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Twin Stage Fuzzy Expert System Modeling for Lung Cancer Risk Diagnosis

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Abstract: Soft computing for medical diagnosis in field of computer science has been a syndicate of methodologies. These all work together in order to provide a facility to make decisions from consistent data or experience of experts of related fields. Many artificial intelligence techniques such as fuzzy logic, neural network, genetic algorithm, etc. or integration of those may be used in the field of medical science. These types of methodologies have also been incorporated in order to diagnose the lung cancer disease. The main objective of this study to develop a fuzzy expert system with number of linguistic variables as fuzzy feature sets along with different membership functions to depict the risk factor in lung cancer disease. The risk level of disease is decided by the rule set of the fuzzy system. For improving the accuracy of the system, we have designed two stage fuzzy expert system with input of six features at each stage. The experimental results make obvious that the proposed work has enhanced accuracy with reduced computing time.

Key words: Fuzzy logic, fuzzy expert system inference engine, lung cancer, demographic features, linguistic variables, cancer risk factor

INTRODUCTION

Lung cancer has been the most common cause of human death all over the world. One can use chemotherapy, radiation therapy, etc. for treatment of this deadly disease. The early detection and action at initial stage of localized tumors are the dependable for the diagnosis and cure of this disease where a well 5 years patient survival rate is still approximately only 14%. Smoking and drinking are the two root cause of lung cancer. If it is diagnosed at early stage then there are quite good chances of survival up to 49%. Diagnosing of cancer is also one of the foremost challenging issues (Er *et al*., 2010). In recent years, lots of researches are going on detection methodologies in the field of medicine particularly in diagnosis. There are two main types of lung cancer, Non-Small Cell Lung Cancer (NSCLC) and Small Cell Lung Cancer (SCLC). The classification of these stages of lung cancer depends on locality and spreading of tumor from the lungs to the lymph nodes or other nearby organs. Since, the lungs are larger in area; tumors can grow up in them for a long span of time before they are undergoing for diagnosis. Even when related symptoms-such as coughing and fatigue are occurring for a long time also, people suppose that they are due to other issues. Due to this fact, early-stage diagnosis of lung cancer is too difficult. Physical characteristics of the lung nodules, for example, growth rate, calcification pattern, marginal types are vital important in the analysis of the isolated lung carcinoma. Every lung nodule tumor cell grows in dimensions over a span of time. However, NSCLC grows at an exponential rate which is typically expressed as a tumor's doubling time duration. NSCLCs have a doubling duration of between 25-450 days whereas the SCLCs are vitally stable and have a doubling duration more than 500 days.

In early decades, Chest X-ray images were taken for lung cancer diagnosis. But here, some of the nodules may not be diagnosed because they may be masked by the primary anatomical structures or the diminished resolution and contrast of the images, etc. Hence, now a days, lung cancer diagnosis from CT images using bio-medical image processing algorithms is an imperative research area. At present, Computed Tomography (CT) is taken as to be more proficient than X-ray in detecting and diagnosing the lung cancer because it provides superior information than conventional X-ray predominantly of soft tissues and blood vessels. Moreover, it is speedy, precise and trouble-free (Penedo *et al*., 1998; Hong *et al*., 2008). Image processing and visualization algorithms for volumetric CT datasets may advance the radiologist's capability to spot small lung nodules. Cancer treatment targets to demolish or control affected tumor cells. Lung cancer patients do not experience any symptoms at initial stages, hence, it

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can be the way to death if not diagnosed and cured in time (Gurcan *et al*., 2002). Primary lung cancer initiates in the lungs whereas secondary lung cancer initiates somewhere else other than lungs and approaches the lungs. Hence, it is crucial to perceive cancer as earliest possible. Early diagnosis also leads to a successful treatment of this disease. The key trouble in the automated screening through Computed Tomography (CT) for lung cancer is the detection of nodules. A pulmonary nodule is a tiny egg or round shaped lesion in lungs. These nodules are usually asymptomatic and they are usually diagnosed by prospect on a chest X-ray which has been taken for some another motive. The dimension of the nodules varies from few millimeters to few centimeters. Due to this deviation in shape and dimension of nodules, the procedure of detection or segmentation is truly an exigent task. Since, a large amount of the nodules are connected to vessels so, it is very complex to discriminate lung nodules from vessels (Samuel *et al*., 2007).

Now a days, the techniques of artificial intelligence have mainly been adopted in the several fields which also incorporate the medical applications. Soft computing tools are one of the interdisciplinary research areas in computational science. A large variety of techniques which have been developed and adopted to unravel the exigent responsibilities in medical and engineering domain areas are such as fuzzy logic, support vector machine, neural networks, genetic algorithms, etc. In recent trends, there are enormous application areas of fuzzy logic and they have been keeping growing in equipments related to use in day to day life to industrial course control, bio-medical instrumentation, decision-making systems, etc. The aim is to imitate the dealings of a domain specialist who can decipher composite problems. Fuzzy logic has been a fantastic tool for such types of decision making systems even if the ample skilled information about the method is accessible then also it seems to be suitable (Taylan and Karagozoglu, 2009). Fuzzy system theory is abet in delivering emblematic awareness information in additional human intelligible or natural form and can hold uncertainties at a variety of levels. These particulars propose that fuzzy system theory can also be engaged for the improvement of a computer based modern diagnosis schemes (Adlassnig, 1986; Walia *et al*., 2015). However, fuzzy system can also be useful in the diagnosing and treatment of diseases of cancer such as lung cancer as it follows human decision making aid in its capability to function from fairly accurate analysis and eventually to discover defined result.

