Journal of Medical Systems (2019) 43: 77
https://doi.org/10.1007/s10916-019-1177-9

IMAGE & SIGNAL PROCESSING

Automatic Detection and Classification of Lung Nodules in CT Image Using Optimized Neuro Fuzzy Classifier with Cuckoo Search Algorithm

R. Manickavasagam [1] · S. Selvan [2]

Received: 7 December 2018 / Accepted: 21 January 2019 / Published online: 13 February 2019

Abstract

The Lung nodules are very important to indicate the lung cancer, and its early detection enables timely treatment and increases the survival rate of patient. Even though lots of works are done in this area, still improvement in accuracy is required for improving the survival rate of the patient. The proposed method can classify the stages of lung cancer in addition to the detection of lung nodules. There are two parts in the proposed method, the first part is used for classifying normal/abnormal and second part is used for classifying stages of lung cancer. Totally 10 features from the lung region segmented image are considered for detection and classification. The first part of the proposed method classifies the input images with the aid of Naive Bayes classifier as normal or abnormal. The second part of the system classifies the four stages of lung cancer using Neuro Fuzzy classifier with Cuckoo Search algorithm. The results of proposed system show that the rate of accuracy of classification is improved and the results are compared with SVM, Neural Network and Neuro Fuzzy Classifiers.

Keywords Lung nodules · Segmentation · Naïve Bayes classifier · Neuro fuzzy classifier · Cuckoo search

Introduction

The most common reason for cancer related death is lung cancer among both men and women. [1]. The second highest commonly detected cancer type is lung cancer. The pulmonary nodules are visible in lung to determine the metastasis from other cancers [2]. The computed tomography (CT) is significant image modality to estimate the advancement / deterioration for surveillance and diagnosis of lung cancer detection. The advantage of CT is early detection of lung cancer, and hence more effective therapies can be suggested by physicians [3, 4]. The prognostic and curative processes for dispersed disease with accurate stages of cancer are needed for the systematic and comforting therapy [5]. The Lung nodule diameters above 10 mm are usually malignant and they are analyzed with PET/CT images. Further, tissue sampling characterization is executed during disease diagnosis either by bronchoscopy or transdermic [6]. The early diagnosis of lung cancer stages is strongly related to the survival rate of the patient [7]. Lung nodules are categorized into two types as solid nodules and ground - glass opacity (GGO) nodules which are characterized using high-contrast, faded distinction and fuzzy limits [8]. Automatic detection is required due to physical exploration time taken is more by the radiologist and missed nodules may be possible [9].

Computer-aided nodule detection system's accuracy and efficiency are potentially improved with LDCT scan image [10]. The lung nodule is hard to detect during its early stage due to the complex anatomical area's small size, low contrast, and nodule location in lung [11, 12]. The diagnosis and detection of tumorous pulmonary nodules in CT thorax images are very difficult as they appear as round and having the sizes of 3 cm or less [13, 14]. The identification of Initial Nodule Candidates (INCs) inside the lung by the effective low-level VQ is used for segmentation and detection. It is also computationally competent compared with existing methods. The feature-

This article is part of the Topical Collection on *Image & Signal Processing*

✉ R. Manickavasagam
manick6apr1979@gmail.com

S. Selvan
selvanpeter@hotmail.com

1 HOD, Department of BME, Alpha College of Engineering, Chennai 124, India

2 St. Peter's College of Engineering and Technology, Avadi, Chennai 54, India

based SVM is combined with rule-based filtering process to reduce the False-positive (FP) rate [15].

The multi-centric approach based research is conducted with 83 chest CT subjects endured six associations form the procedures used for same scanners. The different tube currents: 20, 120 and 240 mA are used in scanners for every subject in a single visit. According to AIDR3D, the axial CT images are reconstructed with thickness of 2-mm [16].

The regional smoothing in image tissue textures and edge sharpness is maintained by Low-dose computed tomography (LDCT) imaging model. It is used to differentiate and recognize the benign and malignant lesions [17, 18]. The existence of juxta pleural nodules, image noise, lung vessels and nodules near pleural wall make the segmentation of lung region very difficult [19]. An adaptive curvature threshold and repetitive weighted average method is projected to achieve more accurate segmentation of lung to detect the presence of juxta pleural nodules, lung vessels and guarantee the smoothness of lung edge for nodule detection [20].

The following are the summarization of existing methods,

- The potential for firm and adaptive detection of pulmonary nodule using CT image is demonstrated and shown its outperformance with reference to various Compter aided Detection models [15]. But the sensitivity of the nodule detection is less.
- False positive reduction, increase in sensitivity of detection, nodule detection with variable size and different shapes attracts attention for further research [17].
- When the image reconstruction is done during analysis with LDCT, the residual error is present [19]. If the reconstruction process is not involved then the residual errors can be avoided.
- The average processing time is higher for the nodule detection which is leading to increase in the overall computational complexity [20].

