Tb  Diagnosis System using Genetic Particle Swarm Optimization Based Neural Network Classifier

P.Prasanna Kumari, B.Prabhakara Rao

Abstract: Classification of medical image is an important task in the diagnosis of any disease. It even helps doctors in their diagnosis decisions. Tuberculosis (TB) is a disease caused by bacteria called Mycobacterium tuberculosis. Recently, several techniques are applied to diagnosis the TB diseases. Unfortunately, diagnosing TB is still a major challenge. Therefore, in this paper an efficient Tuberculosis diagnosis system is proposed using Multi Kernel Fuzzy C Means Rough Set (MKFCMRS) based feature selection and optimal neural network classifier. Our proposed method comprised of four stages namely, feature extraction, feature selection, classification and Region identification. Initially the TB images are extracted from the given input database and that each of the input images are given to feature extraction process, in which statistical, structural and gray level dependent features are extracted. After that, the feature selection scheme is carried out through multi-kernel FCM based rough-set theory. Then, selected features are given to optimal neural network classifier to optimize the weight values of the neural network. In this work proposed classifier is Particle Genetic Swarm Neural Network classifier (GPSO-NN) which Integrates the characteristics of both genetic and particle swarm methods. The proposed system is implemented in the working platform of MATLAB. Compared to previous method our proposed technique is improved in terms of accuracy, sensitivity and specificity.

Keywords: Tuberculosis, GPSO-NN, rough-set theory, multi-kernel FCM, feature extraction, feature selection.

I. INTRODUCTION

With a death rate of over 1.3 million people in 2017 [1] After HIV Tuberculosis (TB) is worldwide, the second leading cause of death from a contagious disease. TB is one of the top ten causes of death. TB is a major global health problem [2]. TB is a contagious disease caused by the bacillus Mycobacterium tuberculosis, which naturally affects the lungs. On the other hand, further financial support is necessary for the tests to analyze TB. In addition, segmentation is one of important step in medical image applications. Due to the difficulty of the lung structure, segmentation is taxing problem in TB diagnosis. To fragment the TB region, different literatures have been proposed in latest years. In [3 and 4], the author offered a segmentation and classification method for TB bacteria identification. Besides, Feature selection and Classification are imperative steps in TB detection. A best feature set should have efficient and discriminating characteristics, while mostly diminish the redundancy of features space to avoid “curse of dimensionality” problem [5].

II. REVIEW OF RELATED WORKS

Quite a lot of methods have been suggested for the lung based automatic disease classification in the literature survey. Among the most newly circulated works are those offered as follows: Shahaboddin Shamshirband et al. [10] have explained the artificial immune recognition system of Tuberculosis Diagnosis System. Implemented classification in their work based on a fuzzy system in which utilized fuzzy rule in the process of labeling in order to normalize the features and are categorized into normal and tuberculosis classes. Because of mixing the fuzzy logic with the artificial immune recognition system the proposed system yields, the better accuracy than other methods. Rui Shen et al. [11] utilized the Bayesian

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method for classification for automatic detection of TB cavities. In their work introduced a hybrid method of knowledge-guided detection and used the measures of circularity and Gradient inverse coefficient of variation in order to categorize detected features. Compared their proposed method with non hybrid techniques and active contour techniques and shown their method yields better accuracy with a low false positive rate.

III. PROPOSED TB DIAGNOSIS SYSTEM

In this article, the suggested method contains four significant phases, (1) Feature extraction, (2) Feature selection (3) TB classification and (4) Region identification. The simple Illustration of proposed approach is presented in “Fig.1”.

A. Database description:
Simulation experiments were carried out with medical CT lungs image dataset, which is publically available in internet. Totally 55 images are collected among them 30 images are abnormal and 25 images are normal. The size of collected database images as 512x512. The experimental used images are given in “Fig.2”.

B. Feature Extraction:
In this section, the computation of feature vector is done for three different categories like statistical, structural and gray level dependent features.

