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Soft Computing Techniques Based Computer Aided System for Efficient Lung Nodule Detection – A Survey

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Abstract— Early detection and treatment of lung cancer can significantly advance the survival rate of patient. However, this is a challenging problem due to structure of cancer cells. Lung cancer detection, classification, scoring and grading of histopathological images is the standard clinical practice for the diagnosis and prognosis of lung cancer. It is a very complex and time-consuming duty for a pathologist to manually perform these tasks. Robust and efficient computer aided systems are therefore indispensible for automatic lung cancer detection. The delineation of anatomical structures and other regions of interest is a key component in CAD systems. This is achieved through soft computing techniques which automatically and accurately highlight potential actionable lung nodules and rapidly compute measurements of detected regions. Soft computing systems like neural networks and fuzzy systems are valuable in lung cancer screening to improve sensitivity of pulmonary nodule detection beyond double reading, at a low false-positive rate when excluding small nodules. Several pilot studies have shown that these CAD modules can successfully locate overlooked pulmonary nodules and serve as a powerful tool for diagnostic quality assurance. This paper reviews the literature pertaining to the different types of novel neural network and fuzzy based automated CAD systems for robust lung nodule detection. Furthermore, prevailing research trends and challenges are acknowledged and guidelines for future research are discussed.

Index Terms—Computer Aided Detection (CAD), fuzzy, Lung Nodule, neural network, sensitivity

I. INTRODUCTION

Lung cancer, a malignant transformation and expansion of lung tissue, is an enormous global health burden touching every region and socioeconomic level. Today, cancer accounts for one in every eight deaths worldwide – more than HIV/AIDS, tuberculosis, and malaria combined and lung cancer is the most lethal of all cancers worldwide. In 2008, there were an estimated 12.7 million cases of cancer diagnosed and 7.6 million deaths from cancer around the world. The American Cancer Society [1] estimates that in 2012 about 173,200 cancer deaths will be caused by tobacco use. Scientific evidence suggests that about one-third of the 577,190 cancer deaths expected to occur in 2012 will be related to overweight or obesity, physical inactivity, and poor nutrition and thus could also be prevented. An estimated 226,160 new cases of lung cancer are expected in 2012, accounting for about 14% of cancer diagnoses. The 5-year survival rate is 52% for cases detected when the disease is still localized, but only 15% of lung cancers are diagnosed at this early stage. Most lung cancer patients are over the age of 60 years when they are diagnosed. Lung cancer takes several years to reach a level where symptoms are felt and the sufferer decides to seek medical help.

Regular screening examinations by a health care professional can result in the detection and removal of precancerous growths, as well as the diagnosis of cancers at an early stage, when they are most treatable. Screening is looking for cancer before a person has any symptoms. This can help find cancer at an early stage. If a screening test result is abnormal, more tests needs to be done to detect cancer.

Pulmonary nodules are small lesions which can be calcified or not, almost spherical in shape or with irregular borders. The nodule definition for thoracic CT of the Fleischer's Society is "a round opacity, at least moderately well margined and no greater than 3 cm in maximum diameter" [2]. Approximately 40% of lung nodules are malignant, that is, are cancerous: the rest is usually associated with infections. With the rapid advancement of computing technology and imaging hardware design, the interaction between engineering, computing, physics, and clinical science has become much closer than it has ever been before. In recent years, serious efforts have been made toward the development- of computer aided diagnosis (CAD) systems in diagnostic radiology. The CAD in radiology is a diagnosis made by a clinician (radiologist) who uses the output from a computerized analysis of medical images as a second opinion. CAD methods apply powerful techniques of physics, mathematics, statistics, and computer science to the anatomical and physiological information contained within medical images. As a software technology, CAD meets three main objectives.

- It improves the quality of diagnosis.
- It increases the therapy start time by early detection of cancer.
- It avoids unnecessary biopsies (surgically testing the tissue).

Chest X-ray films are two-dimensional projection images and the overlapping of bone and organs shadows results in disturbing the detection of small lung cancer nodules at early stage. The introduction of CT technology has helped a lot in increasing the survival rate by diagnosis of cancer at its initial stages. But small nodules are still common to be missed by radiologists in their early stages. The chest CT scanning machine takes many pictures, called slices, of the lungs and the inside of the chest. A computer processes these pictures; they can be viewed on a screen or printed on film.