In order to overcome the limitations of existing systems a new approach based on Naïve Bayes and neuro fuzzy classifiers with cuckoo search optimization is proposed to improve accuracy and sensitivity for the detection and stage classification of lung nodules in CT images.

System description

The general CAD system for CT or MRI images is shown in Fig. 1. In General CAD system, the CT or MRI images are taken from scanner and preprocessing like enhancement and noise removal are employed to improve the image for analysis. The lung region is segmented to process further with area of interest in the image. Then features are extracted from the selected area of interest in an image and feature selection process is used to select the features for classification. Finally, classification process is used for disease identification. The proposed methodology is having two parts. Part 1 consists of four phases. They are Pre-processing, Segmentation, Feature extraction and detection of nodule. First, the pre-processing phase, associated noises can be removed by using Gaussian filtering technique and also perform a background subtraction process. Then the segmentation phase is involved to select the Area Of Interest (AOI) from the gray scale converted image. Third phase is used for nodule feature extraction phase. Here, the nodule's shape and texture features are extracted. Final phase is a classification phase using extracted features. In this phase Naïve Bayes Classifier is used to classify the images into normal or abnormal.

Part 1 – detection of nodule

In this section, the proposed system's Part 1 is described below,

Gaussian filter for pre-processing

The Gaussian filter is used in different contexts of image processing for its benefit of noise removal and reduced delay in response. The presence of noise will be less in Digital CT images. This image is used for post processing through Gaussian filter to get noise free output image. The Gaussian filtering is exploited for the noise elimination process, which is represented as, Fig.2.

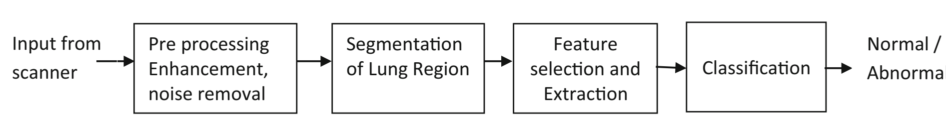
$$G(p) = \exp\left(\frac{-x^2}{2x\sigma^2}\right) \tag{1}$$

Where G(p) is a Gaussian function, x represents the noise and σ denotes a deviation.

Watershed algorithm for segmentation

The purpose of segmentation technique is to slice the similar predetermined classes in an image with the closeness of neighboring pixels, for which the pixel grouping is necessary to form the object from grouped pixels. The watershed technique is used to segment a CT image into a group of non-

Fig. 1 CAD system



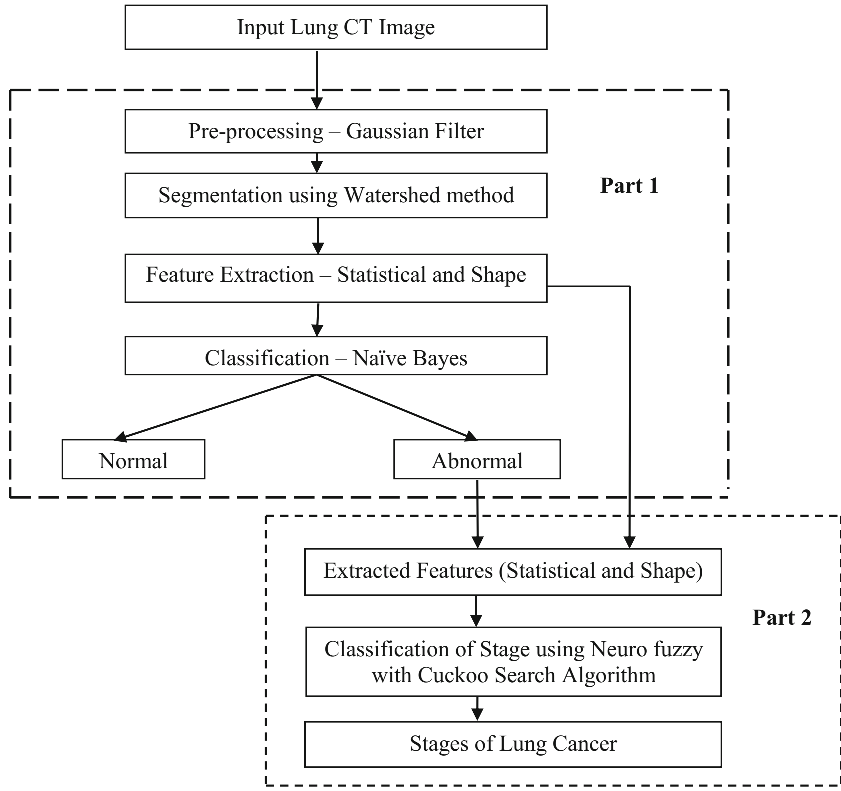


Fig. 2 Proposed lung nodule stage classification

overlapping regions. The watershed algorithm for segmentation performs better, since it is possible to *"recognize"* or *"mark"*, the background contents from forefront objects evidently. The fundamental process of watershed segmentation algorithm involved to segment the expanse of lung in the given CT images is,

- Read the Gray scale Image
- Employ the Gradient magnitude is set for segmentation
- Spot the forefront substance
- Estimate surrounding pointers
- Implement the transform for the segmentation
- Obtain the result

Feature extraction

The statistical and structural features such as shape and texture of nodules are extracted in this extraction phase. The feature extraction phase is categorized as statistical based features and structural features.

