An Automated Lung Cancer Detection Using Soft Computing –A Review

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Abstract: Lung cancer is a disease that causes deaths worldwideto reduce the burden of the radiologists, a review has been done to understand the performance of the machine learning[ML]model for the detection of cancer in the lung nodule.The performance outcomes metrics such as sensitivity, specificity,accuracy, receiver operator characteristic. [ROC] curve and the area under the curve [AUC] are evaluated using the attributes, viz., age factor, CT chest scans, lung nodule, lung cancer, deep learning, ensemble and classic methods for inclusion earliest and the attributes such as age factor,positron emission tomography [PET] hybrid scans, chest X-ray [CXR],and genomics for exclusion crises.

Keywords: Lung cancer detection,machine learning.

Introduction: Lung cancer is the most frequent cancer in men and women around the world. It is by far the leading cause of death on the planet. Cancer kills more people than any other disease, with 1.38 million deaths per year. Lung cancer is a significant contribution to cancer, a symptom of the disease, and the rate of failure, according to several epidemiological studies undertaken across a variety of demographic groups. According to the GLOBOCAN 2020 reports, the incidence of cancer in India was 1,392,179 for all ages and sexes, with the breast, lung, mouth, cervix uteri, and tongue being the five most common body sites. Breast [57.0%], uterine cervix [60.0%], head and neck [66.6], and stomach [50.8%] cancers are the most common. Although the majority of patients were diagnosed at a locally advanced stage, males [44.0%] and females[47.6%] with lung cancer have distant metastases. Adenocarcinoma has surpassed squamous cell carcinoma as the most frequent histologic type of lung cancer in most Asian and western countries. This trend appears to be linked to a shift in smoking habits as well as an increase in the incidence of lung cancer in women and non-smokers. However, squamous cell carcinoma is still the most prevalent histologic in the majority of older and some modern Indian datasets. According to single-center data from established tertiary cancer centers, adenocarcinoma is the most common NSCLC subtype. According to their retrospective analysis of data extracted from a total of 258 consecutive hospitals in – patients with lung cancer at adyta in Chennai between January 2003 and December 2007, the most common histology was adenocarcinoma [42.6%], followed by squamous cell carcinoma [15.6%], large cell carcinoma [2.3%] and others [7%]. Due to the cytological nature of the diagnosis, sub-classifications were not possible in 49 cases [19 percent]. In terms of adenocarcinoma, there was a highly significant link between nonsmokers and smokers, as well as between smokers and nonsmokers intern of squamous cell carcinoma [p=0.0002].Similarly, during three years, 434 pathologically diagnosed lung cancer cases were examined at the all-India institute of medical sciences in Delhi [between July 2008 and 2011]. The most common histological subtype,as mentioned in the initial study, is [33.33 percent]. Adenocarcinoma was discovered to be the most prevalent histologyafter expert pathological evaluation [37.3 percent]. This highlights the current era's crucial importance of pathology review in lung cancer. Tata memorial hospital in Mumbai, Maharashtra, India, supplied and published statistical data showing that 52 percent of 489 patients were nonsmokers, with adenocarcinoma accounting for 43.8 percent and squamous cell carcinoma accounting for 26.2 percent .

Motivation:

Molecular pathology of Non-small cell lung cancer[NSCLC]: The understanding of molecular pathways that result in the malignant phenotype of many types of cancer has progressed dramatically in the recent two decades. It is now possible to have a better-known ledge of the several interwoven networks of signaling pathways involved in cancer cells' ability to grow fast while escaping different cell cycle checkpoints that prevent apoptosis, invade, and develop distant metastasis. This has sparked a flurry of pharmacological and clinical research ina range of malignancies, including NSCLC. The most recent therapeutic medications mostly target alreadyexisting receptors, which are commonly located in the brain.Some of the treatments available contain tyrosine kinase activity, blocking the activation of three kinases in a cascade and therefore preventing the transcriptional changes that create the malignant phenotype. These molecular mutations have a transformative property, suggesting that they could be a precursor to carcinogenesis, causing subsequent genetic changes that lead to cancer cells with malignant characteristics.