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CT reduces radiation exposure and detects up to 10 times more malignant lung nodules than chest X-Ray. CT scans find abnormalities in about 20 to 60 percent of smokers and former smokers, but most of these abnormalities are scars from inflammation or other noncancerous conditions. The CT scan's sensitivity can result in doctors suspecting the possibility of cancer where there really is no cancer, which results in invasive follow-up tests, unnecessary surgery, and anxiety for those getting screened and their loved ones. In other words, screening leads to necessary invasive tests and surgery for lung cancer, but these tests end up being unnecessary if it's eventually determined that the spot first found on a CT scan isn't lung cancer but instead something benign. Moreover, mass screening based on helical CT images leads to a considerable number of images to be diagnosed which is time-consuming and makes its use difficult in the clinic.

II. NEURAL NETWORK TECHNIQUES

A. 3D Motion Estimation

Kun Li et al [3] proposed a new three dimensional two stage motion estimation technique based on matrix completion from multiview video sequences. The two stages involved are separating and merging. This involves estimating the initial motions for each view with a neighboring view and later merging each view. The main advantage of the former stage is accuracy of 3-D motion and later stage assures completeness (denseness) of the 3-D motion field.

The recovery of low-rank data from a highly incomplete set of (possibly corrupted) entries, which is referred to as matrix completion. In the proposed method, a 3-D motion is estimated via matrix completion and then improves the accuracy with spatiotemporal selection. Specifically, initial motion is estimated for each camera and treated as a column vector to form an incomplete and noisy matrix. Since all the estimated results correspond to the same 3-D motion field, the underlying clean version of these vectors lies in a low-dimensional subspace, i.e., the matrix has a low rank which is theoretically one. Hence, the problem of 3-D motion estimation is converted to a problem of recovering a low-rank matrix from noisy and incomplete observations. Finally, accurate estimates are obtained by spatiotemporal selection as a 2-D constraint.

Advantages:

- This method is totally automatic, fast and can estimate both rigid and nonrigid motions within small errors.
- Initial motions are first estimated for each view with a neighboring view.
- The motions obtained by each view are merged together and optimized.
- Computing in a separating mode ensures the accuracy of 3-D motion estimation, while the merging step guarantees the completeness (denseness) of the 3-D motion field.

In this method, a CNN technology software framework called CNN Visual Mouse version 4.1 is used. It based on the Visual Mouse (VisMouse) concept. It is CNN application development and environment toolkit for windows. The VisMouse is a handheld image supercomputer with direct optical input. This input is an artificial "eye", with possible zooming, supported by analogical CNN supercomputer chips.

The various analogical CNN algorithms are selected by functional buttons of the VisMouse for solving different tasks. A two step algorithm is involved; first part involves the detection of the area using filtering methods such as median, diffusion and gradient, peel which are available as different templates within the software. The second part of the algorithm detects the boundary of lung cancer symptoms using the soothing and edge detection template.

Future Scope:

- This work can be extended by applying other type of neural networks to classify the cancer cells into small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC).
- CNN can also be applied for detection of other diseases like heart failure, TB etc.

B. Image Subtraction Based on ANN

Noriaki Miyake et al [4] developed an automatic lung nodule detection system with sensitivity of 80.5% for lung nodules with sizes less than 20mm, and with 7.5 false positives per scan. This method used temporal subtraction based on artificial neural networks. Thoracic multi-detector-row computed tomography (MDCT) images were used as inputs. Initially the candidates for nodules are detected by use of a multiple threshold technique based on the pixel value in the temporal subtraction image obtained by the voxel matching technique. This is followed by reduction of false positives using selective enhancement filter. Finally, a number of features were quantified, and false positives were removed by using a rule-based method and artificial neural network (ANN) classifiers. The various stages of the algorithm are shown in Fig 1.