In this research the aim is to develop a prototype diagnosis system in order to make decision for appropriate treatment relying on the facts that these types of medical issues can be resolved incorporating the simplest rule set followed by the resolution or necessary actions taken by the professionals using the fuzzy systems. This rule set will be basically used during the diagnosis of the nodule depending upon the symptoms of different stages and the course of action to be taken. The fuzzy system is going to enable implication morphology to assemble a system on the basis of a set human language rules provided by the users. Since, fuzzy logic is extremely intangible and transforms these rules to their set of mathematical expressions. This also makes it easier the task of the computer and fuzzy system designer and outcomes in accuracy up to a great extent demonstration of the approach systems perform in the ongoing situations in real life.

Literature review: The literature shows a variety of techniques which have been used for the detection of lung cancer. Seker *et al*. (2003) designed a fuzzy logic system for k-nearest neighbor classifier and the comparison was performed statistical method logistic regression and neural networks using back propagation. Here, they have explained that the precise and consistent decision making in oncology prognosis provides help in the setting up of appropriate surgical procedure and treatments. They aimed to explore the Fuzzy K-Nearest Neighbor (FK-NN) classifier as a fuzzy logic method that avails a confidence level for prognostic judgment and evaluation of the markers and to compare with other methodologies. For analysis, they worked on breast and prostate cancer data sets and the FK-NN-based method was found to be most accurate one.

Dehmeshki *et al*. (2007) adopted optimal thresholding and shape oriented analysis for the segmentation of lesion area. Here, a shape-based Genetic Algorithm Template-Matching (GATM) scheme was developed in order to detect the spherical nodules. For pre-processing, a spherical-oriented convolution-based filtering technique was employed for enhancement. Here, for template matching, lung nodule phantom images were used as base images. In this method, detection rate was found to be approximately 90% as the irregular shaped nodules were not detected which were closer to either chest wall or lung wall. According to Suarez-Cuenca *et al*. (2009), they performed a number of operations for detection of the nodule such as 2D segmentation, region labeling process along with a variety of morphological operations in order to obtain the lung regions matching with original size. A 3D region labeling methodology was also used in order to resolve the situations where lung tissues are at the bottom of the lungs. Gutte *et al*. (2007) implemented a fully automated technique based on artificial neural networks and image processing methods used for the interpretation of combined Computed Tomography (CT), Fluoro Deoxy Glucose (FDG), Positron Emission Tomography (PET), images for the diagnosis of lung cancer. Here, they studied the data of 87 patients who took PET/CT examinations due to suspicious activity of lung cancer used as the training dataset. The test dataset comprised of PET/CT images from 49 patients who were having the suspicious activity of lung cancer. Street, developed a neural network model to predict breast cancer using the data sets. He presented a novel technique to prognostic prediction, using thoughts from nonparametric information to entirely make use of all of the accessible data in a neural architecture. The technique was practiced for breast cancer prognosis which resulted out in flexible, precise models that may take part in preventing redundant surgeries. Here, they were anxious particularly with prognosis. Computer aided diagnosis techniques for CT image classification were proposed by Camarlinghi *et al*. (2012), Abdulla and Shaharum (2012), Cascio *et al*. (2012), Al-Daoud (2010) and Sofka and Stewart (2010).

Wu *et al*. (2010) proposed a stratified statistical learning technique to distinguish the three major lung anatomies, namely vessel, fissure and lung wall. They designed a fully automated voxel-by-voxel segmentation method of anatomies form a 3D lung image, via. an incorporated feature set and classifier beneath provisional random field. Then, to form Probability Co-occurrence Maps (PCM) encoding the spatial background correlations of the candidate nodule, they used the generated class Probability Response Maps (PRM) by voxel-level classifiers. Depending on PCMs, higher level classifiers were trained. They also developed a new iterative fissure structure enhancement filter with advanced performance. For experimental justification, they created database of 784 nodules of a variety of shapes and sizes from 239 patients. The accuracy of multi-class voxel labeling was found to be 89.3-91.2%. Fuzzy classifiers also have been quite useful for classification of pattern recognition class with use of number of member function (Vieira *et al*., 2012; Li *et al*., 2011; Kakar *et al*., 2013; Pimental and Souza, 2013).