Lung Cancer Molecular data from the Indian population: It is unknown how much ethnic and genetic background contributes to the variance in prevalence of distinct receptor mutations. In addition to the genetic background, environmental influences such as cigarette smoking and tobacco chewing may regulate distinct mutations. Molecular testing for lung cancer has been reported multiple times in the Indian population. Several tertiary care centers have substantially higher mutation frequencies and variations than the western population. In addition to the generic background, different environmental influences such as cigarette smoking and tobacco chewing may regulate distinct mutations. Molecular testing for lung cancer has been reported multiple times in the Indian population. Several tertiary care centers have substantially higher mutation frequencies and variations than the western population.

Lung Cancer Therapy: The following therapies can help the patient recover in the early stages of lung cancer. Neoadjuvant chemo radiation is a sort of chemotherapy that is used for the first time after surgery. Palliative care is provided using chemotherapy.

Objectives:

Soft computing methods: Neural networks, rebranded as Deep learning. The overthrow of traditional models in all key tasks is the goal. Deep learning not only speeds up the important process but also increases the computer's precision and CT image recognition and classification ability. The classification of benign and malignant tumors is discussed in this work.Convolutional Neural Networks [CNNs], Deep Neural Networks [DNN], and Stacking Auto Encoders are used [SAE]. The work can be utilized directly as an input to shorten the time it takes to recreate data in the feature extraction and classification process. The log–loss function and the spearmen correlation coefficient were utilized in the other algorithms.

Related work:

Various initiatives are often evolving to improve the accuracy of lung cancer diagnosis utilizing a neural network. Cohen [5] proposed the discrimination between presumably benign uncertain and probably malignant lung nodules, a neural network ensemble [NNE] strategy was proposed. The scheme's classification accuracy [78.7%] was higher than that of the individual classifier, according to the results of the experiments [LVQNN:68.1 percent].Kuruvilla and K.Gunavathi [6] suggested an Artificial Neural Networkbased technique based on texture features [ANN] with a 93.30 percent accuracy rate. Detection and classification using a combination of texture and form features may increase classification accuracy.[8] D Kumar et al. proposed an approach based on Stacked Auto Encoders [SAE] with an accuracy rate of 75.01 percent, with a Deep learning approach.Deep learning is based on the use of a large number of hidden layers. The top two layers of the Deep Belief network [DBN] have undirected connections, but all of the lower layers have downwarddirect connections. It has been used to classify lung module malignancy without having to compute morphology or texture data. The deep belief network has been found to have a sensitivity rate of 73.40 percent and a specificity rate of 82.20 percent. Deep CNN was used in some researchto detect or classify medical images. In [11] W.Shen used a multiscale two-layer CNN to analyze the LIDC database, and the report accuracy was 86.84 percent. In

[12] Shin et al. used the comprehensive analysis of three crucial understudied effects on CNN design, database features, and transfer learning.

Material and Methods:

In this section, the proposed technique was tested on the LIDC-IDRI [13] dataset from the lung imaging database consortium. By directly inputting the source images, the complex stages of image feature extraction in traditional medicine can be minimized.

Convolution Neural Networks (CNN)

A convolution neural network (CNN) is atype of multilayer neural network that has one or more convolution layers followed by one or more fully connected layers,similar to a regular multilayer neural network. In the 1960s, CNN was proposed, using concepts such as local perception, sharing weights, and sampling in space and time.For basic elements of visual animals,such as an angle and arc in the image, the local perception can detect certain local characteristics of the data.It is a type of efficient identification approach which recently gota lot of attention. CNN's have the advantage of being easier to train and having a much smaller number of parameters than fully connected networks with the same number of hidden units. The convolution layer and pool layer are frequently used in Conjunction with the Convolution Neural Network Architecture.The effect of the pooling layer is to disturb the characteristics of a certain point because some aspects of the site are unimportant. Max pooling and means pooling are two operations in the pooling layer.The average neighborhood inside the feature points is calculated using mean pooling, while the maximum neighborhood is calculated using max pooling.the inaccuracy in feature extraction is caused by two factors. The convolution layer parameter estimated error generated by the mean deviation and the neighborhood size constraint imposed by the estimated variance the first mistake can be reduced by using mean pooling, which keeps more image background information. Max pooling can help to lessen the second error by keeping more texture data. In this paper, the architecture of the CNN is shown in Figure1. Each layer is made up of numerous maps. Each map is made up of several neural units. All of which share the same convolution kernel (i.e. weight)and eachconvolutional kernel represents a feature thataccesses the edge of image features. accesses the edge of image features.