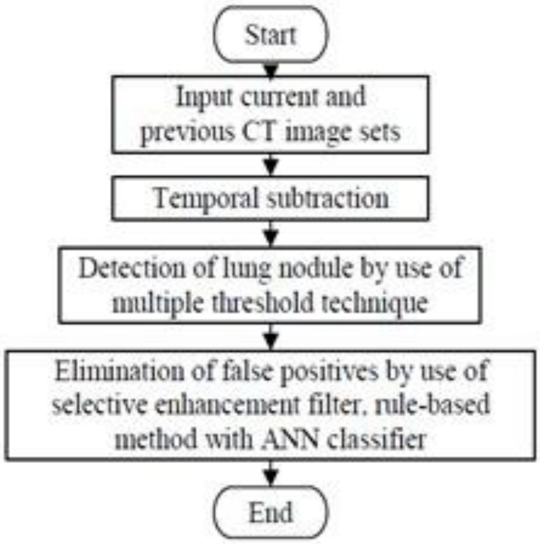

Fig 1. Block diagram of image subtraction method.

C. Gabor Filter with Neural Network Technique:

Hany Ayad Bastawrous et al [5] devised a scheme for detection of ground glass opacities (GGO) nodules in lung ct images using Gabor filters and neural networks. Preprocessing of is done to enhance the intensity levels of the GGO which typically have nodules with faint contrast and fuzzy margins. By applying Gabor filter the detection of the nodules is enhanced by emphasizing their frequency components and rejecting other components. After applying Gabor filter, we perform a threshold process followed by labeling in order to extract all connected objects with high intensity values inside the lung area. This is followed by discrimination of the GGO nodules based on few parameters like area, compactness, irregularity, maximum and mean intensity value. Based on known Gaussian model template matching is performed. The proposed method attained detection sensitivity of 92% with FP rate of 0.76 FP/slice.

In the output layer there were 35 neurons to identify the GGO nodules (18 nodule samples and 17 nodule-like samples). The hidden layer consisted of 10 neurons (this number was set experimentally). Log-sigmoid transfer function was used in this two-layer network. All the network weights are trained using Back Propagation (BP) algorithm, which adjusts the weights iteratively to minimize the total error between the actual output vector and the target vector. After using the ANN we succeeded to decrease the FP rate to 0.25 FP/slice instead of 0.76 FP/slice but at the expense of decreasing the detection sensitivity from 92% to 84% by detecting only 21 nodules and missing 4 nodules

D. Multiscale Neural Network Cad System:

Giuseppe Coppini et al [6] put forward an compound CAD system for lung nodule detection from chest radiograms. Biologically stimulated filters like Laplacian of Gaussian (LoG) filter and Gabor kernels are used to improve significant image features. ANNs of the feedforward type are employed because it provides an efficient use of a priori knowledge about the shape of lung nodules as well as the background structure. The main benefit of LoG filtering is that no prior explicit knowledge about the actual shape of the nodules and the structure of image background is required. In addition, a LoG filter is a good approximation of the receptive fields of many kinds of neurons in biological vision. On the other hand, Gabor kernel is used as specific oriented features and radiogram textures with a different coarseness need to be strongly enhanced.

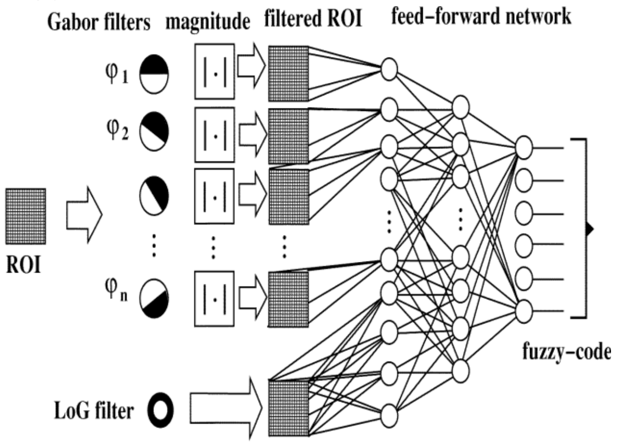

Fig 2. Structure of the multi-scale ANN system.

All the networks shown in Fig 2 of the system included units with a sigmoid logical function (output range:[0,1]), and were trained by using the error back-propagation rule. Uniform random values in the range [-0.01, 0.01] were used to initialize connection weights. Adaptive learning rate and momentum term were adopted. The stopping criteria used for the training process was when the squared sum of errors measured on the test-set data started to increase. Quantitatively the performance of the proposed method is 10.2 FPs at a sensitivity value of 75%. And we have a high accuracy of about 95.7%.