Levner and Zhang (2007), the watershed segmentation scheme was presented with use of creation of topographical function and object markers. Here, two major operations of image processing segmentation and pixel grouping were analyzed by researcher. Since, there are lots of image segmentation techniques therefore, while objects of the similar predefined set are in close propinquity to one another, pixel grouping becomes an important step to group the classified pixels into objects. The water shed algorithm is generally used inside the unsupervised surroundings of segmenting an image into a set of non-overlapping areas. Usually, marker-driven watershed segmentation provides seeds representing the occurrence of objects or background at precise image locations. The proposed technique was unswervingly appropriate to both single channel and multichannel images. In addition instead of flooding the gradient image, they used the inverted probability map as input to the designed algorithm. Experimental results have shown the higher performance of the classification based watershed segmentation algorithm for the different application domains like remote sensing and bio-medical domains.

Sivkumar (2013) developed a competent lung nodule detection system by applying nodule segmentation with use of fuzzy based clustering schemes and classification using a machine learning technique named as Support Vector Machine (SVM). For comparison and better analysis he used different types of kernels during classification and out of those kernels RBF kernel was found to be one giving best performance. SVM performs classification by drawing an N-dimensional hyper plane which precisely differentiates the input data into two categories. Depending on the kernel types, the discrimination of data can be either linear or non-linear. Keshani (2010) worked on CT images for lung nodule segmentation. Here, the ultimate aim was to detect the non isolated nodules automatically and then accurate segmentation of solid and cavity nodules using Active Contour Modeling (ACM). This technique was involving numerous functions to segment lung using ACM, transferring non-isolated nodules into isolated ones, ROI extraction using features and then detection using 3D features. Here, all solid and cavity nodules were detected and the number of FP used was 3/scan.

Street designed an algorithm which is a combination of feature extraction indexing, refinement and decision processes. He also worked on recognition of neighborhoods also. This technique was found to be efficiently faster on CT images. The researcher demonstrated the alignment of about 250 nodules and the algorithm was found to be robust to changes caused which were incorporated by cancer progression and differences in breathing states, scanning techniques and patient positioning. Also, this algorithm was found to be useful both for diagnosis and treatment monitoring of lung nodules. Okada and Akdemir (2005) proposed a new semi-automatic figure-ground segmentation technique for blob-like objects in 3D images. These blob-like structures form various objects which are hard to segment for example, tumor lesions in 3D medical data. The proposed technique was aggravated towards computer-aided diagnosis. For more efficient segmentation realization, robust anisotropic Gaussian Model fitting technique along with likelihood ratio test based non-parametric segmentation techniques was combined. For lung nodule segmentation, the 3D implementation of the proposed algorithm was done. The algorithm was found to be too speedy that on an average it was able to segment the nodule within 3 sec.

MATERIALS AND METHODS

As we have seen the issues related to segmentation, recognition accuracy and algorithm complexity, here, we propose an enhanced recognition scheme for lung nodule classification which uses Fuzzy Expert System (FES) which consists of two basic stages of lung cancer risk, namely First Stage Cancer Risk (FSCR) and Second Stage Cancer Risk (SSCR). The input feature sets for FSCR are four demographic data such as age, gender, drinking, alcohol along with two medical data BMI (Body Mass Index) and DM (Diabetes Mellitus). The inputs for SSCR are clinical data like chest pain, bleeding, loss of weight, vomiting, cough and the output of FSCR.

Fuzzy expert system is vastly used in bio-medical diagnostic situations owing to its inbuilt indistinctness and ambiguity in the medical data. It is truly dependent on imprecision, exclusively, the mode people create decisions on non-numeric imprecise values. Expert system is also a sub domain of artificial intelligence. Fuzzy expert systems imitate the thinking process of a human and try to construct logical decisions consequently particularly in the field of medical science. Fuzzy logic also has two dissimilar meanings. In a precise sense, fuzzy logical system is an extension of multi valued logic. While on the other hand in a broader sense it is roughly identical with the theory of fuzzy sets connecting classes of objects with smoother boundaries in which membership is a concern of level. The main motto of fuzzy logic is mapping an input set to an output set, along with a list of rule sets including set of if-then statements. All these rules defined here are evaluated in parallel manner. Hence, there is no issue of order or precedence of occurring for them. These rules are very helpful, since they pass on to variables and the properties by virtue these variables are described. While designing a system with some rule set we should explicitly define each and every term with their usage of properties and descriptions. Figure 1 provides a blueprint for the fuzzy inference method. It displays the common description of a fuzzy system on the left with a specific example of fuzzy system on the right side. We propose a step-by-step algorithm in modeling lung nodule recognition using the Fuzzy Expert System (FES) as shown in Fig .2. This shows an entire framework to model recognition and treatment which features automatic prediction of the most suitable FES model structure with given fuzzy rule sets and features. The fuzzy system techniques are performed by transforming every input set into a membership rank depending on the