First Order Statistical Features:
1. Mean = \( \mu = \sum_{x=1}^{N_x} x \cdot p(x) \)

2. Variance = \( \sigma^2 = \sum_{x=1}^{N_x} (x - \mu)^2 \cdot p(x) \)

3. Skewness = \( \mu_3 = \sigma^3 \sum_{x=1}^{N_x} (x - \mu)^3 \cdot p(x) \)

4. Kurtosis = \( \mu_4 = \sigma^4 \sum_{x=1}^{N_x} (x - \mu)^4 \cdot p(x) - 3 \)

Spatial grey level dependent features:

5. Angular Second Moment = \( \sum_{i} \sum_{y} \left[ p(x, y) \right] \)
6. Inverse difference Moment = \( \sum_{i} \sum_{j} \frac{1}{1+(x-y)^2} p(x, y) \)

7. Sum average = \( \sum_{x=2}^{2N_x} x p_{i+j}(x) \)

8. Sum entropy = \( -\sum_{x=2}^{2N_x} p_{i+j}(x) \log(p_{i+j}(x)) \)

Surrounding Region dependent features:

9. Horizontal-weighted sum = \( \frac{1}{N} \sum_{x=0}^{m} \sum_{y=0}^{n} r(x, y) \)

10. Diagonal weighted sum = \( \frac{1}{N} \sum_{x=0}^{m} \sum_{y=0}^{n} c^2 r(x, y) \)

11. Grid-weighted sum = \( \frac{1}{N} \sum_{x=0}^{m} \sum_{y=0}^{n} x y r(x, y) \)

\[ N = \sum_{x=0}^{m} \sum_{y=0}^{n} \alpha(x, y) \]  

\[ r(x, y) = \begin{cases} \frac{1}{\alpha(x, y)}, & \text{if } \alpha(x, y) > 0 \\ 0, & \text{Otherwise} \end{cases} \]

Gray Level Run Length Features:

12. Short Run Emphasis = \( \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \frac{p(x, y|\theta)}{j^2} \)

13. Long Run Emphasis = \( \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} y^2 p(x, y|\theta) \)

14. Gray Level Non-Uniformity = \( \frac{\sum_{i=1}^{N_i} \left[ \sum_{j=1}^{N_j} p(x, y|\theta) \right]^2}{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p(x, y|\theta)} \)

15. Run Length Non-Uniformity = \( \frac{\sum_{i=1}^{N_i} \left[ \sum_{j=1}^{N_j} p(x, y|\theta) \right]^2}{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p(x, y|\theta)} \)

16. Run Percentage = \( \frac{\sum_{x=1}^{N_x} \sum_{y=1}^{N_y} p(x, y|\theta)}{N_p} \)

From the feature extraction, we totally extract eighteen features for eight images. With \( N \) number of images we generate the feature vector of \( N \times 18 \) size.

C. Reduction of feature vector

The fundamental plan of this method is to decrease the size of the feature vector by means of Multi kernel fuzzy c-means clustering in addition to roughest theory algorithm. Large feature set is a huge hindrance for the estimation; so it is required to decrease the dimension of the feature vector. To develop the prediction precision, we employ the MKFCMRS algorithm for getting reduced feature set. The main objective function, cluster centers and membership functions are specified beneath as equations 3, 4 and 5.

\[ Q = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \| \varphi_{com}(x_i) - c_j \|^2 \]  (3)

In the equation (3), the cluster centers and membership functions are obtained and specified by:

\[ c_j = \frac{\sum_{i=1}^{N} u_{ij} K_H(x_j, c_i) x_j}{\sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij} K_H(x_j, c_i)} \]  (4)

\[ u_{ij} = \frac{(1 - K_H(x_i, c_j))^{-1/m-1}}{\sum_{k=1}^{C} (1 - K_H(x_j, c_i))^{-1/m-1}} \]  (5)

Where,

\[ K_H(x_j, c_i) = K_1(x_j, c_i) + K_2(x_j, c_i) \]

\( K_1(x_j, c_i) \) and \( K_2(x_j, c_i) \) are linear and quadratic kernels.

After the clustering process by means of MKFCM, performed the process of reduct and core analysis to get reduced feature set. Which is then passed to the next phase of classification.

