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SURVEY ON ARTIFICIAL INTELLIGENCE TECHNIQUES IN THE DIAGNOSIS OF PLEURAL MESOTHELIOMA

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Abstract

Malignant mesothelioma (MM) is a vigorously progressing tumour that results from mesothelium cells of various parts of the body in which pleura usually suffers. The important causes of MM are exposure to a mineral called asbestos, radiation, simian virus 40 infections and also genetic disposition. The diagnosis of MM at the early stage plays a very important role in the patient survival. Artificial intelligence techniques like PNN, DT and MLNN have been used so far in the classification of benign and malignant MM. The aim of the proposed work is to analyse all the artificial intelligence techniques used so far in the diagnosis of malignant mesothelioma. It also analyses Improved MTiling constructive neural network and SVM methods which could be further used in the diagnosis of malignant Mesothelioma.

Keywords: Classification, malignant mesothelioma, accuracy, MTiling.

Introduction

Cancer is a chronic disease with abnormal cell growth which progresses by invading the healthy cells of the body. There are more than 200 types of cancer, and these are caused by several reasons like lifestyle, environmental factors and inherited genetics. Among various types of cancers, Lung cancer also known as lung carcinoma is a type of cancer with low survival rate. Malignant Mesothelioma, a rare kind of cancer that develops in the mesothelium cells of various parts of the body like lungs, abdomen, heart and testicles. Pleural mesothelioma is a type of cancer that develops in the pleura of the lungs. It is diagnosed mostly in the third stage of cancer, and the patient survives only for 9 to 12 months after diagnosis. Exposure to a mineral called asbestos, radiation, simian virus 40 infections and also genetic disposition are the causes of MM. Asbestos fibres when inhaled, becomes embedded in the lining of the lungs causing harmful inflammation of the pleura resulting in mesothelioma. The highest per capita incidence of malignant mesothelioma in the world is the aboriginal people of Western Australia and now-closed asbestos mine may be to blame. There have been a few published reports of mesotheliomas that developed after people were exposed to high doses of radiation to the chest or abdomen as the treatment for another cancer. Some lab studies have suggested that SV40 infection might cause mesothelioma. Malignant mesothelioma has to be diagnosed at the earlier stage to avoid low survival rates and hence classification is crucial. Brauseet.al [1] stated that the task of learning to diagnosemakes the physicians confronted .Certain basic difficulties that physicians experience are listed out here:

- Valid diagnosis requires experienced cases which are attained in the middle of the physician's career.
- Even for experienced physicians, the diagnostic capability is same as newcomers when they handle rare cases like mesothelioma.
- Principally, pattern recognition systems resemble statistic computers but humans don't. Though humans recognize patterns or objects very easily, they fail when probabilities have to be assigned to observations.
- The diagnosis of rare diseases is becoming quite challenging as the new results disqualify the older treats, new cures and by the new drugs being introduced day by day.

Pleural Mesothelioma being a rare disease faces almost all the difficulties stated above by Brause.Diagnosis of Pleural Mesothelioma is done by various methods like X-Ray, CT scan, PET-CT, MRI and Biopsy. Mass screening is done by CT scan, which is a promising method for cancer detection. Long term safety of computerized tomography method is not established due to the risk of exposure to radiation. Use of microarray datais an alternative approach but quite expensive. Hence, features from the CT scan images are usedfor early detection of cancer. Malignant mesothelioma is always confused with benign mesothelioma which can also form in the pleural surroundings of the lungs. It is called asbenign fibrous mesothelioma, but it might not be visible in CT as this tumour actually does not start frommesothelial cells. Fibrous mesothelioma is usually benign, and are about 1 in 10 are cancerous.

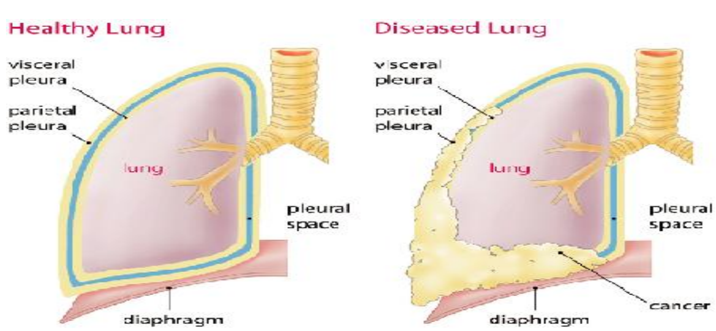

Fig.1 Healthy and MM affected lung.

