Diagnosis of Lung Cancer Disease using Neuro-Fuzzy Logic

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Abstract

Artificial Neural Network and fuzzy logic are the branch of Artificial intelligence, have been accepted as a new technology in computer science. Neural Networks and fuzzy logic has rapidly become one of the most successful of today's technologies especially in the field of medicine, particularly in the fields of radiology, urology, cardiology, oncology and etc. In this paper, an attempt has been made to make use of neural networks and fuzzy logic in the medical field (carcinogenesis (pre-clinical study)). In carcinogenesis, neuro-fuzzy have been successfully applied to the problems in both pre-clinical and post-clinical diagnosis. . In this study, a fuzzy logic-based system for diagnostic decision support for pre-clincial diagnosis of cancer diseases is presented.

Keywords: Neural networks, fuzzy logic, carcinogenesis, lung cancer , rule extraction, back propagation , medical decision making, decision support systems, rule extraction, membership function , fuzzy inference model , Machine learning, etc,.

1.0 Introduction

Neuro-fuzzy applications are used in a wide range medical diagnosis. Even today, the diagnosis cancer disease represents a serious clinical problem. The medical knowledge in this field is characterized by uncertainty, imprecision and vagueness. Medical diagnosis is one of major problem in medical application.

Several research groups are working world wide on the development of neural networks in medical diagnosis. A detailed study on Artifical Neural Network (ANN) can be seen in "Neural and Adaptive Systems: Fundamentals Through Simulations "by Principe, Euliano, and Lefebvre(2000). Paulo J. Lisboa and Azzam F.G. Taktak (2006) had done a systematic review on artificial neural networks in decision support in cancer. This paper reports on a systematic review that was conducted to assess the benefit of artificial neural networks (ANNs) as decision making tools in the field of cancer. This paper reviews the clinical fields where neural network methods figure most prominently, the main algorithms featured, methodologies for model selection and the need for rigorous evaluation of results. Theakos N (2004),developed a fuzzy system to understand a disturbance occurred after a diagnosing . Zarkadakis G (1989), Monitored the arterial acid-base status of ICU patients .He measured and calculated the acid-base variables pH, the partial pressure of carbon-dioxide (PCO2) and the bicarbonate-ion concentration ([HCO-3]).Based on these values he had developed a computer program for the multivariate evaluation and graphical monitoring . A composite index is introduced for the monitoring of all three laboratory values. Jari J. Forsstrm , Kevin J. Dalton (1995) developed connectionist models such as neural networks, which define relationships among input data that are not apparent when using other approaches. They also reviewed the use of neural networks in medical decision support. Paulo J. Lisboa , Azzam F. G. Taktak(2006) assess the benefit of artificial neural networks (ANNs) as decision making tools in the field of cancer. In the work of G Wilym s. Lodwick,M.D.,Richard Conners and Charles A. Harlow (1979), an efficient neural network model has been developed to diagnosis the carcinogenesis. Neural network have been applied to breast cancer diagnosis. Kiyan and Yildirim(2003) employed Radial Basis Function, General Regression Neural Network and Probabilistic Neural Network in order to get the suitable result.

1.1 Cancer disease pre-clinical Detection and Neural Networks

Carcinogenesis (the creation of cancer), is the process by which normal cells are transformed into cancer cells. (In other words, uncontrolled and dangerous cell growth). Cancer is the general name for over 100 medical conditions involving uncontrolled and dangerous cell growth. One of the major determinants of an individual susceptibility to cancer is sex - An obvious distinction that accounts for much of the variation in cancer g known carcinogens. Compared to nonsmokers, men who smoke are about 23 times more likely to develop lung cancer and women who smoke are about 13 times more likely. Smoking causes about 90% of lung cancer deaths in men and almost 80% in women. (For women, the risk of cervical cancer increases with the duration of s incidence. There are a number of cancers to which only males are susceptible or to which only females are susceptible. For eg., females have no risk of ever experiencing cancer of prostrate, penis and males are not threatened by ovarian ,endometrial or cervical cancers. The next factor of susceptibility to cancer is age –Susceptibility to cancer is low for persons under thirty years of age and increases steadily in subsequent age groups, while middle aged persons and particularly older persons are more susceptible to cancer. The third factor is genetic predisposition - Some adult cancers show the effects of genetic transmission of susceptibility although other factors may be more prominently associated with their development. Lung cancer is an example of such inherited susceptibility. In case of female breast cancer, close relatives of breast cancer patients have a high risk of breast cancer two or three times that of women with no family history of breast cancer. The fourth factor considered is geographic variations - Scientists suggest that some cancer is caused by environmental conditions. Today, cancer constitutes a major health problem .Penedo et al (1998) developed a system that employed an artificial neural network to detect suspicious regions in a low-resolution image and employed another artificial neural network to deal with the curvature peaks of the suspicious regions, which was used in the detection of lung nodules found on digitized chest radiographs. Bartfay (2006) proposed a neural network model. Utilizing data on patients from two National Cancer Institute of Canada clinical trials, he compared predictive accuracy of neural network models and logistic regression models on risk of death of limited-stage small-cell lung cancer patients.