D. TB Diagnosis System Using GPSO-Neural Network Classifier

After the reduction of feature set, the selected features are given to the input of GPSO-NN Classifier for classification of input TB-CT images. The steps in this process are explained below.

Weight optimization via GPSO Model:

Step 1: Solution representation

The first step in the GPSO algorithm is solution representation, which symbolizes set of weights. solution is represented as a dimension vector with \( SL_d \) dimension which is symbolized as a weight. Where \( k \) specifies the number of solutions in the population varying from 1 to z. The length of solution resembles the weights allocated in the Neural Network. The “Fig.3”, demonstrates the representation of solution.
Fig. 3. A single solution representation format

Step 2 : Fitness function and selection operation
An objective function is required to be performed for measuring the individual performance, there by fitness of a solution can be assessed. With the help of fitness function individual fitness of every solution can be computed. The error value $E_N$ can be computed to know, how the solution is most appropriate for optimizing the weights.

$$E_N = \frac{1}{2} \sum_{i=1}^{p} (O_i - T_i)^2$$

A roulette wheel selection is employed based on the fitness function to safeguard best solutions, where the worst solution in each generation is substituted by the best solution found so far.

Step 3 : PSO based Updation
After the fitness calculation, the solutions are updated with the help of PSO, cross over and mutation operator. In PSO, the solutions are updated based on velocity and position. The velocity and position Updation is mentioned in equation (7) and (8)

$$V_{t+1}^i = wV_t^i + C_1R_1(p_{t}^i - X_t^i) + C_2R_2(P_{t}^i - X_t^i)$$

(7)

$$X_{t+1}^i = X_t^i + V_{t+1}^i$$

(8)

Where,

$I$ - $t^{th}$ iteration in the evolutionary process
$W$ - inertia weights
$C_1, C_2$ - acceleration constants
$R_1, R_2$ - Random values

After the PSO Updation, further increase the performance of the solution are again updated using cross over and mutation operations.

Step 4 : Crossover operation
It creates the new generation offspring by using the process in which genes are selected randomly from both the parent chromosomes and new offspring is created. Single point crossover in which choosen point randomly and exchanging genes before and after random point and is demonstrated in “Fig.4”.

Parent 1

| A | B | C |

Offspring 1

| A | E | C |

Parent 2

| D | E | F |

Offspring 2

| D | B | F |

Fig. 4. Crossover process

Step 5 : Mutation
This operation is necessary of genetic algorithm convergence. In the process of mutation select some genes for each offspring and change its value. It must be used for preserving diversity.

Step 6 : Termination Criteria
when number of iterations reached the maximum count value, then proposed GPSO algorithm stops its implementation there by getting best solution and is precisied as best feature in the process of testing.

E. Prediction Process
The selected features are given to the prediction process which uses Artificial Neural Network. In this network a single input and single output layers are present and number of hidden layers, each having computing elements known as hidden neurons which are connected through adaptive weights. The developed neural network structure is presented in “Fig.5”.

Fig. 5. Used neural network structure

To train this network, the selected feature set from different types of classes (normal or abnormal) are collected and are applied to the neural network for the purpose of training. Large feature set improves the test performance, but it consumes more time to converge. To reduce this training time effectively we have utilized Scaled Conjugate Gradient (SCG) Back propagation algorithm which provides best train and test efficiency in least possible time. The input TB image is fed into the trained neural network after the preprocessing and applying feature extraction. The classifier compares the trained data with those of the input image feature data and classifies it into Abnormal or normal.

F. Region segmentation
Once classified the TB images using GPSO-NN classifier, the TB region is identified via morphological operator. At first the input TB image converted into binary image which can be represented as

$$B_{shape}(k, y) = \begin{cases} 
0, & \text{if } B_{grey}(k, y) <= \text{Threshold} \\
1, & \text{Otherwise} 
\end{cases}$$

(9)

Morphological operation like dilation is applied to extract the abnormal region. After the process of classification. If the test input image is identified as abnormal then segmented the abnormal region and corresponding segmentation results area shown in “Fig.6”.

