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Texture Feature Analysis and Soft Computing Method Based Lung Cancer Classification System

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***Abstract* - Magnetic Resonance Imaging (MRI) might be a problematic assignment for tumor fluctuation and complexity because of lung image classification. This work presents the lung cancer classification system using Back Propagation Neural Network (BPNN) algorithm based on MRI Lung images. The proposed tumor recognition framework comprises of four stages, to be specific preprocessing, feature extraction, segmentation, and classification. Extraction of identified tumor framework features was accomplished utilizing Gray Level Co-occurrence Matrix (GLCM) strategy. At long last, the Back Propagation Neural Network Classifier has been created to perceive various kinds of lung disease. The proposed framework can be effective in grouping these models and reacting to any variation from the abnormality. The entire framework is isolated into different types of phases: The Learning/Training Phase and the Recognition/Test Phase. A BPNN classifier under the scholarly ideal separation measurements is utilized to decide the chance of every pixel having a place with the foreground (tumor) and the background. The simulation of the proposed system is also developed using MATLAB software. The simulation result of the proposed method demonstrates the stability of lung cancer analysis. It shows that the proposed lung cancer classifications are superior to those from lung MRIs than existing lung cancer classifications. The overall accuracy of the proposed system is 98.45%**

***Index Terms* - Image pre-processing, Segmentation, Back Propagation Neural Network (BPNN), Classification.**

1.INTRODUCTION

Cancer has become the most dangerous threat to humankind in the last two decades. Proper treatment to completely cure the disease has not yet appeared. According to the World Health Organization 7.6 million deaths in 2005 indicate cancer caused by tumors growing larger than 2 mm every three months. It multiplies out of control and spreads to other parts of the body. It destroys healthy tissue. The body part is usually named where the cancer started. While the majority (at least 60%) of lung nodules are due to benign (not cancerous) conditions, it is important for your doctor to work to determine the cause. When lung cancer is detected early and still small, there is a great chance that it can be cured.

Computed tomography (CT) is an important imaging procedure to diagnose lung cancer at an early stage. However, chest radiographs (CXRs) are more commonly used for chest diseases because they are less expensive, usually available, and a lower dose diagnostic tool. Because CXRs are so widely used, improvements in the detection of CXRs lung nodules may have a significant impact on the early diagnosis of lung cancer. Studies, however, have shown that 30% of the nodules in CXRs are radioactive, in which the nodules are able to feel backwards, and 82-95% of the missed skin nodules are hidden in the bones of the ribs and alkaloids. Such knots are more stylized for soft-tissue images obtained using the dual energy subtraction technique.

The computer aided detection (CAD) technique of lung nodules has become available based on the automatic identification of nodules as relatively round areas of increased density compared to those surrounding low-density lungs. Adequate software algorithms allow differences in other areas of soft tissue atrophy with nodules and different shapes (vessels, lungs, chest wall). The use of these tools is suitable for readers with varying degrees of experience in small and medium, but it has been demonstrated that lung nodules can increase the sensitivity of individual human readers, especially when it is said to be relatively inexperienced readers.

CAD and visual reading are more sensitive than dual reading by humans. This may be due to the fact that humans tend to detect and miss the same nodules whereas CAD and humans and miss the same knots whereas different knots miss. Currently, automated CAD tools only have to be used in conjunction with visual reading for false and false negative results