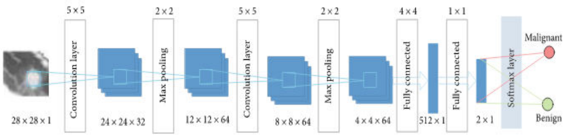

Figure1: The architecture of CNN

Table-1 shows the CNN in more depth. The distortion resistanceof the input data (image data) is very high by setting the convolution kernel size and parameter which generates the multistage convolution image feature. T information from many perspectives is generated in the feature space.

Layer Type	Input	Kernel	Output
Convolution	28x28x1	5x5	24x24x32
Maxpooling	24x24x32	2x2	12x12x64
Convolution	12x12x64	5x5	8x8x64
Maxpooling	8x8x64	2x2	4x4x64
Fully Connected	4x4x64	4x4	512x1
Fully Connected	512x1	1x1	2x1
Softax	2x1	N/A	Result

Table1: Parameter of CNN

Deep neural network [DNN]

In a simple neural network, a DNN is an increase in the number of hidden nodes. Because each hidden layer can be a nonlinear transformation of the output layer. The neural network can be used to perform more complex input calculations, and the deep neural network is better. Because, when the activation function is linear, the depth of the hidden layer of the network does not improve the ability to express when compared to a single hidden layer neural network. Nonlinear should be utilized for each hidden layer.to maintain a high amount of information during the training process. The original image is used as the input layer parameters.The DNN architecture's input layer,hidden layer, and output layer are all connected, and there is no convolution layer in

the DNN.The DNN architecture receives DNN training images and labels. Each layer of the weight in the first training is generated randomly using a Gaussian distribution with the bias which is set to zero. The forward propagation calculates the output value, whereas the backpropagationcalculates the update parameters.Figure2 depicts the DNN structure and Table2 lists the DNN parameters. Fine-tuning, boosting the data amount, and regularization are required to overcome the problem because the DNN parameters are prone to overfitting.

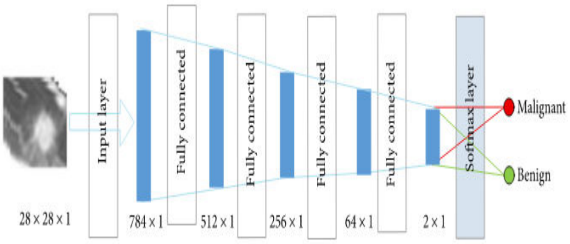

Figure2: The architecture of the DNN

Layer Type	Input	Output
Input	28x28x1	784x1
Fully connected	784x1	512x1
Fully connected	512x1	256x1
Fully connected	256x1	64x1
Fully connected	64x1	2x1
Softax	2x1	Result

Table 2: parameter of DNN.

Sparsed Auto Encoder and Stacked AutoEncoder [SAE]

A neural network with a Stacked Auto Encoder [SAE] is a multilayer sparse autoencoder. The Staked Auto Encoder is an unsupervised learning technique with input, hidden, and output layers. The input and output layers each have the same amount of neurons,while the hidden layer has fewer hidden neurons than the input layer. The SparsedAuto Encoder is depicted in Figure3.Furthermore, the SparsedAuto Encoder is split into two stages. Coding and Decoding. The coding stage involves mapping the input layer to the hidden layer.The mapping of the hidden layer to the output layer is the decoding phase.Multiple hidden layers and a final classifier are used in this paper.

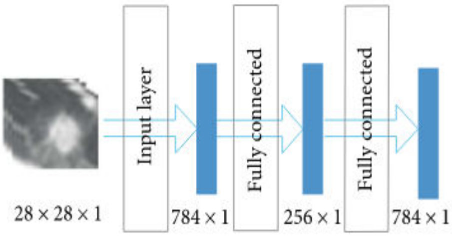

Figure3: SparsedAuto Encoder

The Stacked Auto Encoder neural network design is shown in Figure4. After the training is done in the hidden layer of the single sparse autoencoder, each Sparse Auto Encoder deletes the Decode Layer and uses the encoding process straight for the next sparse Auto Encoder of the output. This gives the fine-tuning of the output.

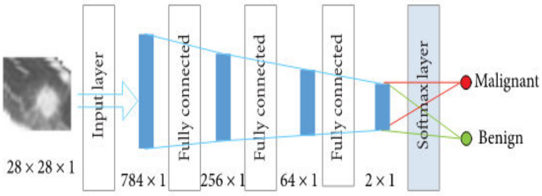

Figure4: Stacked autoencoder.