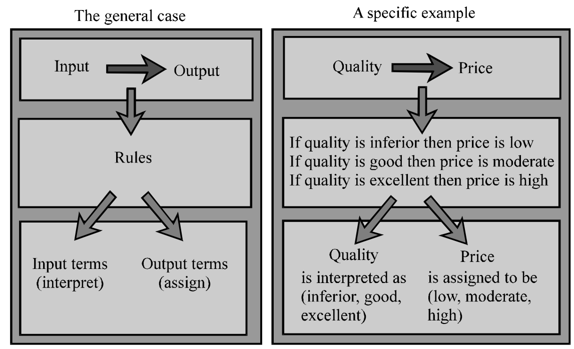

Fig. 1: Example of a fuzzy system

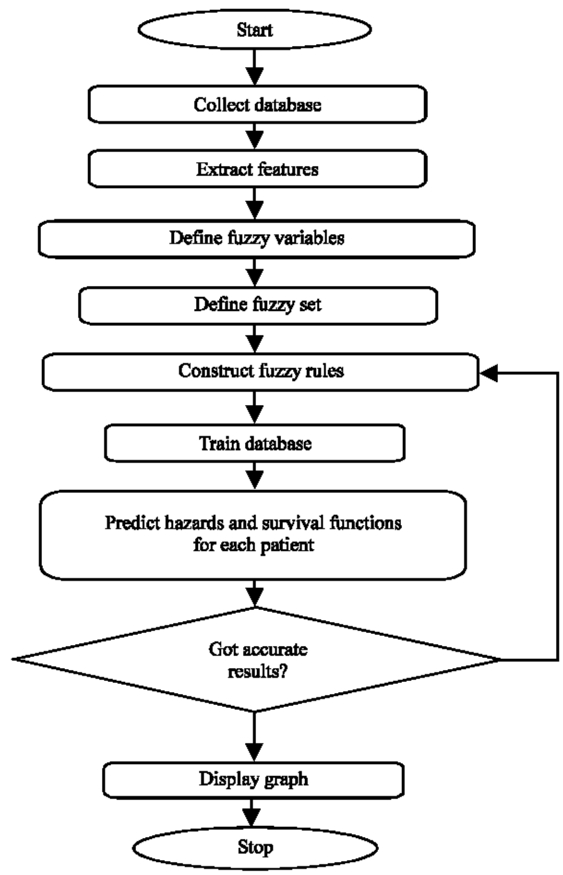

Fig. 2: Flow of proposed work

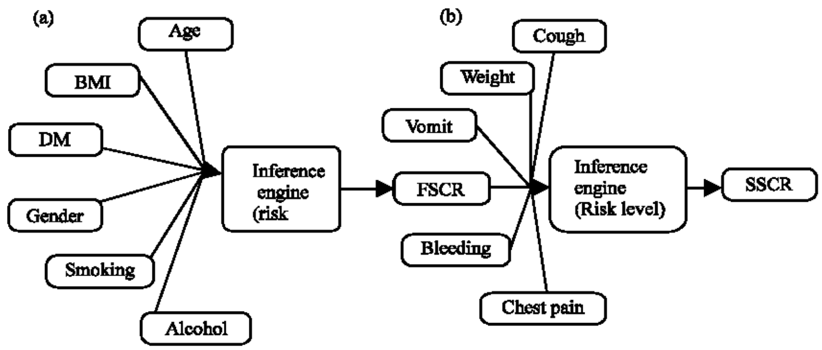

Fig. 3: a) FES for FSCR and b) FES for SSCR

Table 1: Linguistics values for feature sets for FSCR

Feature set	Linguistics value
Age	Young, moderate, old
Gender	Male, female
BMI	Low, medium, high
DM	Low, medium, high
Smoking	No, occasional, regular
Alcohol	No, occasional, regular

defined membership functions and application of the appropriate fuzzy operators for operating the fuzzy reasoning method to obtain the fuzzy set. This process will be kept on repeating until the accurate results are obtained. The fuzzy expert system modeling will take place in various steps such as; identification of the input data variables, output data variables, fuzzy set and fuzzy numbers); fuzzification interface; fuzzy assessment methodology and defuzzification interface. Here, we use linguistic data variables realize a fuzzy expert system. These variables can be depicted by words by giving the values in its particular range. These linguistic values for the defined feature sets for FSCR are takes as shown in Table 1.

FES rules are detailed rules with linguistic value sets using IF-THEN rules. It is having two parts; the first part is forerunner block that lies between the IF and THEN and the second part is a subsequent block that follows THEN. The membership function is the main basis of a fuzzy logic controller. Their role is to convert the non-fuzzy values data in to fuzzy data. They contain the fuzzy variable sets. Special types of fuzzy sets which will be going to restrict the probable types of membership functions are known as fuzzy numbers. The fuzzy controller is consisting of the membership functions, inference engine rules and defuzzification function. The FES taken for proposed work for FSCR and SSCR are shown in Fig. 3a and b, respectively.

