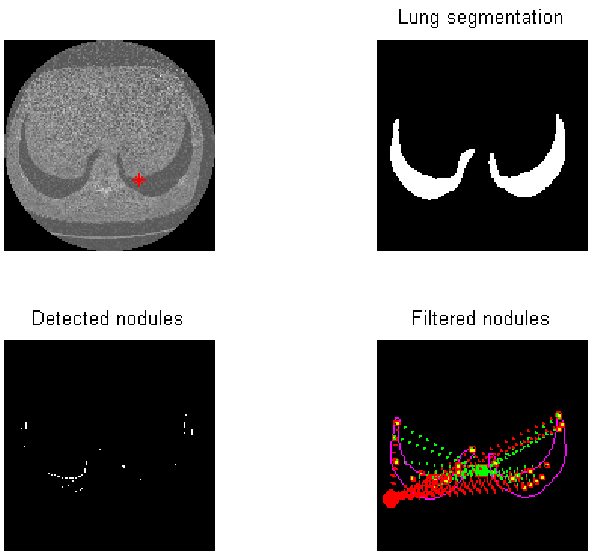

Fig.5.6 Lung Segmentation, Detected nodules and Filtered nodules.

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Figure 5.4 shows the filtered nodules image. Figure 5.6 shows the filtered nodules, detected nodules, lung segmentation of the medical image. Here, the input CT image is applied to lung segmentation and also removal of artifacts. After this step the candidate detection is done. Then, the first stage feature collection are computed and then reduction of error rate, classifier is used to reduce the error rate. Then, once again second stage features of the image are computed. Then we have applied different classification methods like ANN, KNN and SVM methods.

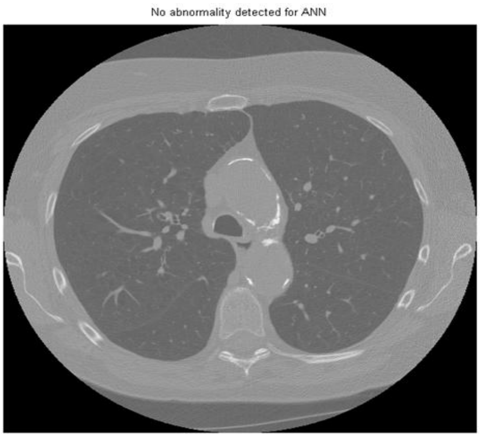

Fig.5.7 No abnormality detected for ANN method

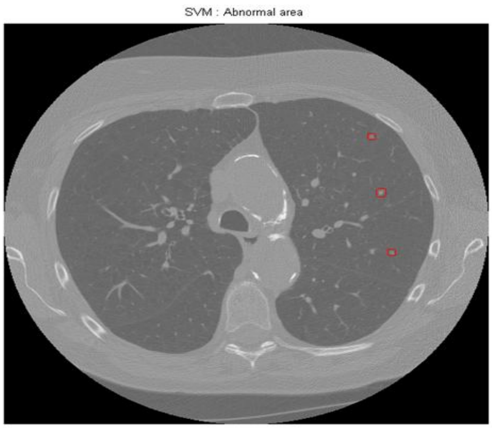

Fig.5.8 SVM - abnormal area detected

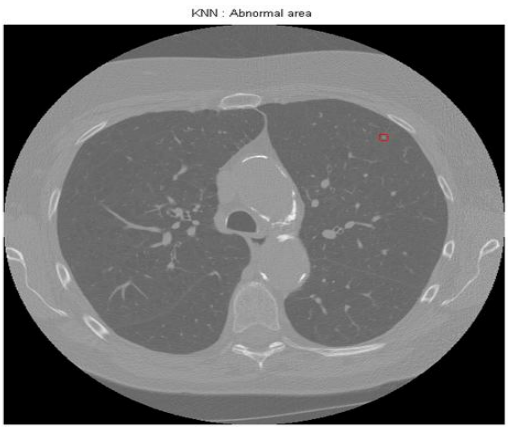

Fig 5.9 KNN - abnormal area detected.

5.1 Analysis Performed Using ANN

Table 5.1 Efficiency results of ANN

Training ratio	Efficiency
0.100000	0.857768
0.200000	0.964989
0.300000	0.919037
0.400000	0.971554
0.500000	0.982495
0.600000	0.971554
0.700000	0.971554
0.800000	0.980306
0.900000	0.986871
1.000000	0.993435

5.2 Analysis Performed Using KNN

Table 5.2 Efficiency results of KNN

Training ratio	Efficiency
0.100000	0.957812
0.200000	0.963676
0.300000	0.967746
0.400000	0.970810
0.500000	0.976280
0.600000	0.981007
0.700000	0.986565
0.800000	0.990810
0.900000	0.995842
1.000000	1.000000