Statistical feature extraction The mathematical values of pixel intensity based description of image features are extracted. The GLCM (Gray level co-occurrence matrix) algorithm is used to extract the statistical features which are describes the non-deterministic gray level relationships of image.

Structural feature extraction The structural features of segmented images are extracted using regionprops method. The regionprops method used to measure the properties of segmented region.

In feature extraction process of proposed system, the four statistical features like correlation, contrast, homogeneity, energy, and six structural shape features like area, perimeter, minor axis length, eccentricity, major axis length and filled area are extracted.

Naïve Bayes classifier for classification

Based on the above statistical and shape features, classification is performed with the aid of Naïve Bayes classification technique as normal and abnormal. If the classification is abnormal, the proposed system initiates the process of stage of the lung cancer evaluation by selecting the next Part.

The probability value based classification is done in Naive Bayes classifier with the support of well-known Bayes theorem with strong presumption. It doesn't require a large sample number of datasets for efficient training is the advantage of this method. The proposed Naive Bayes classifier's functional methodology is,

The training sample set T is assumed. All samples (SA) is described by the dimensional vector (d) and every vector defines the attributes (At).

For any identified sample SA, Naïve Bayes classifier estimates the highest probability associated class.

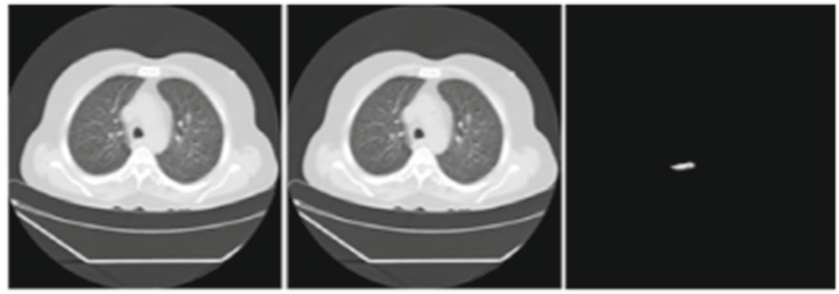


Fig. 3 Input image, output image after pre-processing and nodule segmented image

Otherwise, SA is a prediction which fit for the class C_x is represented in eq. (2),

$$P(C_x|SA) > P(C_z|SA); for\ 1 \leq z \leq n, z \neq x \tag{2}$$

As a result maximized value of $P(C_x|SA)$ for any class is found. As per bayes theorem, $P(C_x|SA)$ is denoted in eq. (3)

$$P(C_x|SA) = \frac{P(SA|C_x)P(C_x)}{P(SA)} \tag{3}$$

The value of *P(SA)* is same for all classes, henceforth it is required to estimate the highest $P(SA|C_x)P(C_x)$. If the probability of prior the class C_x is not identified, then the probability of similar classes is same. Hence $P(C_1) = P(C_2) = \ldots = P(C_n)$. At the end of Part 1 of the proposed method, the output result is normal or abnormal state of nodule presence.

Part 1 - results

The proposed lung nodule detection CAD system uses LIDC database for the assessment and its nodules have been completely glossed by several radiologists. Totally 275 CT images of different individuals are taken for the assessment of lung nodule detection. Out of the considered images, there are 150 images having nodules. Figure 3 shows that the original input and output images of post processing and segmentation process in the Part 1 of proposed CAD system. The noise removed, smoothened surface boundaries of ROI are identified in post processed image.

The classifier performance is explored through evaluation metrics of accuracy, sensitivity, specificity and precision values. The mathematical relationships of the evaluation metrics are mentioned in Table 1.

Here, TP is True Positive, FP is False Positive, TN is True Negative and FN is False Negative.

The classifier performance is listed in Table 2 for the different ratio of training and testing set samples. From the comparison, it is understand that the accuracy, sensitivity and precision is improved in 80–20 training and test data set when compared with all other combinations.

The classifier used in Part 1 as Naïve Bayes is compared with SVM classification method and listed in Table 3, for 50–50, 60–40, 70–30 & 80–20 training and test data sets. It clearly shows that the parameters under consideration for SVM are significantly low when compared with the Naïve Bayes for all training and test data set ratios. The Naïve Bayes classifier is achieves the improved results because Naïve Bayes classifier depends on feature values and SVM uses the range of feature values for the detection.