Next, we go for fuzzification which transforms these fuzzy sets values into the linguistic terms by use of fuzzy membership functions. Fuzzification uses member function and the factors (weights). These all formulation steps are done with the lots of study of literature and with aid of the experts. For the proposed research, we have used the following membership functions and formulations:

$$\text{Age}\,(A) = 1;\ a>84\ \ a\ ;0 \le a \le 84$$

$$\text{BMI}\,(b) = 1\ ;\ b>30\ \ b\ ;0 \le b \le 30$$

$$\text{Smoking}\,(S) = 1;\ s>25\ \ s\ ;0 \le s \le 25$$

$$\text{Alcohol}\,(Al) = 1;\ al \ge 5.5 al\ ;0 \le al<5.5$$

In the set of above derived rules the linguistic variables are being used are age, smoke and alcohol, BMI and DM. The linguistic expressions for the linguistic variable can be derived easily. For example for linguistic variable age:

$$\mu_{yong}(A) = \ a/28\ ;0 \le a \le 3.5\ \ 0;\ \text{otherwise}$$

$$\mu_{moderate}(A) = 0;\ a \le 3.5 a/10\ ;\ 3.5<a \le 6.5\ \ 0;\ \text{otherwise}$$

$$\mu_{old}(A) = 0;\ a \le 8.5\ a/9;\ a>8.5$$

Also, factors (weights) of age are defined as:

$$W_{Age} = -1;\ 0 \le \mu_{Age} \le 0.4\ \ 0.1;\ 0.4<\mu_{Age} \le 0.6\ \ 0.3;\ 0.6<\mu_{Age} \le 1$$

Similarly, we can determine the linguistic expressions and weights expressions for other input feature sets such as BMI, DM, smoking and alcohol. Further, the output factor of this first level fuzzy logic can be calculated with exclusive use of all linguistic expressions given. The probable outcome factors will be depicted as low, medium and high expressed using the derived formulas. Next, we

Table 2: Rule sets for FSCR

Rules	Age	BMI	DM	Gender	Smoking	Alcohol	FSCR
R1	Y	L	L	F	No	No	L
R2	Y	L	L	F	No	O	L
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
R485	O	H	H	M	R	No	M
R486	O	H	H	M	R	R	H

Table 3: Rule sets for SSCR

Rules	FSCR	Cough	Chest pain	Weight loss	Vomiting	Bleeding	SSCR
R1	L	Yes	No	No	No	No	L
R2	L	Yes	Yes	No	No	No	L
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
R95	H	Yes	Yes	Yes	No	No	M
R96	H	Yes	Yes	Yes	Yes	Yes	H

convert these quantifiable values into desired fuzzy values by the process of defuzzification. The decision value set or the specific real values will be converted version of membership function degrees of fuzzy data sets. The overall performance of our fuzzy expert system will be improved by use of fuzzy operator. The fuzzy assessment method performs following steps:

- Selection of appropriate the membership function and fuzzy operator
- Calculation of probability for given fuzzy rules
- Computation of correlation for given fuzzy logic
- Evaluation of the rules by logical or operation
- MIN operator will be mapping the forerunner part of the rule set into result and SUM operator will be going to combine the output of each rule set into a single set

The First Stage Cancer Risk (FSCR) can be derived from demographic data and routine activites of patient such as age, gender, BMI, DM, smoking parameter and alcohol parameter are defined as linguistic variables. The designed fuzzy expert system has 486 rules that frames a total of 486 pairs of output which are associated with the risk factors of lung cancer. With this we are able to develop a fuzzy system that can accurately calculate the first stage cancer risk factor level of the patient suffering from lung cancer disease. For example, rule1 says if Patient is of young age, gender is female, both BMI and DM is low and no smoking and alcohol habit then the FSCR will be low. These developed 486 FES rules are used to evaluate FSCR and are tabulated as in Table 2.

The Second Stage Cancer Risk (SSCR) can be derived from FSCR output and clinical or medical symptoms of patients such as chest pain, cough, weight loss, bleeding, vomit, etc. The designed fuzzy expert system has 96 rules that frames a total 96 pairs of output which are associated with the risk factors of lung cancer. With this, we are able to develop a fuzzy system that can accurately calculate the second stage cancer risk factor level of the patient suffering from lung cancer disease. For example, rule 1 says if FSCR is low, patient has symptoms of cough = yes, vomit = no, weight loss = no, bleeding = no, chest pain = no then the SSCR will be low. These developed 96 FES rules are used to evaluate SSCR and are tabulated as in Table 3.

RESULTS AND DISCUSSION

We have designed the fuzzy expert system using MATLAB (Matrix Laboratory) Software. In MATLAB, for designing FES there is an exclusive toolset known as fuzzy logic toolbox. The proposed design has been experimented on real time database collected from KMC and Oncology Department Ramaiah Hospital, Bangalore. The designed fuzzy expert systems for proposed work FSCR and SSCR are as shown in Fig. 4 and 5, respectively. The membership function for FSCR which is also an input for SSCR is also shown in Fig. 6-8. It is designed from the output obtained from FSCR which basically depends on the inputs of FSCR, i.e., age, BMI, DM, gender, smoking and alcohol. The FSCR outputs are generally low, medium and high. The FSCR value is depicted low if its obtained weighted value is ≤ 0.25, medium if it is from 0.25-0.70 and high if it is ≥ 0.70. Further, depending on this FSCR and the clinical parameters such as cough, chest pain, bleeding, vomit and weight loss, we have calculated the output of SSCR. The output weight for SSCR was calculated depending on the related membership functions and linguistic expressions. The SSCR outputs are generally low, medium and high. The SSCR value is depicted low if its obtained weighted value is ≤ 0.25, medium if it is from 0.25-0.70 and high if it is ≥ 0.70.