E. Two-Level Ann Architecture Based Cad System

Small tumors possess and identifiable signature in curvature-peak feature space, where curvature is the local curvature of the image data when viewed as a relief map. The usefulness of the curvature-peak space is demonstrated by Manuel G. Penedo et al [7] by a CAD system based on two-level ANN. The first ANN accomplishes the detection of suspicious regions in a low-resolution image. The curvature peaks is computed for all pixels in each of these suspicious regions and is supplied as input to the second ANN. The free-response receiver operating characteristics method is utilized to evaluate the performance of the system. It provides mean number of false positives (FP's) and the sensitivity as performance indexes to estimate all the simulation results. 89%–96% sensitivity and 5–7 FP's/image is achieved through this two-level architecture depending on the size of the nodules.

Two algorithms were used for the training. In an initial phase, with the aim of adapting the learning process to the topology of the error function, the resilient backpropogation (RPROP) algorithm was used. The second phase of the training carry out a fine learning process, starting from the basis that the structure already has dynamic knowledge of the surface on which it moves. For this, the learning algorithm for the generalized delta rule [8] was used, using the momentum for weight modification. The proposed system results in a great degree of robustness in that a low number of criteria are used for making decisions, taking advantage of the natural capacity of generalization of artificial NN's. In addition to this, the system is competent of detecting nodules when they are in their initial stages, facilitating their early diagnosis, thus, improving the patient's survival rate.

III. FUZZY BASED CAD SYSTEMS FOR LUNG NODULE DETECTION

A. An Approach for Learning And Tuning Gaussian Interval Type-2 Fuzzy Membership Functions:

A genetic algorithm (GA)-based approach to address the application of the interval type-2 fuzzy logic system (IT2FLS) for the problem of nodule classification in a lung CAD system was developed by Rahil Hosseini, et al [9]. In this approach learning of a Gaussian interval type-2 fuzzy membership function (IT2MF) and its Footprint of certainty (FOU) is based on the following two methods:

- Learning an IT2MF that is based on a T1FLS; and
- Learning an IT2MF that is based on the training dataset.

The advantage of the first method is the simplicity in the design of the T1MF and the IT2FLS parameters can be more intelligently estimated based on the T1FLS parameters. The second method is useful when there is difficulty in the design of the T1FLS because of the knowledge acquisition issues that are related to extracting intuitive information from different experts with different levels of experience. The maximum accuracy is accomplished for the IT2FLS algorithm that is based on the uncertain T1FLS defined by experts, with an average ROC accuracy result of 95%. Moreover, IT2FLS is more capable of confining the uncertainty in the model and achieving better performance results. For the lung nodule classification, the IT2FLS performance is 30% better than the T1FLS. Fig 3 shows the architecture and Fig 4 shows the flowchart of the type-2 fuzzy system algorithm.

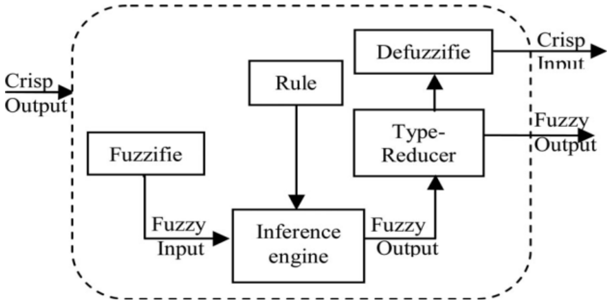

Fig 3. Architecture of type-2 fuzzy system

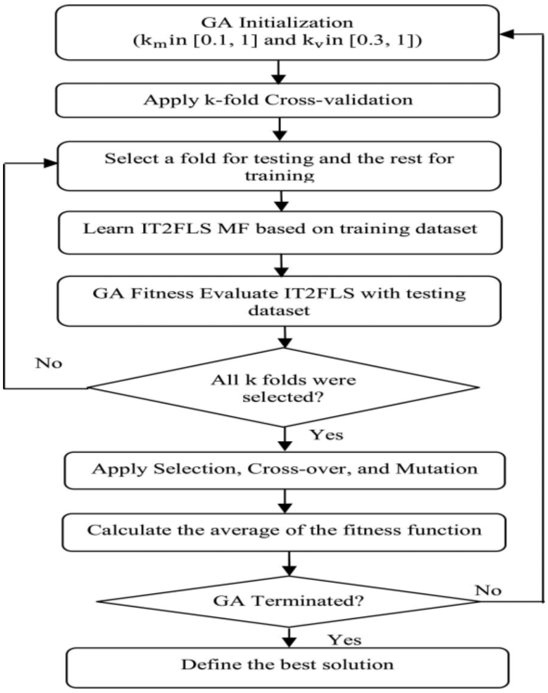

Fig 4. Flowchart of IT2FLS learning algorithm.