Part 2 – classification of the stages of lung nodules

In Part 2, the proposed technique is used to classify the stage of the nodules. The Neuro Fuzzy Classifier with Cuckoo Search (NFCS) method is utilized to classify the stage of lung cancer. The execution is carried out in MATLAB with the help of Lung Image Database Consortium images (LIDC). The efficiency of the proposed methodology is analyzed with the parameters such as the accuracy and precision.

Table 1 Evaluation metrics and its mathematical relationship

Classifier Evaluation Parameter with Expression	Description
$\text{Accuracy} = \frac{\text{TN+TP}}{(\text{TN+TP+FN+FP})}$	The accuracy is the definite positive and negatives are correctly identified.
$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP+FN})}$	The quantity of definite positives which are exactly predictable.
$\text{Specificity} = \frac{\text{TN}}{(\text{TN+FP})}$	The specificity is the degree of negatives which are accurately predictable.
$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})}$	The amount of predicted nodules that are originally related to the cancer.

Table 2 Evaluation measures for normal and abnormal classification using Naïve Bayes

Naïve Bayes Classifier Training and Testing set sample ratio (%)	Accuracy	Sensitivity	Specificity	Precision	Computation Time (Sec)
50–50	74.074	73.333	75	78.571	1.26
60–40	81.481	80	83.333	85.714	1.39
70–30	88.889	86.667	91.667	92.857	1.54
80–20	96.296	93.333	100	100	1.87

Neuro fuzzy classifier

The output of the Naïve Bayes classifier predicts the presence of the nodule and if the nodule is present then it is classified as abnormal otherwise normal. If abnormality is present then the necessity arises to classify the stage of the lung cancer. The neuro fuzzy classifier is used to find the stage of the lung cancer. It is a five layer Sugeno model neuro fuzzy classifier, which has two inputs A and B, where A represents the statistical features (A1, A2, A3 and A4) and B represents the shape and texture features (B1, B2, B3, B4, B5 and B6).

Fuzzification The extracted set of features A and B is applied to neuro-fuzzy classifier and then Membership Function (MF) is involved to fuzzify these input extracted feature values. It facilitates to map each feature with different stages as shown in Fig.4. The membership function matrix contains ten rows and four columns, where, row represents no. of features and column represents no. of stages.

The membership function matrix $f_{(g,s)}(y_g)$ is formed; it labels the fitting grade of distinct features (G) to various stages (S).

Where, y_g - g^{th} value of feature in pattern in Y.

$$g-1,2,\ldots\ldots G, G=10$$
$$s-1,2,\ldots\ldots S, S=4$$

The pattern Y represented as,

$$Y = [y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9, y_{10}]^T \tag{4}$$

In neuro fuzzy classifier, Gaussian type membership function (MF) is used to classify the feature values as it is having the benefit of generating smooth output. Crisp values of features are transformed into fuzzy values using four membership functions. The membership matrix involves of 40 permutations from which 6 rules are framed for the classification. Further, the stage of lung cancer is identified as classes from the rules. The four rules formed to combine the input fuzzy values are listed in eqs. (5) to (10).

$$\begin{aligned} R1: & \text{ IF (A1 is Low) and (A2 is Low) and (A3 is Low) and} \\ & \text{(A4 is Low) and (B1 is Low) and (B2 is Low) and} \\ & \text{(B3 is Low) and (B4 is Low) and (B5 is Low) THEN} \\ & \text{(f1 is High)} \quad ——— \end{aligned} \tag{5}$$

$$\begin{aligned} R2: & \text{ IF (A1 is Low) and (A2 is Medium) and (A3 is Low)} \\ & \text{and (A4 is Medium) and (B1 is Low) and (B2 is Low)} \\ & \text{and (B3 is Medium) and (B4 is Low) and (B5 is Medium)} \\ & \text{THEN} \quad \text{(f1 is High)} \quad ——— \end{aligned} \tag{6}$$

$$\begin{aligned} R3: & \text{ IF (A1 is Medium) and (A2 is Medium) and (A3 is Medium)} \\ & \text{and (A4 is Medium) and (B1 is Medium) and (B2 is Medium)} \\ & \text{and (B3 is Medium) and (B4 is Medium) and (B5 is Medium)} \\ & \text{THEN (f2 is High)———} \end{aligned} \tag{7}$$

Table 3 Comparison for normal and abnormal classification of Naïve Bayes with SVM

Training and Test Data Set Ratio (%)	Method	Accuracy	Sensitivity	Specificity	Precision	Computation Time (Sec)
50–50	SVM	62.963	62.5	63.636	71.429	1.2
	Naïve Bayes (Proposed)	74.074	73.333	75	78.571	1.26
60–40	SVM	70.37	71.429	69.231	71.429	1.32
	Naïve Bayes (Proposed)	81.481	80	83.333	85.714	1.39
70–30	SVM	85.185	85.714	84.615	85.714	1.58
	Naïve Bayes (Proposed)	88.889	86.667	91.667	92.857	1.54
80–20	SVM	92.593	92.857	92.308	92.857	2.06
	Naïve Bayes (Proposed)	96.296	93.333	100	100	1.87