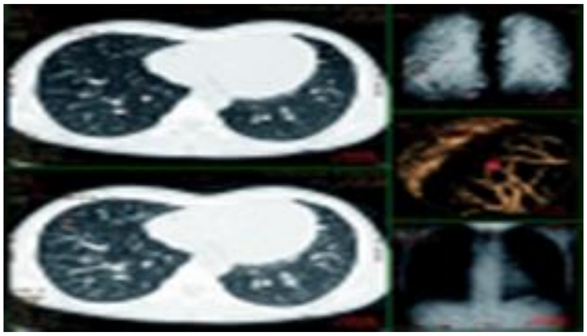

Figure 1 computer aided detection of pulmonary nodules

2. MATERIALS AND METHODS

The MRI based lung cancer detection is an essential area of debate for lung tissue and tumor segmentation. It employs an automated technique and textural features that are proposed to define the blocks of each nerve in the lung MRI section as well as other elements. As in scanned MRI image needs a trained classifier is used to detect the difference between the tumor blocks and the normal blocks in the lung image. The proposed automated lung tumor detection algorithm consists of several steps which are namely preprocessing, segmentation and classification of the lung images.

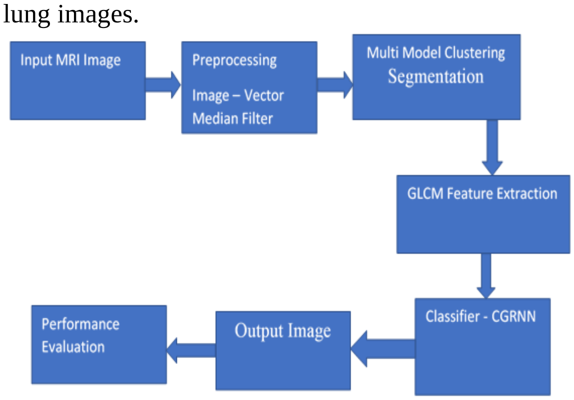

Figure 2: Block Diagram of Proposed System

The Back Propagation Neural Network -based lung tumor discovery and classification framework is appeared in Figure 1. The proposed tumor recognition framework comprises of four stages, to be specific preprocessing, feature extraction, segmentation, and classification. The exploration work will be clarified in the accompanying sections.

2.1 Preprocessing Vector Median Filter

AVMF for satellite images is currently used to reduce image noise and is a type of nonlinear filtering described in the spatial domain. With AVMF, all the pixels in the neighborhood are currently based on the intensity level, and the pixel grading process at the center is converted to half that pixel. AVMF softened satellite images by utilizing the neighborhood pixel average. The fact that the Adaptive Vector Median Filter protects the sharp edges due to the average filter usage of the noise filter to eliminate the noise current of satellite images is a much faster method compared to conventional filtering. To remove the noise from the image, the algorithm described below is used.

AVMF Algorithm:

Step 1: A two-dimensional window of size 2x2 is chosen and centered on the practiced pixel P (a, b) in the dishonored image.

Step 2: Organize the pixels in the chosen window consistent with the ascending order and discover the

1. Median pixel value indicated by C_{med},
2. Maximum pixel value (C_{max}) and Minimum pixel value (C_{min}) of the organized vector V0.

Step 3: If the practiced pixel is inside the range $C_{min} <$ P (a, b) $< C_{max}$, $C_{min} > 0$ and $C_{max} < 255$,

1. Classified as virtuous pixel and left unbothered.

Step 4: Else

1. P (a, b) is classified as dishonored pixel

Step 5: replace the dishonored pixel P (a, b) with Cmed

Step 6: Step 1 to step 4 are iteratively repeated until the processing is accomplished for the entire image

a) Input _image b) Preproceced_image

Figure 3 Result of Preprocessing

The above Figure 3 demonstrates the preprocessed output image utilizing Gaussian filter. In Figure 3a is an input image and 3b shows preprocessed image. As compared with input image the preprocessed image was look more energetic view and the preprocessed image is utilized for contribution to segmentation system

2.2 Multi-Model Clustering Segmentation

Segmentation refers to the division of a partitioned computerized image into multiple locales and the reason for division (pixel gatherings) to disentangle the processing of images that are investigated all the more seriously. The consequence of image segmentation is a gathering that by and large covers the entire image area or shape. Comparative with a similar feature (one or more), nearby areas are altogether extraordinary. The proposed strategy requires enlisting the divisions between all the data. Once the clustering is finished, the delegate feature vector enrollment esteems are conveyed indistinguishably to all individuals from the quantization level. Since the altered multi model clustering algorithm utilizes a diminished dataset, the joining rate is profoundly enhanced when contrasted and the regular multi model clustering.