IV. RESULTS AND CONCLUSION
The proposed technique for TB diagnosis is implemented in MATLAB. The results obtained from the experimentation are used to compare with the performance of our proposed algorithm namely GPSO with neural network against that of KNN classifier, SVM classifier, Random forest, Neural Network and GANN classifiers. From the Table 1, one can observe that GA with neural network based
TB diagnosis method and our proposed one yield the best performances, followed by neural network classifier. The performance metrics used to evaluate performance of proposed method for TB diagnosis are as follows:

i) Positive Predictive value PPV = \frac{TP}{TP+FP} 

ii) Negative Predictive Value NPV = \frac{TN}{TN+FN} 

iii) Accuracy = \frac{TP+TN}{TP+TN+FP+FN} 

iv) Sensitivity = \frac{TP}{TP+FN} 

v) Specificity = \frac{TN}{TN+FP} 

vi) False Negative Rate FNR = \frac{FN}{TP+FN} 

vii) False Positive Rate FPR = 1 - \frac{TN}{TN+FP} 

viii) False discovery Rate FDR = \frac{Number of False Positives}{Number of True Positives + Number of False positives} 

“Fig.7” shows the performance of TB diagnosis using accuracy plot for different number of hidden neurons, similarly “Fig.8” and “Fig.9”, shows the performance of TB diagnosis using sensitivity and specificity plots. Here also we obtain the very good specificity value compare to existing approaches. “Fig.10”, shows the performance of GPSO-NN classifier for 10 hidden neurons, obtained the maximum accuracy of 90 %, which is 85 % for GA-NN and 76% for NN classifier. In “Fig.11”, shows the performance of TB diagnosis using sensitivity plot for 10 hidden neurons. we obtain the sensitivity of 83% for using GPSO-NN which is more than the remaining methods. Similarly specificity plot for 10 hidden neurons is shown in “Fig.12”.

Table -1 : Performance Comparison of GPSO-NN classifier with other classifiers for TB diagnosis

| Method          | True Positive | True Negative | False Positive | False Negative | PPV   | NPV   | FPR   | FNR   | FDR   | Sensitivity | Specificity | Accuracy  |
|-----------------|---------------|---------------|----------------|----------------|-------|-------|-------|-------|-------|-------------|-------------|-----------|
| SVM classifier  | 11            | 10            | 2              | 4              | 0.846 | 0.714 | 0.167 | 0.267 | 0.154 | 0.733       | 0.833       | 0.778     |
| KNN classifier  | 4             | 7             | 5              | 11             | 0.444 | 0.389 | 0.417 | 0.733 | 0.556 | 0.267       | 0.583       | 0.407     |
| Random Forest classifier | 9            | 6             | 6              | 6              | 0.6   | 0.5   | 0.5   | 0.4   | 0.4   | 0.6         | 0.5         | 0.556     |
| NN classifier   | 1             | 15            | 0              | 5              | 0.75  | 0     | 0.833 | 0     | 0.167 | 1           | 0.762       |           |
| GA-NN classifier| 4             | 14            | 1              | 2              | 0.8   | 0.875 | 0.067 | 0.333 | 0.2   | 0.667       | 0.933       | 0.857     |
| GPSO-NN classifier | 5           | 14            | 1              | 1              | 0.833 | 0.933 | 0.067 | 0.167 | 0.167 | 0.833       | 0.933       | 0.905     |

Original input images

![Original input image](image1)

Segmented output images

![Segmented output image](image2)
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![Fig. 6. Segmentation output of the proposed approach](image)

Fig. 6. Segmentation output of the proposed approach

![Fig. 7. Performance of TB diagnosis using Accuracy plot](image)

Fig. 7. Performance of TB diagnosis using Accuracy plot

![Fig. 8. Performance of TB diagnosis using Sensitivity Plot](image)

Fig. 8. Performance of TB diagnosis using Sensitivity Plot

![Fig. 9. Performance of TB diagnosis using Specificity Plot](image)

Fig. 9. Performance of TB diagnosis using Specificity Plot

![Fig. 10. Accuracy plot](image)

Fig. 10. Accuracy plot

![Fig. 11. Sensitivity Plot](image)

Fig. 11. Sensitivity Plot

![Fig. 12. Specificity Plot](image)

Fig. 12. Specificity Plot
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