The neural network's loss function following is the loss function:

$$c(w,e) \equiv \frac{1}{2n}\sum\|y(x)-a\|^2+\frac{1}{2n}Y\sum\omega^2$$

Where C is the cost function. W isweight. bis bias. n is the number of training dataset instances. x is the image pixel value as an input parameter. The output value is denoted by *a*. The DNN is used to conduct out the backpropagation procedure to alter the weight *w* and the paranoid*b* so that the variation in the predicted and the real value is getting very tiny and thus there is the highest accuracy. The sum of all weights is divided by 2, and another way to prevent overfitting is a dropout, which randomly covers some neurons before backpropagation,and the deceived neurons do not update the parameters.Because the DNN demands a big amount of data, it also needs a large amount of memory. As a result, to adjust the parameters more quickly, a backpropagation must be performed every time. The neural network'sactivation function is leaky. Re L U can improve the ability of non-linear modeling. The formula for the Re L U activation function is as follows:

$$y=\begin{cases} x & if x\geq 0 \\ 2a & if\ x<0 \end{cases}$$

Where *x* is the product of weighed priority multiplication and paranoid addition, and y is the activation function's output.The derivate of Re L U is 0 if x<0, otherwise 1. As a result, Re L U solves the problem of the sigmoid activation function gradient. The weight, however, cannot be updated by training, which is known as "the output of Re L U, on the other hand, is greater than 0. Indicating that, the neural network's output is off. Leaky Re L U can be used to solve the problems mentioned above. The activation function formula for leaky Re LU is as follows:

$$y=\begin{cases} x & if x\geq 0 \\ 2a & if\ x<0 \end{cases}$$

When *a* is set to 0.1, the leaky Re L U is fixed, but the Re L U is not fixed.

LIDI-IDRI

The LIDC-IDRI database, which included 2,44,527images of the 1010 cases, has been released. Each subject contains images from clinical thoracic CT scans as well as an XML file with the results of a two-phase image annotation process carried out by four expert thoracic radiologists. In lung nodules, there is a wide range of CT image thicknesses that are available. The pulmonary nodules in this patient are 3mm in size. The number of benign nodules with a small diameter is increasing, while the number of malignant nodules with a bigger diameter is decreasing. However, it is uncertain if the majority of benign and malignant nodules cluster in the 5-10 mm range. The location of lung nodules and their degree of malignancy are retrieved from the patient's XML commentary file in this research. Four radiologists examine the pulmonary nodules in the XML file. The degree of malignancy of pulmonary nodules is divided into five categories by radiologists: a) Cancer is extremely importable. b) Cancer is fairly unlikely. c) Cancer risk is indeterminate. d) Cancer risk is moderate. e) Cancer is very suspect. The first two groups are deemed to be harmless. The latter two categories were determined to be cancerous. To obtain the textual and size features of the pulmonary nodules is uniformly set at 28x28 to the lung nodules. To begin, the image of the pulmonary nodules was created using binary processing, which can approximate the shape of the nodules. The pulmonary nodule values were then restored to the pixels of the pulmonary nodules in the subsequent image. Finally, noise can be reduced around pulmonary nodules. Figure5 shows the difference between the original and binary images.

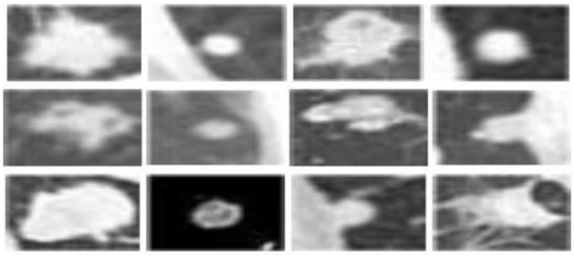

Figure 5: Nodular images.

To satisfy the neural network training, a significant number of positive and negative samples are required.Before pilling the image into the neural network, the image processing operations of translation, rotation, and flip are achieved,that increase the sample data of the input image. A high amount of sample data can help to increase neural network training and testing accuracy, as well as minimize the loss function and improve the robustness of neural networks.

Conclusion

Three major deep neural networks were used and thoroughly reviewed.LIDC-IDRL assessed the accuracy of prediction in the classification of benign and malignant lung nodules.A set of data the CNN performed better than the DNN and SAE in the experiments. Because of the constraints of the data sets, the layers of the neural network in this article are rather small.

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