Classification, an important tool of data mining has been used to classify the benign and malignant cells of mesothelioma. Usage of artificial intelligence methods for classification purposes in medical field have been increasing recently. Features extracted from malignant mesothelioma patients and benign cells are used here for classification.These features are; age, gender, city, asbestos exposure, type of MM, duration of asbestos exposure, diagnosis method, keepside, cytology, duration of symptoms, dyspnoea, ache on chest, weakness, habit of cigarette, performance status, White Blood cell count (WBC), haemoglobin (HGB), platelet count (PLT), sedimentation, blood lactic dehydrogenise (LDH), Alkaline phosphatise (ALP), total protein, albumin, glucose, pleural lactic dehydrogenise, pleural protein, pleural albumin, pleural glucose,dead or not, pleural effusion, pleural thickness on tomography, pleural level of acidity (pH), C-reactive protein (CRP), class of diagnosis. The paper describes the various classifiers used in classifying benign and malignant cells of mesothelioma in related work, followed by the implementation ofMTiling in the classification of MM in proposed methodology.

Methods:

National Institute for Health Research (NIHR) has highlighted the research into mesotheliomawith a high priority- which is funded by the PSP. It is an unusual and often fatal form of cancer with very poor survival rates. The main cause of Pleural Mesothelioma is asbestos which gets embedded in the pleura of the lungs. Pleura have two layers, visceral pleura and parietal pleura. These two layers contact and slide over each other when we breathe with the help of fluid present inbetween them. As the body's immune system tries to rid of the asbestos fibres out of the body, it causes permanent scarring and toughening of the nearby tissue. As the disease progresses, the lining of the lung thickens. This results in the formation of tumours making the blood vessels leak, resulting in pleural effusion. [2] Shows the statistics of MM with 90% of the pleural mesothelioma patients have lung fluid build-up, 79% have shortness of breath, 64 % have chest pain, 36 % have dry cough and 30 % have weight loss. Researches for the classification of MM are carried out by measuring the levels of mesothelin, a protein present in the samples. Automatic diagnosis methods are carried out in which features are extracted from CT scan images of patients. Zhen J. Wang et al [3] had suggested thatCT is the most sensitive modality widely used for the diagnosis of Mesothelioma. The primary imaging modality used for the evaluation of MPM iscomputerized tomography technique. The invasion of the pericardium results in nodular pericardial thickening or pericardial effusion which is explicit in CT findings. Interlobar fissure thickenings and pulmonary metastases of MPM are also apparent as nodules and masses which rarely, diffuse miliary nodules are identified in CT images. Despite the limitations of its accuracy being suboptimal, CT remains the imaging study of choice for initial evaluation of patients with MPM. Furthermore, the accuracy of tumour detection is enhanced by multi–detector row CT with multiplanar reformatting capability. The use of three-dimensional reconstruction of CT data is shown to be useful in the staging of neck and lung cancer as well. It is credible that volumetric CT technique can enhance the visualization of tumour extent, especially in regions such as diaphragm that may be strenuous to evaluate with axial imaging. Brims et al [4] had proposed a model for the classification ofpatients with high and lower risk of MPM using a simple, clinically relevant decision tree.The dataset is a set of parameters collected from the time of diagnosis which includes age; sex; date of diagnosis; histological findings; symptoms at presentation, including dyspnea, chest pain, and weight loss, ECOG PS, routinely performed haematological investigations and biochemical investigations and date of death. Chi-square significance test at each split in the decision tree was used with either categorical or non-discrete variables which divides it into two at the place of best fit. Despite its advantages of being extremely fast at classifying unknown records, handling continuous and distinct attributes well and working with recurrent attributes being fair enough, it still suffers. Small variations in the data leading to different looking trees, sub-trees being duplicated several times and as expected, the performance of the model not being strong on an external data set are the few corns of this model. A neural network is a "tie-in" computational system in which the computational systems written are procedural. One of the important aspects of a neural network is its ability to learn. Several artificial neural network techniques like PNN, MLNN and LVQ structures have been used for the classification of benign and malignant mesothelioma.Among feed forward and back propagation algorithms, back propagation is identified as a strong tool for training of MLNN structures and is extensively used in resolving many practical problems. OrhanEr at al [5] had proposed a model for theclassification of benign and malignant mesothelioma using various neural network techniques. They had used the same dataset with 34 features for classification. PNN was implemented in the first stage of the study with one real valued input vector in input layer, single hidden layer and two outputs with index of two classes in the output layer. Here output layer uses 'winner takes all' attitude to compare the probability density of each condition in the output layer.In the second stage of the study, the MLNN with two hidden layers was used. The steepest descent method to modify the weights was used here and hence, it suffers from a slow convergence rate and often yields suboptimal solutions. At the third stage of this study, a learning vector quantization neural network was used for the MM's disease diagnosis which had a multi-layered structure. He finally concluded that the most suitable neural network structure is PNN structure for classifying MM's data. Though PNN is well suited for classification of MM, it requires more memory space which is a key point to be considered. Ascertaining appropriate neural network architecture is quite challenging and suffers from two opposing objectives. Firstly the decision boundary has to be adequately defined and for this the network it must be large enough. Secondly for improved generalization the network must be as small as possible. All the ANN classifiers suffer from balancing these two objectives except CONN. A constructive algorithm learns the topology in a style specific to the problem rather than learning on a pre-specified network topology and at the same time its generalization capability is much better. Tiling, tower, pyramid, upstart, sequential are the various CONN algorithms for constructing and training the neurons.