2.2.1 Algorithm

1. Initially, all pixel drive aspects are switched to double demarcation. Since the power is relative to the range from 0 to 255, 8 bits are used to resolve each pixel.
2. The division between the basic pixels and any remaining pixels is estimated to be solved step by step. It shows the graphical aspects for the two pixels. The attribute used to evaluate the segment measure in another table called the response table 3.1. It shows a general association around the response table.

Table 1 General Response Table arrangement

	Subject 1 '1'	Subject 2 '0'
Subject '1'	*A*	*b*
Subject '0'	*c*	*d*

Table 1 demonstrates a 2×2 Response Table since just two subjects '1' and '0' are included in the double portrayal.

3. The condition "11" blend referred to in Table "A" occurred at virtually the same piece position for the two information pixels. The condition "10" at "B" is mixed in the case of a similar piece, which requires Gander. The "c" involved in the condition "01" is mixed with a similar partial position, and "d" to consider that sometimes "00" mixing occurs in the near-position position.
4. Two partitioning steps used to do this work. In the first position, the parameters "pick out" (M) and "dice" (d) are evaluated, and further, the package finds the values of (1-M) and (1-d) utilized. "Quickly sort out" this parameter is evaluated by running the equation.

$$M = \frac{a+b}{a+b+c+d} \quad (2)$$

Another parameter 'Dice' is resolved to utilize the accompanying equation

$$D = \frac{2a}{2a+b+c} \quad (3)$$

5. 5Through the "sort out" of the last division of the measure through the discovery (1-M), and through the "scorpion" separation measures to control the coordination (1-d). For the input aspect that appears in Table 5.2, the parameter "M" produces an estimate of 5/8 and a 4/9 check of "d".
6. The measure of closeness (or) similarity between the two pixels can be achieved by separating these traits and edges relative to the coordinates. Since two subjects (1 and 0) were added to the combined portrayal, the purpose of controlling gratitude was set to 0.01 to 0.5 based on the number of pixels. Because the depth feature analysis requires a minimum of 0.01 to 0.5.
7. A face-lifting pixel whose detachment training requires at least a pixel for comparing social events to make each person's near frame. This method is repeated until each person of the pixel has a place with a social occasion.
8. The amount of the package is recorded and picked up from each representative. The interior is used to pick up pixels from every social occasion. Therefore, the data set is reduced with amazing strategic recommendations.
9. Conventional FCM calculations and bolsters relative to the cause
10. The calculated FCM is compatible with the re-hash check data set. The calculation of the iteration method with the appointment is completed, focusing on the pillow aspect.
11. Before using the implementation discussion to participate in the mission strategy system

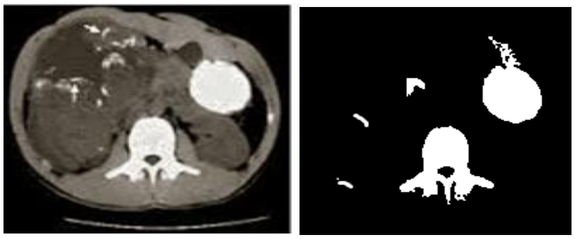

Figure 4 a) Preprocessed Image Figure 4 b) Segmentation image

In Fig. 4(a) above, an input image of an image for preprocessing is taken. The importance of the segmented image distributed by the proposed method is illustrated in Figure 4(b).