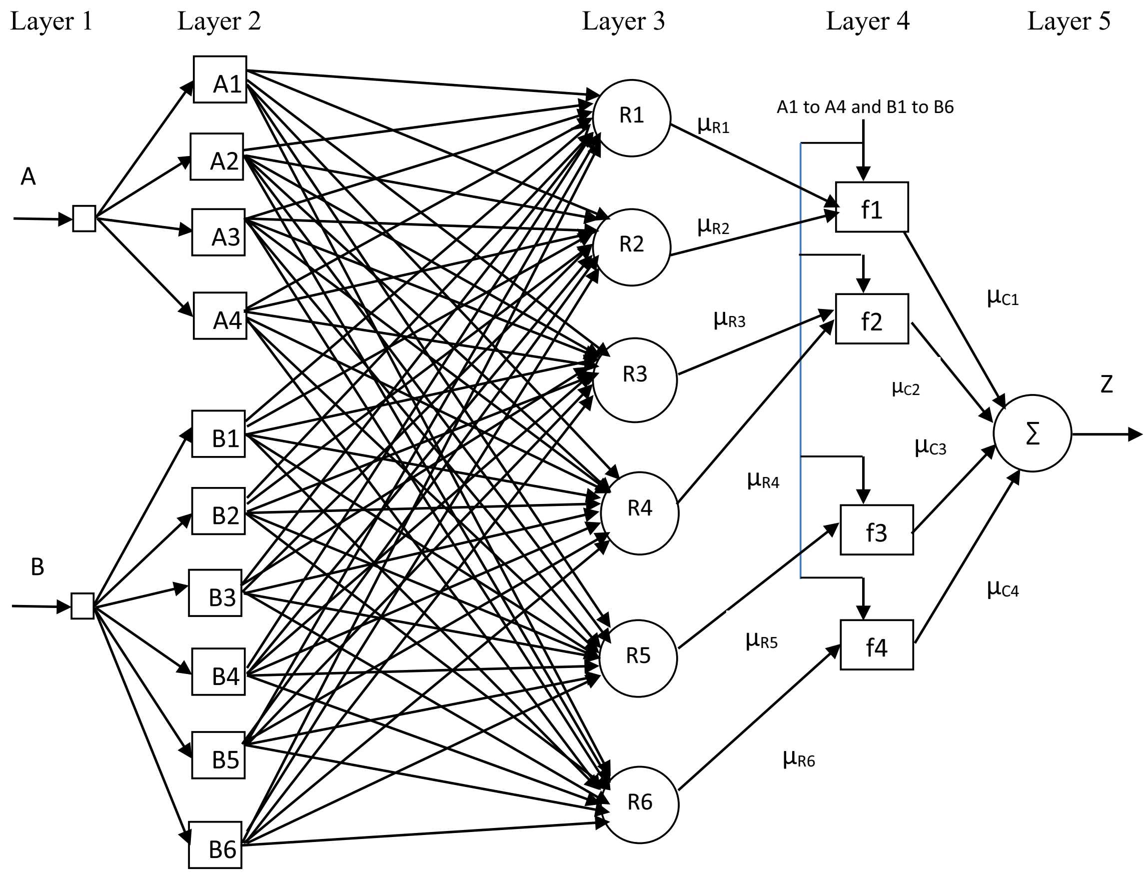


Fig. 4 Proposed neuro-fuzzy classifier

$$\begin{aligned}R4: &\text{ IF (A1 is High) and (A2 is Medium) and (A3 is High)}\\ &\text{ and (A4 is Medium) and (B1 is Medium) and (B2 is High)}\\ &\text{ and (B3 is Medium) and (B4 is High) and (B5 is Medium)}\\ &\text{ THEN (f2 is High)}------\end{aligned} \tag{8}$$

$$\begin{aligned}R5: &\text{ IF (A1 is High) and (A2 is High) and (A3 is High)}\\ &\text{ and (A4 is High) and (B1 is High) and (B2 is High)}\\ &\text{ and (B3 is High) and (B4 is High) and (B5 is High)}\\ &\text{ THEN (f3 is High)} ----\end{aligned} \tag{9}$$

Table 4 Evaluation measures for stage classification using NF- CS

Training and Testing Data Set Ratio (%)	Accuracy	Precision	Computation Time (Sec)
50–50	90.909	86.667	1.9
60–40	92.727	90	2.36
70–30	90.909	90	2.72
80–20	96.364	96.667	3.18

$$\begin{aligned}R6: &\text{ IF (A1 is Very High) and (A2 is Very High) and}\\ &\text{ (A3 is Very High) and (A4 is Very High)}\\ &\text{ and (B1 is Very High) and (B2 is Very High)}\\ &\text{ and (B3 is Very High) and (B4 is Very High) and}\\ &\text{ (B5 is Very High) THEN (f4 is High)} ----\end{aligned} \tag{10}$$

Defuzzification The defuzzification is done at the output node of neuro-fuzzy classifier by performing the MAX operation. The single output is obtained as z_1, z_2, z_3, or z_4 for a given CT image. From this value, it is possible to identify the stage of the lung cancer.