For performance analysis of the proposed research, we have also developed the confusion matrix using MATLAB. The confusion matrix has basically four components namely True Positive (TP), True Negative

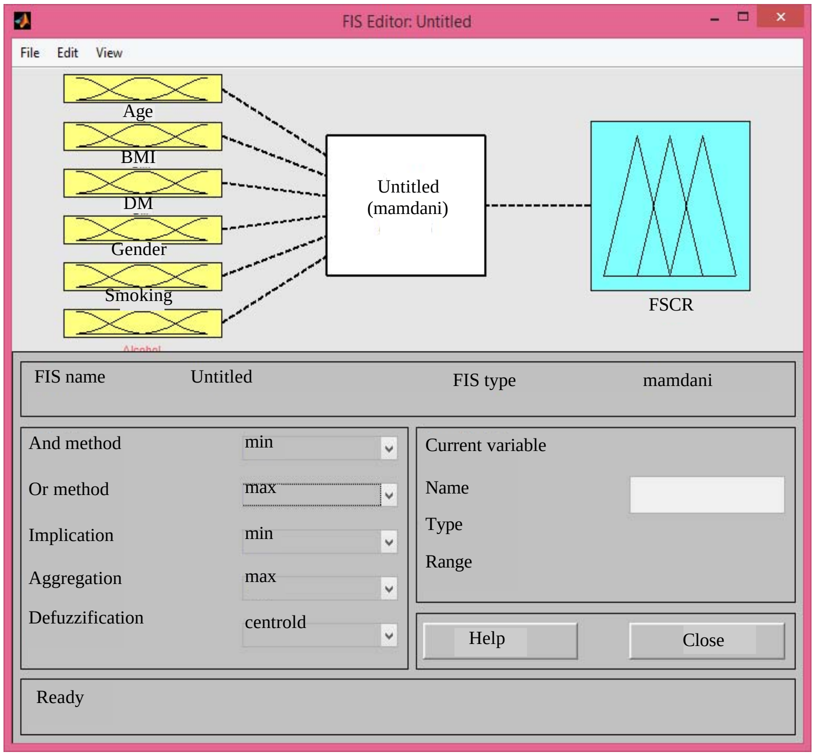

Fig. 4: Designed FES in MATLAB for FSCR

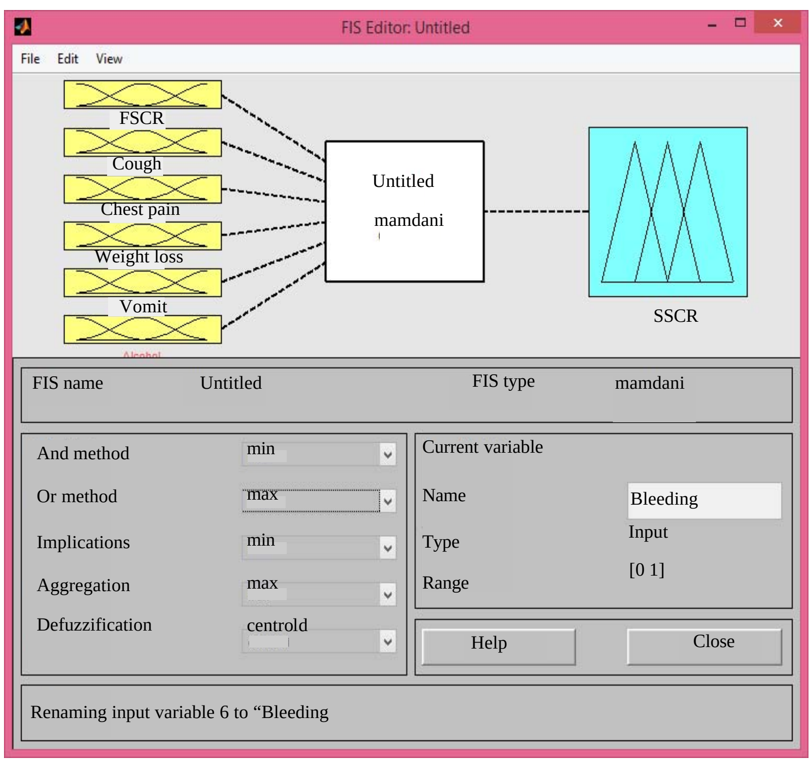

Fig. 5: Designed FES in MATLAB for SSCR

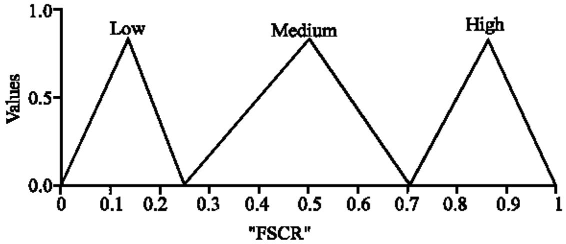

Fig. 6: Membership function for FSCR

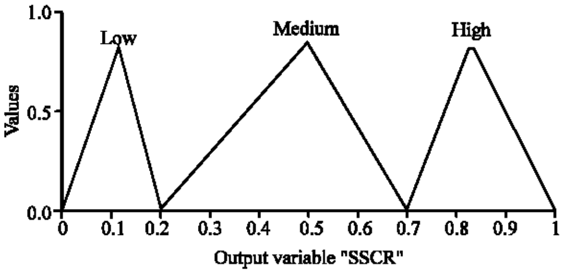

Fig. 7: Membership function for SSCR

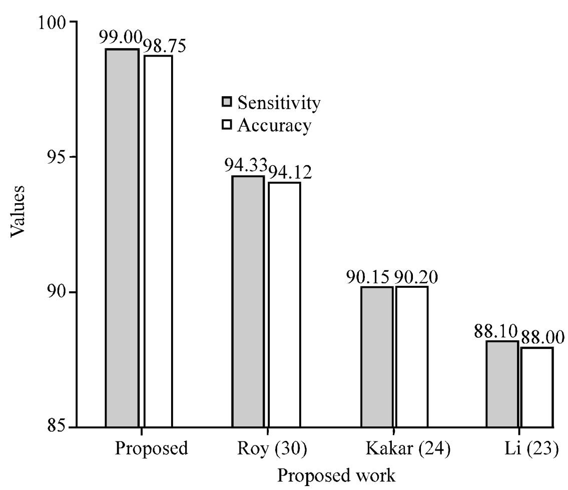

Fig. 8: Comparative analysis of accuracy and sensitivity for proposed work with existing works

(TN), False Positive (FP) and False Negative (FN). Where, TP and TN are the correct classified output and FP and FN are the wrong classification output. These all four parameters help us to calculate the different parameters such as sensitivity (True Positive Rate, TPR), Specificity (True Negative Rate, TNR) and accuracy. These all parameters have been formulated in equation set. For the proposed work, the accuracy achieved is 98.75%. Also, the comparative analysis of sensitivity and accuracy with existing papers has been shown in Fig. 6:

$$\text{Sensitivity}\left(\text{TPR}\right) = \text{TP/P where, P} = \text{TP+FN}$$

$$\text{Specificity}\left(\text{TNR}\right) = \text{TN/N where, N} = \text{TN+FP}$$

$$\text{Fall Out}\left(\text{FPR}\right) = \text{FP/N}$$

$$\text{Miss Rate}\left(\text{FNR}\right) = \text{FN/P}$$

$$\text{Accuracy} = \left(\text{TP+TN/P+N}\right)\times 100\%$$

CONCLUSION