Dr.S.S.Sridhar et al [6] suggested that out of various CONN algorithms; multi category tiling architecture (MTiling) is the best for its various advantages out of which a few are listed below

- Guaranteed convergence does not require the input patterns to be projected, normalized or quantized as the network itself is a vector quantizer.
- A reliable representation of training set is ensured
- As the neurons are only trained, it is faster than other constructive algorithms.

They proposed a new MTiling CONN architecture which constructs a layered network of threshold neurons through MTiling algorithm. This algorithm constructs layers of master neurons to classify maximum patterns along with ancillary neurons to address the misclassifications. MTiling architecture was found to behave better than other constructive neural networks when used with improved adaptive learning strategy. It was implemented with unsupervised learning strategy on datasets of binary pattern for achieving better performance in terms of generalization capability, faster convergence and less connection thereby requiring less storage as reported in[7].

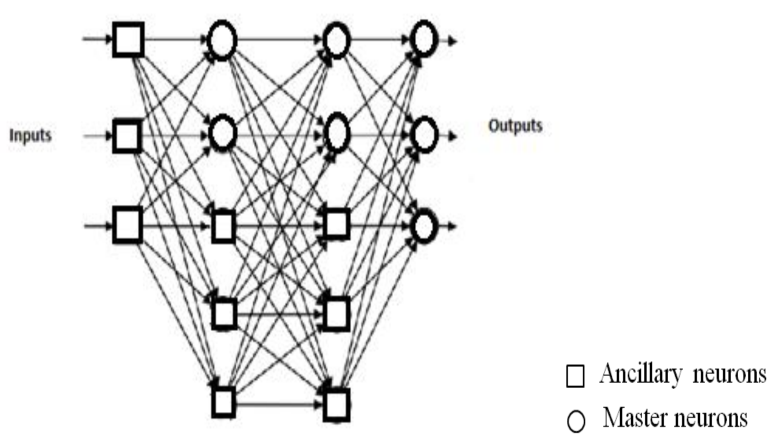

Fig 2.MTiling architecture.

The elimination of unnecessary network elements in the neural network architecture was done by network pruning. Parekh et al [8] studied the applications of pruning techniques ofMTiling to handle the real-valued pattern attributes and multiple output classes. Pruning with dead neurons, correlated neurons and redundant neurons are the three simple methods of MTiling algorithm that was discussed. Groups of one or more ancillary neurons were trained at a time in an attempt to make the current layer faithful. He considered a dataset of 2 spirals (2sp), BUPA liver disorder (liver), image segmentation (seg), wisconsin diagnostic breast cancer (wdbc), and wine recognition (wine). For runs with and without network pruning, the number of neurons pruned, the total time for pruning, the network size, the total training time and the generalization performance over the 10 runs were recorded. The winner-take-all (WTA) strategy was used to compute the outputs for datasets involving more than two pattern classes. The experimental results demonstrated a moderate to significant reduction in the network size. It must be noted that these improvements come at an additional cost of identifying the neurons that can be pruned. He concluded that the additional time spent in pruning was a small fraction of the total training time of the MTiling network. Although there was a reduction in network size, the generalization performance of the networks seemed to remain nearly the same with or without pruning.

In the last decade a growing trend is eminent in the use of other supervised learning techniques, like SVMs and BNs, towards cancer prediction and prognosisperformance. Support vector machine depends on the structural risk minimization (SRM) principle founded on the statistical learning theory, which enhances generalization capabilities.Exarchos KP et al [9] proposed a predictive model for breast cancer recurrence within five years after surgery. An initial dataset of 193 variables were selected out of which, only 14 features were considered based on their clinical knowledge. The authors employed SVM, ANN and Cox-proportional hazard regression for producing the models and to find the optimal one. On considering accuracy, sensitivity and specificity as the metrics for the efficiency of the classifier, the authors claimed that BCRSVM outperformed ANN and Cox regression models with an accuracy of 84.6%, 81.4% and 72.6%, respectively. Xuangao et al [10] proposed a model for classification of mediastinal lymph nodes. They used Gaussian radial basis function (RBF) as kernel function of support vector machine (SVM). From PET images twenty-two dimensional texture eigenvectors, 512 dimensional multi-resolution histogram eigenvectors from CT images and 534 dimensional combined eigenvectors from the PET and CT images. He had developed SVM models for CT, PET, and combined PET/CT images and labelled it as SVM1, SVM2, SVM3, respectively. He obtained a sensitivity result of

