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Lung Image Segmentation using Neural Network

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Abstract:
Lung diseases are disorders that affect lungs. Its severity is a worldwide problem, especially in India. In this work pleural effusion and normal lung are classified. This paper presents computer aided classification using computerized Tomography (CT), images of lungs developed using BPNN. The purpose of this work is to detect and classify lung diseases by feature extraction, Dual Tree Complex Wavelet Transform and Grey Level Co-occurrence Matrix methods. These parameters give maximum classification accuracy. Fuzzy Clustering is proposed to segment the lesion part from the abnormal lung.

Keywords: Segment lesion, Fuzzy Clustering, DTCWT, BPNN.

1. INTRODUCTION

Lung cancer is the leading cause of cancer death worldwide. While cigarette smoking is a major risk factor for lung cancer, other factors such as family history of lung cancer, prior diagnosis of malignant tumor, occupational exposure to asbestos, and pre-existing lung disease such as chronic obstructive pulmonary disease (COPD) can also increase the risk of lung cancer.

The major deaths occurring due to lung cancer is found to be especially in men. Lung CT image segmentation is a necessary initial step for lung image analysis, it is a prerequisite step to provide an accurate lung CT image analysis such as lung cancer detection.

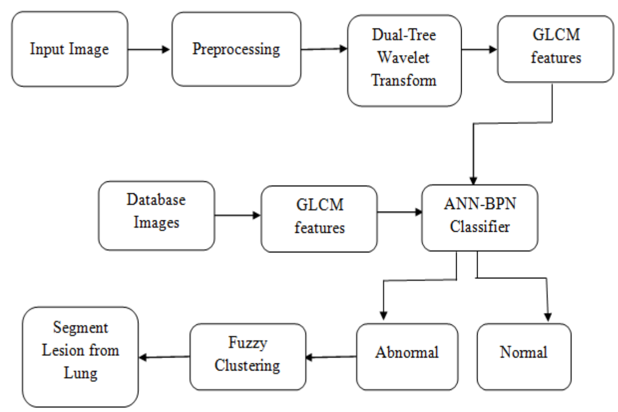
If the diagnosis is done at an earlier stage, we can prevent the lung cancer from spreading to different parts of the body. We can thereby dramatically increase the survival rate of patients. As radiologist have to interpret numerous medical images, it is necessary to reduce the time they take to interpret a medical image. In this work, we introduce a lung CT image segmentation using the Back Propagation Neural Network (BPNN) which is one of the most used architectures in deep learning for image segmentation.

2. PROPOSED METHOD

The segmentation algorithm proves to be simple and effective. Gray Level Co-occurrence Matrix (GLCM) is performed well in Back Propagation Neural Network (BPNN). Better texture and edge representation.

Threshold segmentation provides better clustering efficiency. Dual Tree Complex Wavelet Transform (DTCWT) is suggested for perfect reconstruction by means of four level decomposition (Figure 2), approximate shift invariance and better directional selectivity. Parenchyma mask is applied by using watershed algorithm.

PROPOSED BLOCK DIAGRAM



2.1 IMAGE SEGMENTATION

Image segmentation is a fundamental step in computerized image analysis and it deals with separating classes in an image into continuous and separate regions. For example, a CT slice from a thoracic (e.g., Figure 1(left)) scan may contain chest wall, heart segments in addition to lung tissues. The goal of segmentation in this case is to isolate the lung tissue (Figure 1(right)) to boost the precision and interpretability of an image.

2.2 PRE-PROCESSING

Medical Image processing is an emerging area in the research for various disease detection and diagnosis which aids the medical practitioner for easy diagnosis of diseases accurately. Hence, it is necessary to preprocess the images for noise elimination. Preprocessing is a process which is used to boost the precision and interpretability of an image.

2.3 GRAY LEVEL CO-OCCURENCE MATRIX

For medical image processing, certain GLCM parameters are considered.
Contrast: Measures the local variations and returns the intensity contrast between a pixel and its neighbor in the whole image.
Correlation: It returns a measure of how well a pixel is correlated to its neighbor in the whole image.

Homogeneity: Measures how well the elements in GLCM are closely distributed with GLCM diagonal.
Energy: It is a measure of the homogeneousness of the image and can be calculated from the normalized COM.
Entropy: Entropy is a measure of textural uniformity of the image. Complex textures tend to have higher entropy**.**

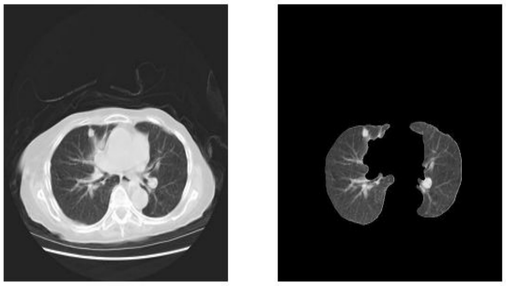


Figure 1: Illustration of the segmentation process. Left: a CT slice from a thoracic scan,