Lung cancer disease is life frightening and is not curable in the advanced stages. Hence, the only key to cure is the early stage detection. A two stage fuzzy expert system based approach presented in this study is a step for early detection of lung nodule from the demographic data with basic clinical details. We have meticulously analyzed the effect of each feature set input on the various outputs. Therefore, at first stage of fuzzy expert system we have used 486 fuzzy rules while for the second stage total 96 fuzzy rules have been used. The results obtained here were compared with the results obtained by Li *et al.* (2011), Kakar *et al.* (2013) and Roy *et al.* (2015) and found to be more accurate for the same database. This is due to incorporating two stages of fuzzy expert system and using six feature sets at each stage. Also, the proposed research was found to be quite speedy to generate final results. The accuracy achieved with proposed work was found to be 98.75%.

RECOMMENDATION

The future scope of the proposed research is to include a third stage of fuzzy expert system by using statistical features of lung nodule extracted from the CT images in order to increase the accuracy further and to analyze the tumor growth with suggestions for the proper treatment techniques for curing the disease.

REFERENCES

Abdulla, A.A. and S.M. Shaharum, 2012. Lung cancer cell classification method using artificial neural network. Inf. Eng. Lett., 2: 52-58.

Adlassing, K.P., 1986. Fuzzy set theory in medical diagnosis. IEEE Transac. Systems Man Cybernetics SMC, 16: 260-265.

Al-Daoud, E., 2010. Cancer diagnosis using modified fuzzy network. Universal J. Comput. Sci. Eng. Technol., 1: 73-78.

Camarlinghi, N., I. Gori, A. Retico, R. Bellotti and P. Bosco *et al*., 2012. Combination of computer-aided detection algorithms for automatic lung nodule identification. Int. J. Comput. Assisted Radiol. Surgery, 7: 455-464.

Cascio, D., R. Magro, F. Fauci, M. Iacomi and G. Raso, 2012. Automatic detection of lung nodules in CT datasets based on stable 3D mass-spring models. Comput. Biol. Med., 42: 1098-1109.