1.2 Cancer disease pre-clinical Detection and Fuzzy

Today, cancer constitutes a major health problem Lung cancer is one of the most common and deadly diseases in the world. It is the second leading cause of death .The most common risk factor for lung cancer is smoking, due to the harmful carcinogens found in tobacco smoke. Lung cancer is one of the most common and deadly diseases in the world. Detection of lung cancer in its early stage is the key of its cure. Several hundred papers based on fuzzy set theory in medicine were published in different aspects of application: diagnosis, differential diagnosis, therapy, image analysis, pattern recognition, patient monitoring, medical data analysis, data bank, text analysis and etc,. John, R.I (2005) describes a fuzzy approach to computer-aided medical diagnosis in a clinical context. It introduces a formal view of diagnosis in clinical settings and shows the relevance and possible uses of fuzzy cognitive maps. A lightweight fuzzy process is described and evaluated in the context of diagnosis of two confusable diseases. The process is based on the idea of an incremental simple additive model for fuzzy sets supporting and negating particular diseases. These are combined to produce an index of support for a particular disease. The process is developed to allow fuzzy symptom information on the intensity and duration of symptoms. Results are presented showing the effectiveness of the method for supporting differential diagnosis. Elpiniki I. Papageorgiou (2009) ,developed a new approach for the construction of Fuzzy Cognitive Maps augmented by knowledge through fuzzy rule-extraction methods for medical decision making is investigated. The system proposed is based on diagnosis cells that depending upon the type of knowledge, can be fuzzy inference systems, neural networks, neuro-fuzzy networks, other type of hybrid systems or even simple fuzzy or crisp mathematical formulas.

1.3 Neuro Fuzzy System - Neural Model

Neural Network Model

The construction of the neural network involves three different layers with feed forward architecture. This is the most popular network architecture in use today. The input layer of this network is a set of input units, which accept the elements of input feature vectors. The input units(neurons) are fully connected to the hidden layer with the hidden units. The hidden units (neurons) are also fully connected to the output layer. The output layer supplies the response of neural network to the activation pattern applied to the input layer. The information given to a neural net is propagated layer-by-layer from input layer to output layer through (none) one or more hidden layers.

Important issues in Multilayer Perceptrons (MLP) design include specifications of the number of hidden layers and the number of units in these layers. The number of input and output units is defined by the problem the number of hidden units of use is far from clear. That is the amount of hidden layers and their neurons is more difficult to determine. A network with one hidden layer is sufficient to solve most tasks. There is no theoretical reason ever to use more than two hidden layers. It is also been seen that for the vast majority of principal problems .Those problems that require two hidden layers are only rarely encountered in real life situations. Using more than one hidden layer is almost never beneficial. It often slows dramatically when more hidden layers are used .None of the known problems needs a network with more than three hidden layers in order to be solved error. Choosing an appropriate number of hidden nodes is important.

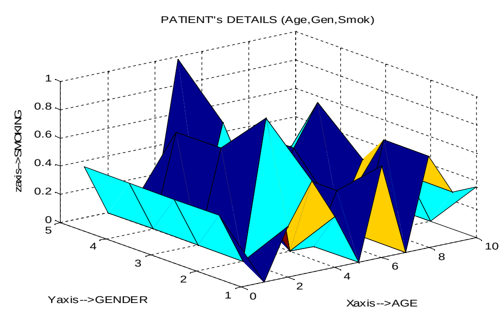
In the network the input neuron values are the demographic data concerns information such as patient's age, sex etc. The hidden neuron values are based on heuristic diagnostic knowledge represents experience accumulated through years and concerns the way an expert uses the patient data to make diagnoses.