96% for PET/CT images. Their study was actually limited by a small number of malignant lymph nodes. The composition of benignity and malignancy in training sets, extraction of texture eigenvectors, and formation of final SVMs would have been affected by the low proportion of malignant lymph nodes. Besides, a synchronous manual way of segmentation was done in the extraction of lymph nodes which would have hindered the performance of SVM.

Yuan Sui et al [11]proposed a novel SVM classifier model merged with random under sampling (RU) and SMOTE. They proposed a SVM classification algorithm for lung nodule recognition (RU-SMOTE-SVM) and created a database with 150 nodules and 908 non nodules from CT images of lungs. Eight features were extracted from each sample for training and testing. They were able to balance the training samples and remove noise and duplicate information in the training sample thereby retaining only the useful information to enhance data utilization effectiveness. The pulmonary nodules classification under the unbalanced data gets ultimately improved by the performance of RU-SMOTE-SVM algorithm. The average classification accuracy was found to be 81.57% in the classification of lung nodules.

Swati et al [12]had developed a CAD system for the diagnosis of lung cancer using SVM classifier. A hyper plane in which the distance from it to the nearest data point is maximum on each side was selected. This is called as the maximum margin hyperplane and it defines a linear classifier which is known as a maximum classifier and hence the classification was done using linear classifier of SVM. The data set consists of 25 diseased lung computer tomography image JPEG images of size196x257 out of which 7 features were considered for the proposed method. SVM provides an accuracy of 92.5% in the classification of benign and malignant lung tumours.The drawback of this system is the usage of a small database which could have hindered the accuracy of system.

Analysis:

The methods discussed above are summarized in two different tables below. The traditional method used so far, its advantages and disadvantages, Improved MTiling and SVM methods used in diagnosis of various other carcinomas are explicitly mentioned with its models and methods for analysis.

Table I: Performance of ANN techniques on Pleural mesothelioma.

ANN Techniques	Methods	Advantages	Disadvantages
PNN	Random search method	96.3% accuracy	increased memory utilization
Decision tree	Chi square significance test	94.5% sensitivity	Small variations in the data leading to different looking trees sub-trees being duplicated

MLNN	Non-linear sigmoid activation function	94.41% accuracy	Requires tuning lot of parameters for achieving targeted accuracy

Table II: Performance of MTiling and SVM.

ANN techniques	Models	Methods	Advantages
MTiling	Constructive neural network with improved adaptive learning strategy	Faster than other constructive neural networks	Reduced training time with no misclassifications
SVM	Predictive model for breast cancer recurrence	BCRSVM	BCRSVM outperformed ANN and COX regression models
SVM	Predictive model for mediastinal lymph nodes	Gaussian radial basis function of SVM	96% of sensitivity
SVM	Predictive model for lung nodule recognition	RU-SMOTE-SVM	classification accuracy of 81.57% was achieved
SVM	Model for diagnosis of lung cancer	Linear classifier of SVM	92.5% accuracy in recognition of lung carcinomas

Out of the various methods used, random search method yields highest accuracy in spite of its increased memory utilization. Table 2 discusses the usage of improved Mtiling and SVM classifiers in the diagnosis of various carcinomas. It is evident from table 2 that Mtiling and SVM will certainly provide higher classification accuracy in the diagnosis of malignant mesothelioma than the other traditional methods used so far.

Conclusion

Malignant mesothelioma, an occupational disease with less survival time after prognosis, faces a tough challenge in early diagnosis. In this study, thediagnosis of pleural malignant mesothelioma using various artificial techniques has been discussed. The paper also analysesMTiling and SVM methods which have been used in the classification of various other tumours. These methods overcome the issues faced by traditional artificial techniques used so far in the diagnosis of malignant mesothelioma. In future we would like to implement improved adaptiveMTilingneural networkfor the diagnosis of malignant mesothelioma. SVM which provides betterclassification accuracy than other traditional ANN methodshave been used in the diagnosis of various carcinomascan certainlyserve as a promising tool for the classification of malignant and benign mesothelioma.Features of Improved MTiling and SVM can also be combined together for enhancing the accuracy of classification rate as a future work.

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