Dehmeshki, J., X. Ye, X. Lin, M. Valdivieso and H. Amin, 2007. Automated detection of lung nodules in CT images using shape-based genetic algorithm. Comput. Med. Imaging Graoh., 31: 408-417.

Er, O., N. Yumusak and F. Temurtas, 2010. Chest diseases diagnosis using artificial neural networks. Expert Syst. Appl., 37: 7648-7655.

Gurcan, M.N., B. Sahiner, N. Petrick, H. Chan, E.A. Kazerooni, P.N. Cascade and L. Hadjiiski, 2002. Lung nodule detection on thoracic computed tomography images: Preliminary evaluation of a computer-aided diagnosis system. Med. Phys., 29: 2552-2558.

Gutte, H., D. Jakobsson, F. Olofsson, M. Ohlsson and S. Valind *et al*., 2007. Automated interpretation of PET/CT images in patients with lung cancer. Nucl. Med. Commun., 28: 79-84.

Hong, H., J. Lee and Y. Yim, 2008. Automatic lung nodule matching on sequential CT images. Comput. Biol. Med., 38: 623-634.

Kakar, M., A. Mencattini and M. Salmeri, 2013. Extracting fuzzy classification rules from texture segmented HRCT lung images. J. Digital Imaging, 26: 227-238.

Keshani, M., 2010. Lung nodule segmentation using active contour modeling. Proceedings of the 6th Iranian Conference on Machine Vision and Image Processing (MVIP), October 27-28, 2010, IEEE, Isfahan, Iran, ISBN:978-1-4244-9706-5, pp: 1-6.

Levner, I. and H. Zhang, 2007. Classification-driven watershed segmentation. IEEE Trans. Image Proces., 16: 1437-1445.

Li, D.C., C.W. Liu and S.C. Hu, 2011. A fuzzy-based data transformation for feature extraction to increase classification performance with small medical data sets. Artif. Intell. Med., 52: 45-52.

Okada, K. and U. Akdemir, 2005. Blob segmentation using joint space-intensity likelihood ratio test: Application to 3D tumor segmentation. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR) Vol. 2, June 20-25, 2005, IEEE, San Diego, California, USA., ISBN:0-7695-2372-2, pp: 437-444.

Penedo, M.G, M.J. Carreira., A. Mosquera and D. Cabello, 1998. Computer-aided diagnosis: A neural-network-based approach to lung nodule detection. IEEE Trans. Med. Imaging, 17: 872-880.

Pimentel, B.A. and R.M.D. Souza, 2013. A multivariate fuzzy C-means method. Appl. Soft Comput., 13: 1592-1607.

Roy, T.S., N. Sirohi and A. Patle, 2015. Classification of lung image and nodule detection using fuzzy inference system. Proceedings of the International Conference on Computing, Communication and Automation (ICCCA), May 15-16, 2015, IEEE, Noida, India, ISBN:978-1-4799-8890-7, pp: 1204-1207.

Samuel, C.C., V. Saravanan and M.V. Devi, 2007. Lung nodule diagnosis from CT images using fuzzy logic. Proceedings of the International Conference on Conference on Computational Intelligence and Multimedia Applications Vol. 3, December 13-15, 2007, IEEE, Sivakasi, Tamil Nadu, India, ISBN:0-7695-3050-8, pp: 159-163.

Seker, H., M.O. Odetayo, D. Petrovic and R.N.G. Naguib, 2003. A fuzzy logic based-method for prognostic decision making in breast and prostate cancers. IEEE. Trans. Inf. Technol. Biomed., 7: 114-122.

Sivkumar, S., 2013. Lung nodule detection using fuzzy clustering and support vector machine. Intl. J. Eng. Technol., 5: 179-185.

Sofka, M. and C.V. Stewart, 2010. Location registration and recognition (LRR) for serial analysis of nodules in lung CT scans. Med. Image Anal., 14: 407-428.

Suarez-Cuenca, J.J., P.G. Tahoces, M. Souto, M.J. Lado, M. Remy-Jardin, J. Remy and J.J. Vidal, 2009. Application of the iris filter for automatic detection of pulmonary nodules on computed tomographyimages. Comput. Biol. Med., 39: 921-933.

Taylan, O. and B. Karagozoglu, 2009. An adaptive neuro-fuzzy model for prediction of student's academic performance. Comput. Ind. Eng., 57: 732-741.

Vieira, S.M., J.M. Sousa and U. Kaymak, 2012. Fuzzy criteria for feature selection. Fuzzy Sets Syst., 189: 1-18.

Walia, N., S.K. Tiwari and R. Malhotra, 2015. Design and identification of tuberculosis using fuzzy based decision support system. Adv. Comput. Sci. Inf. Technol., 2: 57-62.

Wu, D., L. Lu, J. Bi, Y. Shinagawa and K. Boyer *et al*., 2010. Stratified learning of local anatomical context for lung nodules in CT images. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 13-18, 2010, IEEE, San Francisco, California, ISBN:978-1-4244-6984-0, pp: 2791-2798.