The future work of this research is to learn rules in an IT2FLS for uncertain environments where defining the system rules can be challenging.

B. Mamdani Model and Sugeno Model Of The Fuzzy Logic System

Rahil Hosseini et al [10] proposed a scheme for classification of lung digital images based on fuzzy logic system. There are two main sources of uncertainty coupled with CAD applications that have be considered and tackled by applying two different models of type-1 fuzzy logic systems namely Sugeno and Mamdani systems. These two issues are

- Imprecision in input data and features of patterns and noisy measurements
- Uncertainty inherited in classifiers input from all previous processes of image enhancement, segmentation, edge detection, converting a 3-D image to a 2-D image, gray level, texture, etc.

Mamdani fuzzy rule:

If x1 is Ai1 and … and xn is Ain then y is Bi (1)

Where Ri is the label of the ith fuzzy rule, x=(x1, x2, … , xn) is an n-dimensional input vector and includes features, Ai1 … Ain which are antecedent fuzzy sets which shows linguistic terms, y is an output variable and Bi is a consequent fuzzy set. An example of this type is "If x1 is small and x2 is large then y is small".

Takagi and Sugeno rule:

If x1 is Ai1 and … and xn is Ain then y = fi(x) (2)

fi(x)=bio+bi1x1 + …. + binxn (3)

where bij is a real number (j =1, 2, … , n). An example of a fuzzy rule of this type is "If x1 is small and Ax2 is small then y = 0.50 + 0.25x1 + 0.3x2".

The suggested future work is to apply diverse methodologies for incorporating more sources of uncertainty such as inter- and intra-operators observer variability and thus improving the system performance.

C. Fuzzy C-Mean (FCM) Morphology Technique :

A new method for lungs nodule detection from CT images by using Fuzzy C-Mean (FCM) and morphological techniques was developed by M. Arfan Jaffar et al [11]. The various steps involved in the algorithm are discussed below:

Step 1: Pre-processing:

This is done by a novel technique to remove background automatically.

Step 2: Fuzzification:

The histogram is found out and the FCM algorithm was employed to create a fuzzy partition that appropriately describes the image using only the pixel intensity feature. The cluster validity measures used was the partition coefficient (PC) and the partition entropy (PE).

Step 3: Optimal Threshold:

The Optimal threshold stage takes fuzzy membership matrix from previous stage and provides an objective function that is used to find out adaptive, optimal and dynamic threshold which is used in the next stage to segment the image.

Step 4: Edge detection & Thinning:

To detect edges, we have found the difference between the processed image by above process and the image before dilation and Susan thinning algorithm [12] was applied to reduce the borders to the width of one pixel.

Step 5: Extraction of ROI and post processing:

Thinning is followed by region filling to extract the lung parts and by applying a double threshold, the required ROI alone is extracted and pruned. A 3D image is formed by using all slices of ROI images.

Step 6: Classification by fuzzy C -mean:

After construction of 3D ROI image, we pass this 3D image to the FCM with 3 numbers of clusters. The dark cluster represents the nodule part in the image and we got only those ROIs that represent nodules. The resultant images after applying 3D convolution and fuzzy c-mean are images that have no false positive (FP).

D. Shape Based CAD System:

A novel CT image lung nodule CAD procedure is proposed for detecting both solid nodules and ground-glass opacity (GGO) nodules by Xujiong Ye et al [13]. The lung region is segmented by fuzzy thresholding method. Then, the 3-D local geometric and statistical intensity features for potential solid and GGO nodule detection was calculated. These calculations were based on local Gaussian and mean curvatures and the "dot" map was constructed using Eigen values of the Hessian matrix. This enables the enhancement of specific shapes. Anti-geometric diffusion for the edges and Gaussian filtering to remove noise are used as preprocessing step. Rule-based filtering is first used to remove easily dismissible non-nodule objects. This is followed by a weighted support vector machine (SVM) classification to further reduce the number of false positive (FP) objects. The flow of the various stages involved is shown in Fig 5.