Right: segmentation output, showing the isolated lung tissue

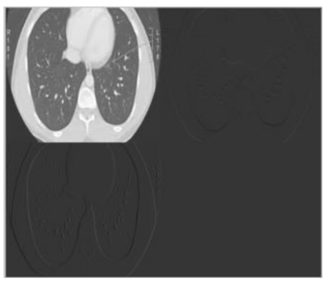


Figure.2. DTCWT 4 level decomposition

2.4 BACK PROPAGATION NEURAL NETWORK

Neural Networks (NN) are important tool used for classification and clustering. It is similar to a machine that will mimic brain activities and be able to learn on based on data incorporated into it. NN usually learns by examples. Basic NN is composed of three layers, input, output and hidden layer. Each layer can have different number of nodes from input layer which are connected to the nodes of hidden layer. Nodes from hidden layer are connected to the nodes of output layer. Those connections represent weights between nodes. There are two types of NN , one which can be supervised where output values are known beforehand (back propagation algorithm) and the other one is unsupervised where output values are not known (clustering). Activation function gets mentioned together with learning rate, momentum and pruning. Back propagation algorithm, probably the most popular NN algorithm is demonstrated. The idea behind BP algorithm is quite simple; output of NN is evaluated against desired output. If results are not satisfactory, connection (weights) between layers are modified and process is repeated again and again until error is small enough. Classification is grouping of the objects or things that are similar.

2.5 FUZZY CLUSTERING

Fuzzy clustering generalizes partition clustering methods by allowing an individual to be partially classified into more than one cluster. In regular clustering, each individual is a member of only one cluster. Suppose we have K clusters and we define a set of variables mi_1, mi_2, mi_K, Λ, that represent the probability that object i is classified into cluster k. In partition clustering algorithms, one of these values will be one and the rest will be zero. This represents the fact that these algorithms classify an individual into one and only one cluster. In fuzzy clustering, the membership is spread among all clusters. The mi k can now be between zero and one, with the stipulation that the sum of their values is one. We call this a fuzzification of the cluster configuration. It has the advantage that it does not force every object into a specific cluster. It has the disadvantage that there is much more information to be interpreted. We have chosen four clusters(Figure 3) and performed segmentation of abnormal region of lung (Figure 4).

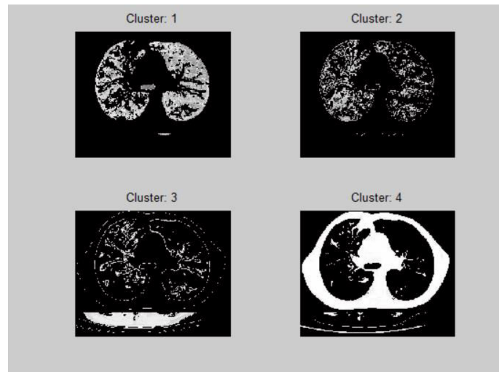


Figure .3. Fuzzy clustering

2.6 FUZZY ALGORITHM

Fuzzy seeks to minimize the following objective function, C, made up of cluster memberships and distance

$$C = \sum_{k=1}^{K} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} m_{ik}^2 m_{jk}^2 d_{ij}}{2\sum_{j=1}^{N} m_{jk}^2}$$

where mi k represents the unknown membership of the object i in cluster k and dij is the dissimilarity between objects i and j. The memberships are subject to constraints that they all must be non-negative and that the memberships for a single individual must sum to one. That is, the memberships have the same constraints that they would if they were the probabilities that an individual belongs to each group (and they may be interpreted as such).

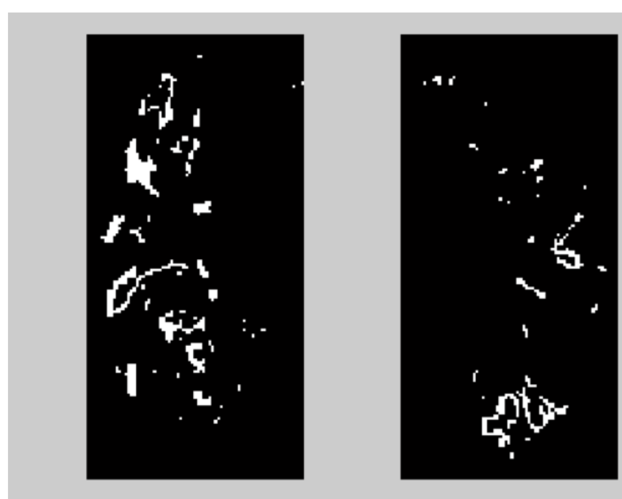


Figure.4. Segmented results

3. EXPERIMENT

We evaluate database and input images for training and testing, using GLCM features. Classification in BPNN is done by comparing GLCM features. Classification accuracy of BPNN is given by

$$\text{Accuracy} = \frac{(\text{True Positive} + \text{True Negative})}{\text{Total no of samples}}$$

The evaluation is done by considering 10 samples in database images and 10 samples as input images and accuracy is determined.

4. CONCLUSION

We proposed Back Propagation Neural Network (BPNN) as an efficient method for classification of lung disorders at the initial stages from CT scan lung images.

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