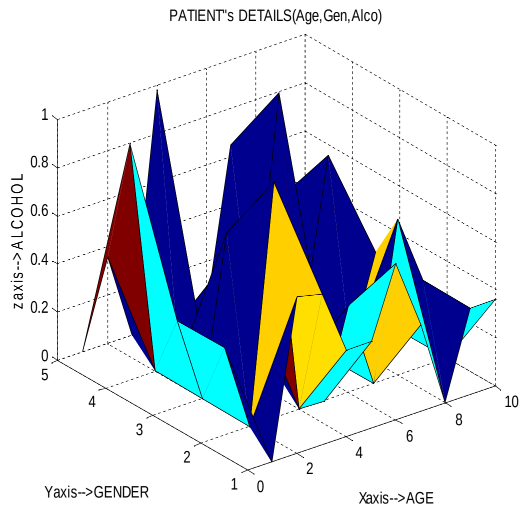
***Training the model*:**

Once a network has been structured for a particular application, that network is ready to be trained. To start this process the initial weights are chosen randomly. Learning techniques are often divided into supervised, unsupervised and reinforcement learning.

Nominal variables are used to represent the input values in the the nodes of the input layer . Nominal variables may be two-state or many-state.A two-state nominal variables is easily represented by transformation into a numeric value .For e.g, Male =0 , Female=1.Many-state nominal later. In order to test the real generalization abilities of a network to unknown data, it must be tested by classified, but yet unknown data, the test data that should not contain samples coming from patients of the training data. We have to face the fact that patient data is very individual and it is difficult to generalize from one patient to another. Ignoring this fact would pretend better results than a real system could practically achieve. Initially 100 lung cancer patients data has been collected from various hospitals and trained with the neural networks. It gives more than 87% of accuracy. Data description and Training data using neural – network model MATLAB is derived from MATrix LABoratory. The MatLab programming language is exceptionally straightforward since almost every data object is assumed to be an array it is an interactive, matrix-based system for scientific and engineering numeric computation and visualization. It includes high-level functions for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. Initially 100 lung cancer patients' data has been collected from various hospitals and trained with the neural networks. It gives more than 87% of accuracy. The results are found to be better using back propagation algorithm.

For e.g age<35={1,0,0},age>=35<=55={0,1,0}, age>55={0,0,1}.Similarly the other input values are represented .Neural networks has facilities to convert both two-state and many-state nominal variables equals the number of possible values ;one of the N variables is set and the others are cleared.





Neuro Fuzzy System - Fuzzy Model

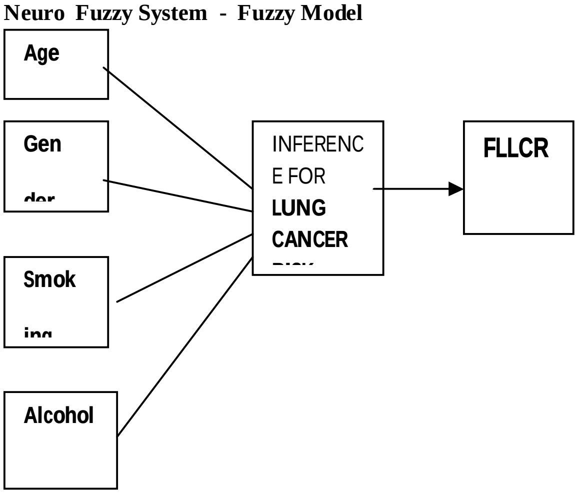


Fig 1 - Model of First Level Lung Cancer Risk

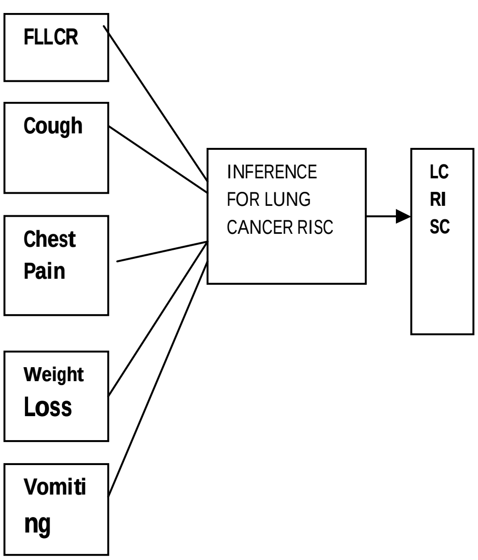


Fig 2 - Model of Second Level Lung Cancer Risk

FLLCR- First Level Lung Cancer Risk

The first level lung cancer risk is based on the patient history such as age, gender, smoking and alcohol. Fuzzy system (first level) works with 54 rules. This gives a total of 54 output pairs. It is necessary to find the exact level of risk of the patient. This will also aid in the development of automated systems that can precisely classify the risk level of the lung cancer patient under observation. Hence an optimization of the outputs of the fuzzy system is necessary. This will improve the classification of the patient. The fuzzy rules are For example, Rule 1, Rule 2,Rule 52, Rule 53 and Rule 54 can be interpreted as follows:

Rule 1	If age = Young and gender = F and Smoking = No and Alcohol = No then Cancer Risk = Low.
Rule 2	If age = Young and gender = F and Smoking = No and Alcohol = Occasional then Cancer Risk = Low
Rule XXX	-- -- --
Rule 54	If age = Old and gender = M and Smoking = Regular and Alcohol = Regular then Cancer Risk = High

Table 1 – FLLCR Rules

The second level lung cancer risk is based on the output of first level and clinical symptoms, such as cough , chest pain ,loss of weight and vomiting with 48 rules . This gives a total of 48 output pairs. The outputs of these proposed fuzzy systems are optimized. For example, Rule 1, Rule 2,Rule 40, Rule 47 and Rule 48 can be interpreted as follows

Rule 1	If FLLCR = low and cough =yes and chest pain = yes and loss of weight =yes and vomiting =yes then Lung Cancer Risk = Medium
Rule 2	If FLLCR = low and cough =yes and chest pain = yes and loss of weight =yes and vomiting =no then Lung Cancer Risk = Low.
Rule XXX	-- --
Rule 48	If FLLCR = high and cough =no and chest pain =no and loss of weight =no and vomiting =no then Lung Cancer Risk = Low.

Table 2 – SLLCR Rules

Linguistic variables

Fuzzy logic uses linguistic variables to describe a system. Linguistic variables are described by words, rather than a value like normal Boolean variables

Age	Age*W	Gen	Gen*W	Smok	Smok*W	Alco	Alco*W	FLLCR	FLLCR
.071429	0.07143	0.4	0.08	0	0	.001	.0001	.00867	Low

Table 3 – FLLCR values for an Input

Age	Age*W	Gen	Gen*W	Smok	Smok*W	Alco	Alco*W	FLLCR	FLLCR
.071429	0.07143	0.4	0.08	0	0	.001	.0001	.00867	Low

FLLCR	cough	Gen chest pain	weight loss	vomiting	SLLCR	FLLCR
0.008671	0.6	0.4	0.2	0.1	0.523469	Low

Table 4 – SLLCR values for an Input

Comparison of neural networks model and fuzzy model

Chin-Teng Lin and C. S. George Lee (1991) proposed neural-network (connectionist) model for fuzzy logic control and decision systems . This connectionist model, in the form of feedforward multilayer net, combines the idea of fuzzy logic controller and neural-network structure and learning abilities into an integrated neural-network-based fuzzy logic control and decision system.

In our proposed neuro-fuzzy model patient details are compared with neural netwok model and fuzzy model. In neural network model, for example the patient age is 30, gender is male and smoking habit is no and the alcohol is no then the chance (output) of getting cancer is 0.15 (almost nil) . In fuzzy model, for the same input values the chance of getting cancer is low. Similarly comparing the details of various patients' demographic data the neural and fuzzy model gives 82% of accurate results. For instance, the linguistic variable "age" may have "young," "middle," and "old" defining its range of values. Linguistic rules describing the control system consist of two parts; an antecedent block (between the IF and THEN) and a consequent block (following THEN). Membership functions are used to convert non-fuzzy data to fuzzy data. Moreover, membership functions are a set of fuzzy variables. For example, a range of gender values may be represented by a fuzzy variable subset "F" and "M". Each input feature is classified into various fuzzy linguistic levels a typical fuzzy controller is composed of membership functions, rules, and a defuzzification unction. This mapping produces a fuzzy membership function. For example the value if FLLCR is 0.00867143 (low) and SLLCR is 0.523469 (medium) after defuzzification. The corresponding calculated values of FLLCR and SLLCR are given below.

2.0 Conclusion

Lung cancer is one of the most common and deadly diseases in the world. Detection of lung cancer in its early stage is the key of its cure. The automatic diagnosis of lung cancer is an important, real-world medical problem. In this paper we have introduced the use of fuzzy methodology and fuzzy system for pre-clinical lung cancer. The main advantage of the model is its simplicity and good accuracy. The study has made use of common data obtained from the patients of KMC and M S Ramaiah hospital, Bangalore .

In this paper the author has shown how neuro – fuzzy system is used in actual clinical diagnosis of lung cancer . In this work, the performance of neural network structure was investigated for lung cancer diagnosis problem.

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