Cuckoo search

The Cuckoo search optimization algorithm presents the reproduction action of cuckoo and reduces the outcome. There are many nests available in cuckoo search process. The egg position is considered to be resolution and cuckoo's egg represents the fresh new solution. The processes involved in cuckoo search are,

Table 5 Comparison of stage classification for NFCS with NF and NN

Training and Test Data Set Ratio (%)	Methods	Accuracy	Precision	Computation Time (Sec)
50–50	NN	82.727	78.333	2.83
	NF	88.182	83.333	1.86
	NFCS (Proposed)	90.909	86.667	1.9
60–40	NN	88.182	88.333	3.21
	NF	89.091	86.667	2.27
	NFCS (Proposed)	92.727	90	2.36
70–30	NN	85.455	83.333	3.94
	NF	89.091	93.333	2.6
	NFCS (Proposed)	90.909	90	2.72
80–20	NN	90.909	90	4.48
	NF	92.727	93.333	3.1
	NFCS (Proposed)	96.364	96.667	3.18

- Only one egg is laid by cuckoo at a time. Cuckoo lays the egg in a indiscriminately preferred nest.
- The fixed number of host nests is available and high class egg in the nests will raise and reach the grownup state.
- If the host bird sees cuckoo's egg, the egg can be thrown away from the nest or the nest is discarded and new nest is formed.

This idealized breeding behavior of cuckoo is applied for optimization in classification. The four outputs of the defuzzification process z_1, z_2, z_3, or z_4 will be further optimized with the use of cuckoo search.

Part 2 - results

The performance of the Part 2 classification is analyzed with the evaluation metrics of Accuracy, and Precision values. The classifier performance measures under different ratio of training and testing set samples are listed in Table 4. The results of neuro fuzzy classifier are improved as the classification is performed with fuzzy rules and the knowledge base by neural network.

The NFCS algorithm as classifier used in Part 2 is compared with two other algorithms namely Neuro Fuzzy (NF) and Neural Network (NN) and listed the values in Table 5, for

Table 6 Comparison of combined techniques to detect and classify the nodules

Training and Test Data Set Ratios (%)	Methods	Accuracy	Precision	Computational Time (Sec)
50–50	NB + NN	72.5931	77.2926	4.09
	NB + NF	77.2647	81.3572	3.12
	NB + NFCS [Proposed]	82.4915	80.6039	3.16
60–40	NB + NN	77.1195	80.5519	4.6
	NB + NF	79.3358	82.1093	3.66
	NB + NFCS			
[Proposed]	83.4514	85.2836	3.75	
70–30	NB + NN	80.7148	85.1159	5.48
	NB + NF	83.9528	86.6	4.14
	NB + NFCS [Proposed]	89.899	90.0773	4.26
80–20	NB + NN	91.3195	94.0594	6.35
	NB + NF	94.04129	95.709	4.97
	NB + NFCS [Proposed]	97.7969	96.8803	5.05