5.3 Analysis Performed Using SVM

Table 5.3 Efficiency results of SVM

Training ratio	Efficiency
0.100000	0.955667
0.200000	0.961313
0.300000	0.967877
0.400000	0.969891
0.500000	0.971597
0.600000	0.969934
0.700000	0.968096
0.800000	0.969628
0.900000	0.970066
1.000000	0.969365

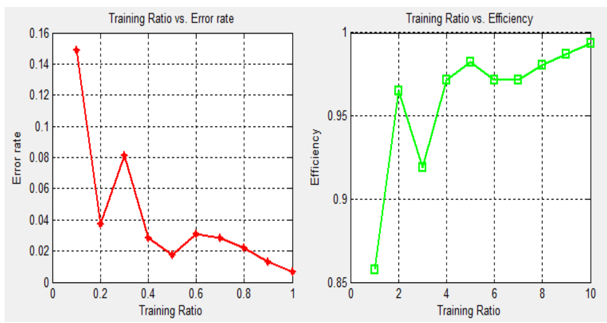

Fig.5.10 Showing error rate and efficiency of ANN

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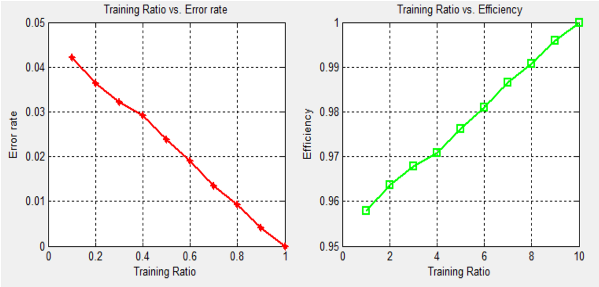

Fig.5.11 Showing error rate and efficiency of KNN

Fig.5.12 Showing error rate and efficiency of SVM

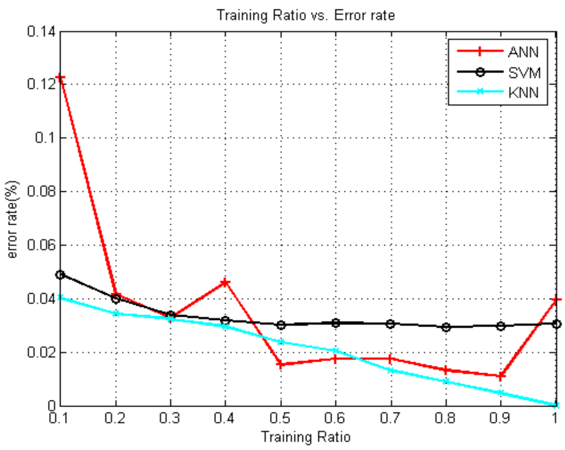

Fig.5.13 Comparisons of ANN, KNN & SVM method for training ratio vs. error rate (%).

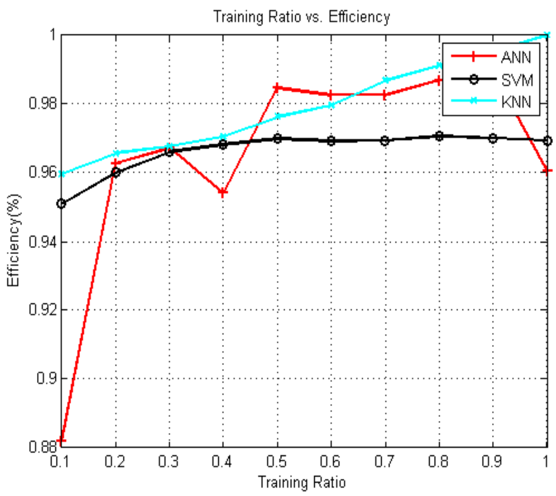

Fig.5.14 Comparisons of ANN, KNN & SVM method for training ratio vs. efficiency (%).

From figure 5.13 and figure 5.14 we can observe that the KNN method gives better efficiency as well as less error rate for a given training ratio compared to other two methods like ANN and SVM methods.

6. CONCLUSION AND FUTUTE SCOPE

In the proposed system a CAD system is designed to detect lung cancer. A number of CT images were trained and tested and classification was done using three different classifiers like SVM, ANN, KNN and efficiency and error rate is calculated to detect the nodules. Different techniques were used for feature extraction to detect the abnormal nodules According to the analysis performed SVM gives the error rate of 0.031 and efficiency is 0.969365 (96.93%), ANN gives the error rate of 0.01 and efficiency is 0.993435 (99.34%) and KNN gives the error rate of 0.00 and efficiency is 1.000000 (100%). From this we can observe that the KNN classifier gives better efficiency as well as less error rate for a given training ratio compared to other two classifiers in detecting the lung nodules efficiently.

This work can be extended by extracting more context features using different techniques on different database collection of CT images.

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