2.3 Feature Extraction- Gray Level Co-occurrence Matrix (GLCM)

The GLCM is a way of pushing the practical second-order statistical system features. Therefore, the main purpose of feature extraction technology is accurately retrieved spectral or texture features. The GLCM method is used to extract second-order statistical texture features. The GLCM method does not need additional feature extraction proposes, because the Feed Forward Multi-Layer Perceptron classifier has the internal function of matrix feature extraction. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels in the image. The GLCM matrix is given by Equation (4).

$$Mpm = \sum_{p-1}^{m}\sum_{q}^{n}\begin{cases} 1\,, M1(p,q) = I & ||(p+\Delta v, q+\Delta o = j \\ 0, & otherwise \end{cases} \quad (4)$$

where

P,q = Spatial Positions I,J = Intensity Values

v,o = offset values

A GLCM is a histogram of co-occurring gray-scale values at a given offset over an image. Using this GLCM matrix features of an image are extracted

2.4 Back Propagation Neural Network (BPNN)

The proposed back propagation neural network classification algorithm is a novel method of the information processing system to analyze satellite images to identify colors based on specific objects (regions). back propagation neural network models are used to study biological nervous systems, such as the lung. It is called the working neurons with the unity of solving specific problems and is made up of a large number of interconnected processes. BPNN, are like people, learn by examples. Type recognition or data classification, such as an BPNN, is done through a learning process, if specific applications are built in. Learning in biological systems involves the adjustment of synaptic connections that exist between neurons. MLP defines a series of functions. In the most classic case of a neural network with a single hidden layer, map d vector to m-vector.

$$g(x) = b + w\tanh(c + Vx) \quad (5)$$

where

x = input vector v = input to hidden weights

c = hidden unit biases b = output unit biases

w = hidden to output weights

2.4.1 BPNN Training

Two basic issues guide the different strategies employed in training BPNN:

1. To compete for as much as possible, that is, to make the training fall inaccurately as soon as possible, to avoid getting even a local minimum fixed in a narrow registration or cost function.
2. Control capabilities to avoid maximum simplification during assembly to achieve maximum capacity, ie to minimize errors.

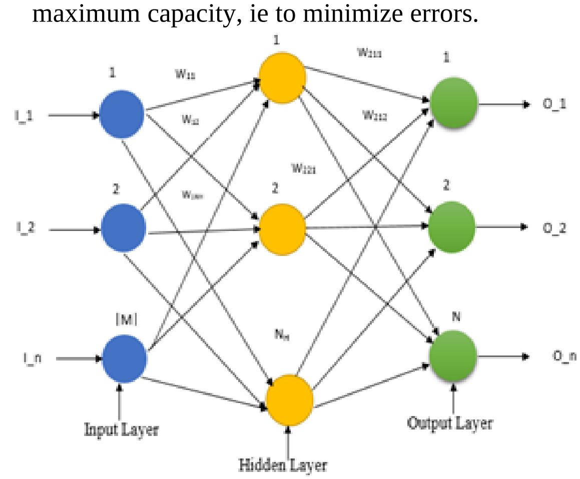

Figure 5 Neuron structure of the proposed system

The neuron structure of the proposed system is shown in Figure 5. In order to know it is required to publish many common neural network models known as the monitored network for desired output in order to learn. The purpose of this network type is to create a model called input and output maps using historical data that can be used for model production when the desired output is known. BPNN can be used to identify trends that are too complex for one's human or other computing techniques to extract their significant capabilities, patterns and material that can be achieved on the basis of information obtained through a piece of tangible or misleading information. Trained as an "expert" in the information category, it has been given an inspection BPNN can be considered. A significant issue that must be tended to in approving a programmed technique for lung tumor classification methods through which the classification is quantitatively evaluated.

Accuracy: It is the level of closeness for estimations of an amount to that amount's actual esteem. It is given as

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad \ldots (13)$$

Sensitivity: It gauges the extent of negatives which are effectively recognized. It is spoken to as

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad \ldots (14)$$

Specificity: It is characterized as the portion of the classified picture, which is applicable to the expectations. It is given as

$$\text{Sensitivity} = \frac{TN}{TN+FP} \quad \ldots (15)$$

3. RESULTS AND DISCUSSION

The better efficiency and simple implementation make the proposed plan beneficial to help a diagnosis before the surgery. Compared to another conventional classifier, our proposed Back Propagation Neural Network (BPNN) method performance by achieving an accuracy a sensitivity and a specificity.