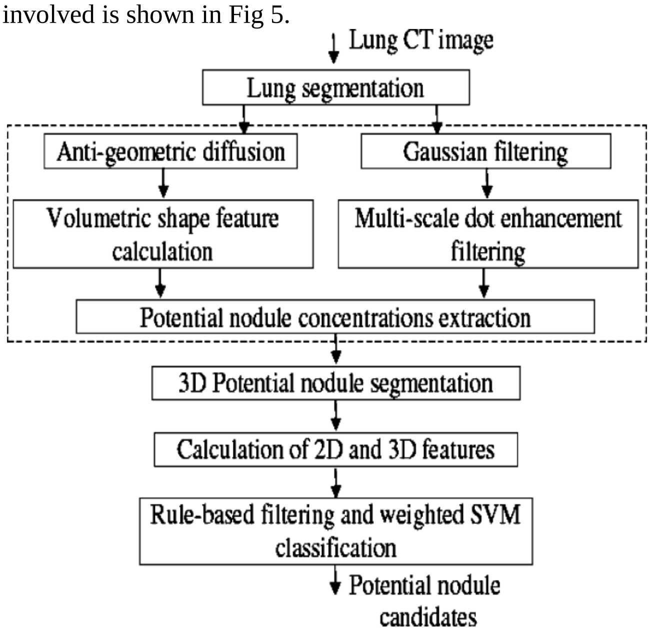

Fig 5. Block Diagram of shape based CAD system.

The average detection rate of this method is 90.2%, with approximately 8.2 FP/scan. Some noticeable advantages of this shape based CAD system are the high detection rate, fast computation, and applicability to different imaging conditions and nodule types. Moreover, the detection sensitivity is high with a low rate of FP regions. All these potential benefits prove that this system is a promising approach for clinical applications.

IV. SVM APPROACHES FOR CAD SYSTEMS

In 2012, Hiram Madero Orozco et al [14] presented a computational alternative to classify long nodules in frequency domain using Support Vector Machines (SVM). The region of interest was extracted from the acquired CT image. The spatial domain of this image was converted to frequency domain using two transformations which have good energy compaction abilities. They are: a) The two dimensional Discrete Cosine Transform (2D-DCT) and b) the two dimensional Fast Fourier Transform (2D-FFT). This is followed by extraction of the statistical texture features from the histogram of the image. Six texture features such as average gray level, standard deviation, smoothness, third moment, uniformity and entropy were computed. After the computation of these statistical texture features, different algorithms as BestFirst, GeneticSearch and GreedyStepwise was tested to measure the relevance of each feature and to reduce the feature set to gray level and third moment. After attribute selection, the classification stage was made using a SVM based on Radial Basis Function (RBF).

The above methodology is capable of successfully detecting nodules of 2 millimeters to 3 centimeters in diameter. The 2D-DCT showed better sensitivity (96.15%) compared with the 2D-FFT (94.44%).Research can be carried out in the future using different classifiers and transforms such as neural networks or boosting and Discrete Wavelet Transform (DWT) or Contourlet Transform.

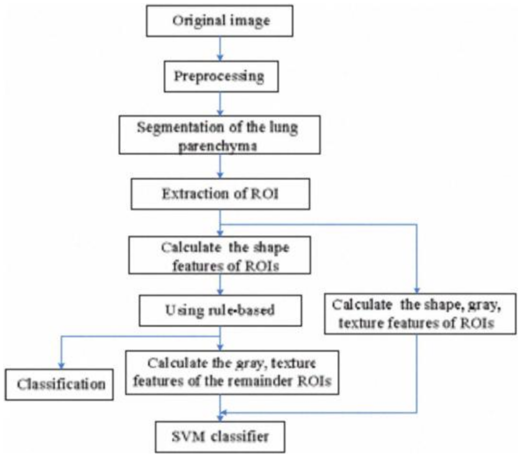

Fig 6. Flow of the algorithm for combined method.