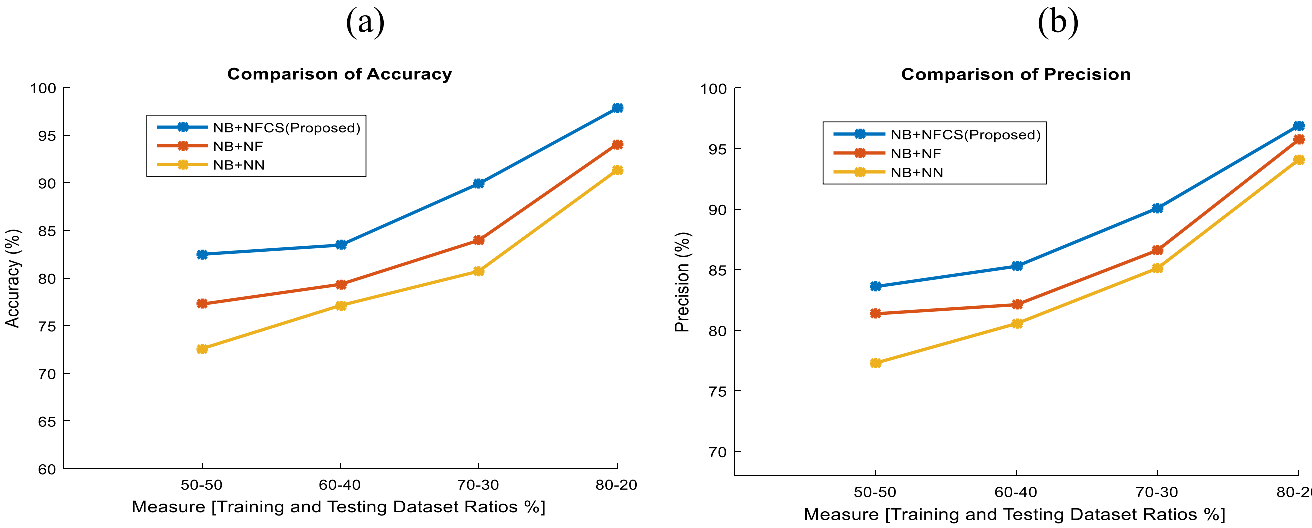


Fig. 5 Comparison of combined techniques (a) Accuracy (b) Precision

50–50, 60–40, 70–30 & 80–20 training and test data sets. For all the training and test ratios the NFCS shows better results when compared with the NN. The performance of the NF is improved when combined with Binary cuckoo search algorithm.

Discussion

The lung cancer detection and classification is performed in Matlab platform. The nodule detection is done with the aid of Naïve Bayes and neuro fuzzy with cuckoo search algorithm is used for stage classification. The combined techniques are executed to detect the lung nodule and classification of stages and the results are tabulated in Table 6. The simulated results show that, there is an improvement in evaluated metrics such as accuracy and precision, when the number of samples is increased for training. The Fig. 5 and Fig. 6 show the performance of the combined techniques such as NB + NN, NB + NF and NB + NFCS [Proposed]. From the comparison, the proposed technique (NB + NFCS) outperforms other techniques.

In Fig. 5 (a), the accuracy is compared under variable training and testing sample ratios which shows the marginal improvement in all ratios. Then the precision values are displayed in Fig. 5 (b), it can be seen that the precision values obtained by the proposed combined technique are better than other techniques.

The Fig. 6 exhibits the computational time comparison; it clearly shows that our proposed combined technique took less time to compute the lung nodule detection and classification

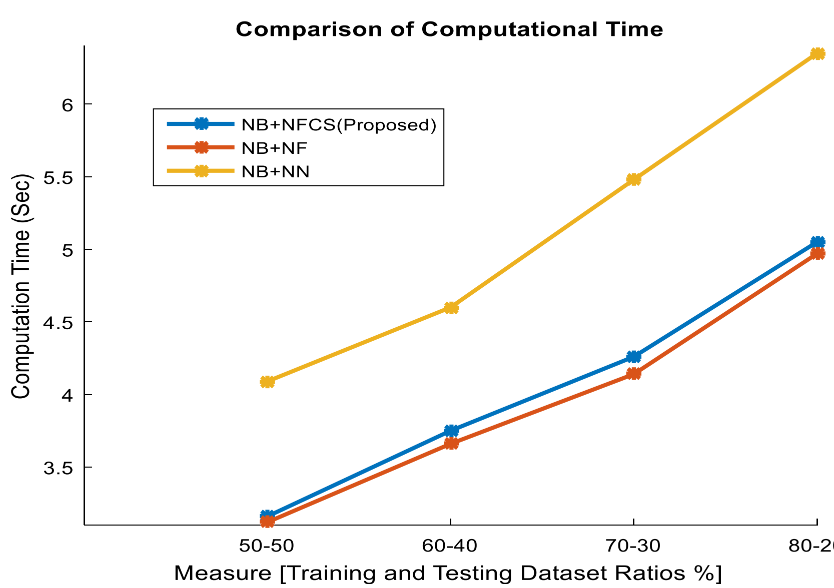


Fig. 6 Computational time comparison of combined techniques

of stages when compared with NB + NN and the computation time is slightly higher than the NB + NF as cuckoo search is used to optimize the result after neuro fuzzy classifier. The assessed computational time is 3.16 s, 3.75 s, 4.26 s and 5.05 s for the 50–50, 60–40, 70–30 and 80–20 sample set ratios respectively.

Conclusion

In this paper the normal and abnormal images are classified by using Naïve Bayes classifier and the stages of the nodule is determined by using neuro fuzzy with cuckoo search. The simulated results have shown that the proposed system is effective in fast diagnosis of the lung cancer and facilitates the small nodule detection with high level of accuracy. The normal and abnormal classification of the nodule comparison shows that the Naïve Bayes algorithm outperforms SVM. Also the stage classification accuracy and precision are increased to 97.8% and 96.88% respectively which are higher than the values of Neural Network and Neuro Fuzzy Classifiers. From the result, it is demonstrated that the proposed classifier will give better assistance to the physician for providing the accurate therapeutical suggestions. This work can be further extended to find the growth rate of the nodule, estimating the size and location of the nodule.

Compliance with Ethical Standards

Conflict of Interest None.

(In case animals were involved) Ethical approval: Animals were not involved.