A. HARDWARE REQUIREMENTS

- Processor - Intel corei3 & Above
- Speed - 2.0 GHz
- RAM - 4 GB (min)
- Hard Disk - 500 GB (min)
- Keyboard - Standard Windows Keyboard
- Mouse - Wired or Wireless Mouse
- Monitor - Color Monitor

B. SOFTWARE REQUIREMENTS

- Operating System - WINDOWS
- Tool - Matlab
- Version - 2016
- Dataset - BRATS 2015

Figure 6 Home Page

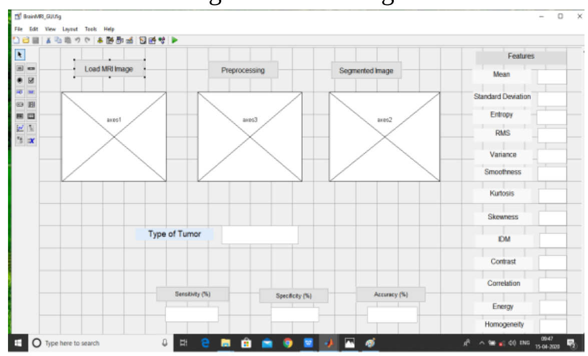

Figure 7 Input Screen

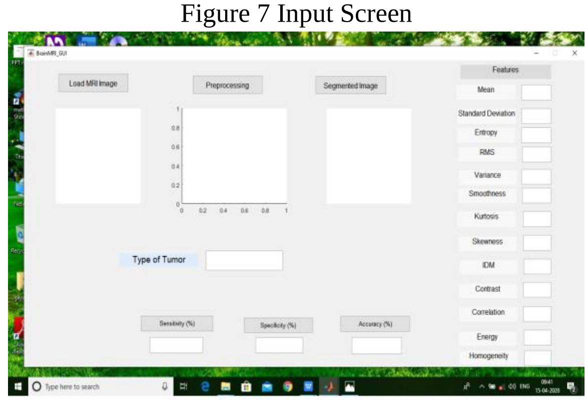

Figure 8 Output Screen

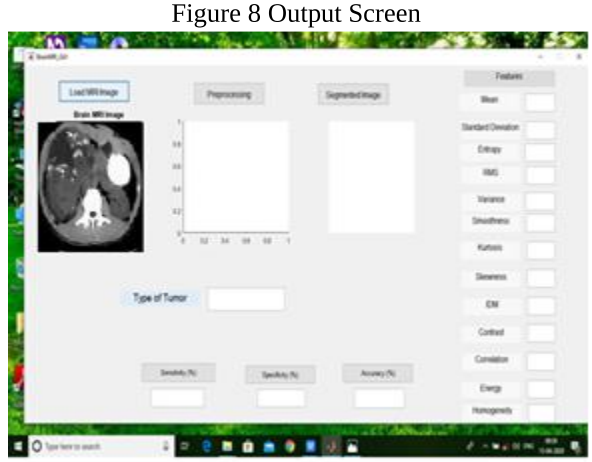

Figure 9 Input Image

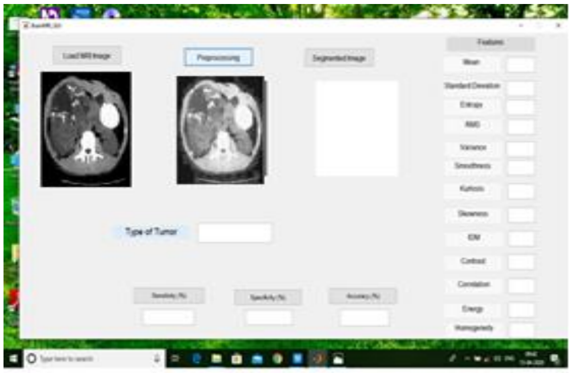

Figure 10 Result of Preprocessing

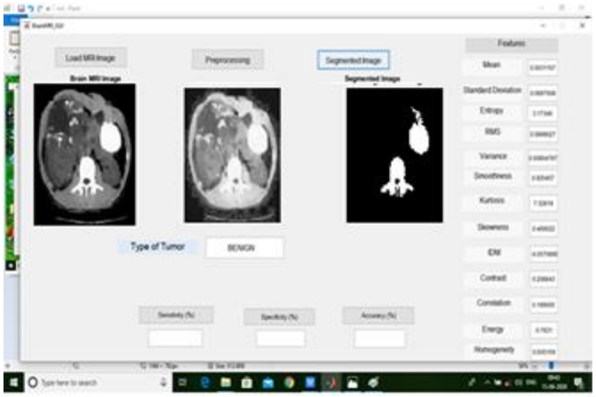

Figure11 Result of Segmentation and Feature extraction

Figure12 Sensitivity Measurement

CONTN.....

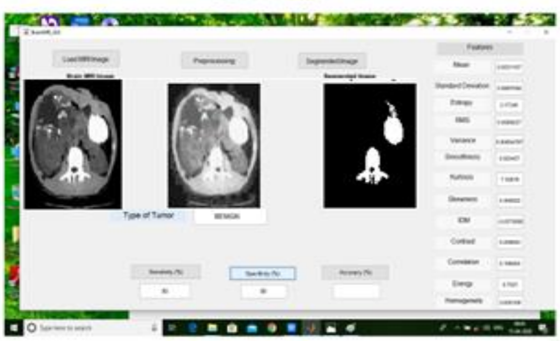

Figure 13 Specificity Measurement

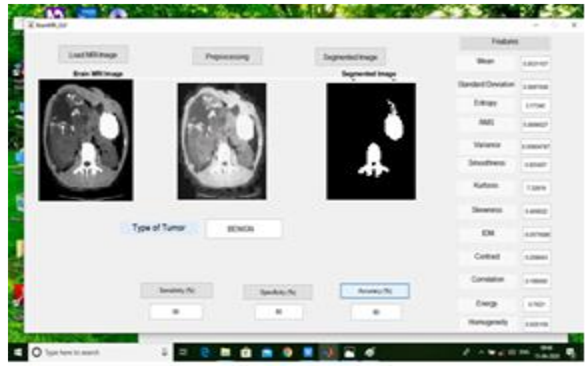

Figure 14 Accuracy Measurement

Table 2: Performance analysis

Methods	Sensitivity (%)	Specificity (%)	Classification Accuracy (%)
Back Propagation Neural Network	97.30	96.54	98.45
SVM-PSO	96.29	89.34	95.87
Support Vector Machine	96.30	83.72	90.72

Table 2 show the comparison chart of the mean ratio and it is compared to the existing method. Moreover, the proposed false method ratio is reduced to 10% which makes our system efficient. The proposed methods achieve the best results of False Positive Rate, False negative Rate, and False Rejection Rate are also significantly decreased when compared to the proposed Back Propagation Neural Network (BPNN) and existing SVM and SVM-PSO method.

4. CONCLUSION

In this work, it is proposed to use the back propagation neural network classification to improve the lung cancer classification accuracy. In these proposed approaches, the lack of measurement is robust enough to train site selection and class definition, and even with a limited number of training pixels, it easily accommodates a different label to create visually and numerically correct maps. To conclude the basis of grayscale distribution features and access area values, this technique classifies satellite images under different types of regions. These techniques produce effective results for image classification, improve accuracy, and reduce misclassifications. Compared with all methods, the proposed method is far better than the results in front of this sinking stage with excellent sensitivity, specificity, and accuracy measures.

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