Zhang Jing, Li Bin and Tian Lianfang proposed a lung nodule classification combining rule-based and SVM [15]. The rule-based approach has no omission, but the misclassification probability is too large; the approach combining rule-based and SVM has higher omission than SVM, but lower misclassification. Furthermore, the approach combining rule-based and SVM is faster than SVM for classification. The efficiency especially reflects its advantages when the dataset is very large. The accuracy of this combined approach is 84.39%. Fig 6 depicts the algorithm used in this combined approach.

Table 1 illustrates the review of the comparison of various CAD systems which have been developed for the past few decades. Different soft computing techniques like fuzzy systems, neural network, genetic algorithm, SVM or a combination of few of these have been employed for efficient and robust lung nodule detection and classification. The table evaluates each of these techniques based on parameters like false positive, accuracy, sensitivity and specificity

Table 1. Comparative study of various CAD systems.

Paper	Authors/Year	Key Concept	Performance
Segmentation of Lesions with Improved Specificity in Computer-Aided Diagnosis Using a Massive-Training Artificial Neural Network (MTANN) [16]	Kenji Suzuki (2008)	massive-training artificial neural network (MTANN) filter in a CAD scheme for detection of lung nodules in CT.	Sensitivity of 96% (66/69), with 1.2 FPs per section
A CAD System for Lung Nodule Detection based on an Anatomical Model and a Fuzzy Neural Network [17]	M. Antonelli, G. Frosini, B. Lazzerini and F. Marcelloni (2006)	Fuzzy C-Means algorithm is applied to classify the lung area and fuzzy neural network is used for recognition of nodules.	Nodule detection rate of 100% , micro-nodule detection rate of 81.820% and 1.4 false positives per slice.

Computer-Aided Diagnosis for Pulmonary Nodules Based on Helical CT Images [18]	K.Kanazawa at el (1998)	Fuzzy clustering algorithm to extract lung and blood vessel region diagnostic rules and for nodule determination.	Cases of 6 false negative cases are involved width such nodules. The sensibility for 120 nodules was 95%
Lung Nodule Diagnosis From CT Images Using Fuzzy Logic [19]	C.Clifford Samuel, V.Saravanan, M.R.Vimala Devi (2007)	Preprocessing using biorthogonal wavelet followed by fuzzy system to find the severity of the lung nodules based on the IF-THEN rules.	--
Experimental Investigation of Fuzzy Enhancement for Nonsolid Pulmonary Nodules [20]	Li Cuifang , Nie Shengdong, Wang Yuanjun, Sun Xiwen (2012)	Pal-King fuzzy enhancement algorithm	--
A Hybrid Neural-Digital Computer-Aided Diagnosis System for Lung Nodule Detection on Digitized Chest Radiographs [21]	Jyh-Shyan Lin et al (1994)	The CNN nodule classifier	80% sensitivity with 2-3 false-positives per chest image.
Development of automated detection system for lung nodules in chest radiograms [22]	Takeshi Hara, Hiroshi Fujita and Jing Xu (1997)	Detection by genetic algorithm and neural networks	The sensitivity and the number of false-positives were 80% (8/10) and 2.4 per image,
Data-Driven Lung Nodule Models for Robust Nodule Detection in Chest CT [23]	Amal A. Farag (2010)	Data-driven nodule models	Sensitivity of 85.22%
Segmentation of Pulmonary Nodules in Thoracic CT Scans [24]	Dehmeshki et al (2008)	Local adaptive segmentation algorithm, fuzzy connectivity map, region growing	84% accuracy

V. CONCLUSION

The paper describes a short survey on diverse types of soft computing techniques used to develop efficient and automatic CAD systems for lung nodule detection. Although only some of the main neural network, fuzzy based and SVM based techniques were discussed in this paper, one can see that there exists a large range of alternatives that exist for identifying lung nodules from X-rays, chest radiograms or CT images. All the major image file formats have their own pros and cons respectively. But efficient detection can be successfully achieved by employing soft computing in CAD systems. They increase the speed, accuracy and efficiency of diagnosis thus boosting the survival rate of patients. Where one system lacks in sensitivity, the other lacks in accuracy.

Thus researchers can decide on which soft computing technique to choose depending on the type of performance of the algorithm and can proceed to enhance some of these CAD systems based on the guidelines provided for each.

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