(And/or in case humans were involved) Ethical approval: This article does not contain any studies with human participants performed by any of the authors.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

1. Brown, M. S., and McNitt-Gray, M. F., Patient-specific models for lung nodule detection and surveillance in CT images. *Proc. IEEE Trans. Med. Imag.* 20(12), 2001.
2. Gomathi, M., and Thangaraj, P., Automated CAD for lung nodule detection using CT scans. Proceedings of IEEE Transaction on Data Storage Engineering (DSDE). 150–153, 2010.
3. Cosman, P. C., Tseng, C., and Gray, R. M., Tree-structured vector quantization of CT chest scans: Image quality and diagnostic accuracy. *Proc. IEEE Trans. Med. Imag.* 12(4):727–739, 1993.
4. Dewes, P., and Frellesen, C., Comparative evaluation of non-contrast CAIPIRINHA-VIBE 3T-MRI and multidetector CT for detection of pulmonary nodules: In vivo evaluation of diagnostic accuracy and image quality. *ELSEVIER J. Eur. J. Radiol.* 85(1): 193–198, 2016.
5. Georg Homann, M. D., and Mustaf, D. F., Improved detection of bone metastases from lung Cancer in the thoracic cage using 5- and 1-mm axial images versus a new CT software generating rib unfolding images. *Elsevier J. Acad. Radiol.* 22(4):505–512, 2015.
6. Mulshine, J. L., and Gierada, D. S., Role of the quantitative imaging biomarker Alliance in optimizing CT for the evaluation of lung Cancer screen detected nodules. *ELSEVIER J. Am. College. Radiol.* 12(4):390–395, 2015.
7. De Nunzio, G., and Massafra, A., Approaches to juxta-pleural nodule detection in CT images within the MAGIC-5 collaboration. *ELSEVIER J. Nucl. Instrum. Methods Phys. Res.* 648(1):103–106, 2011.
8. Ye, X., Lin, X., and Dehmeshki, J., Shape-based computer-aided detection of lung nodules in thoracic CT images. *Proc. IEEE Trans. Biomed. Eng.* 56(7):1810–1820, 2009.
9. Gady Agam, S., Vessel tree reconstruction in thoracic CT scans with application to nodule detection. *Proc. IEEE Trans. Med. Imag.* 24(4):486–499, 2005.
10. Ritchie, A. J., and Sanghera, C., Computer vision tool and technician as first reader of lung Cancer screening CT scans. *ELSEVIER J. Thor. Oncol.* 11(5):709–717, 2016.
11. Yasaka, K., and Katsura, M., High-resolution CT with new model-based iterative reconstruction with resolution preference algorithm in evaluations of lung nodules: Comparison with conventional model-based iterative reconstruction and adaptive statistical iterative reconstruction. *ELSEVIER Eur. J. Radiol.* 85(3):599–605, 2016.
12. Dehmeshki, J., and Siddique, M., Automated detection of nodules in the CT lung images using multi-modal genetic algorithm. *Proc. IEEE Trans. Image Signal Process. Anal.* 1:393–398, 2003.
13. Tariq, A., and Usman Akram, M., Lung nodule detection in CT images using neuro fuzzy classifier. Proceedings of IEEE transaction on computational intelligence in medical imaging (CIMI). 49–53, 2013.
14. Clifford Samuel, C., and Saravanan, V., Lung nodule diagnosis from Ct images using fuzzy logic. *Proc. IEEE Int. Conf. Comput. Intell. Multimed. Appl.* 3:159–163, 2007.
15. Han, H., and Li, L., Fast and adaptive detection of pulmonary nodules in thoracic CT images using a hierarchical vector quantization scheme. *Proc. IEEE Int. J. Biomed. Health Inform.* 19(2):648–659, 2015.
16. Nagatani, Y., and Takahashi, M., Lung nodule detection performance in five observers on computed tomography (CT) with adaptive iterative dose reduction using three-dimensional processing (AIDR 3D) in a Japanese multicenter study: Comparison between ultra-low-dose CT and low-dose CT by receiver-operating characteristic analysis. *ELSEVIER J. Eur. J. Radiol.* 84(7):1401–1412, 2015.
17. Valentea, I. R. S., and Cortezb, P. C., Review automatic 3D pulmonary nodule detection in CT images: A survey. *ELSEVIER J. Comput. Methods Program Biomed.* 124:91–107, 2016.
18. Suia, X., and Meinel, F. G., Detection and size measurements of pulmonary nodules in ultra-low-dose CT with iterative reconstruction compared to low dose CT. *ELSEVIER J. Eur. J. Radiol.* 85(3): 564–570, 2016.
19. Zhang, H., Han, H., and Liang, Z., Extracting information from previous full-dose CT scan for knowledge-based Bayesian reconstruction of current low-dose CT images. *Proc. IEEE Trans. Med. Imag.* 35(3):860–870, 2016.
20. Zhoua, S., and Cheng, Y., Automated lung segmentation and smoothing techniques for inclusion of juxtapleural nodules and pulmonary vessels on chest CT images. *ELSEVIER J. Biomed. Signal Process. Contrl.* 13:62–70, 2014.