JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
SICAIET
2024

Research Article
Collection: Artificial Intelligence and Emerging Technologies

Lungs Tuberculosis (TB) Identification in Computed Tomography (CT) Images Using Automatic Image Segmentation & Artificial Neural Network (ANN)

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Academic Editor: Salman Qadri **Published:** February 01, 2024

Abstract: Lungs Tuberculosis (TB) also called pulmonary tuberculosis is highly infectious disease and it spreads easily by air droplets from a cough or sneeze of an infected person. Pakistan is a third world country and there is a high rate of people in poor living conditions; such as homelessness, over-crowding, poor sanitation as well as poor nutritional conditions. Lack of awareness is another prime factor which leads to the deadly state of health. There are number of international and governmental efforts to reduce the infectious disease, but lack of experienced doctors is another reason behind large number of casualities. Identification of TB needs highly intensive and careful observation of radiographs (including X-Rays and CT-Scans). Thus, due to a large number of patients and very less number of experienced, over-burdened doctors, leads to poor diagnosis and results in more casualties sooner or later. Under such critical situation, there is a dire need of standard computer aided diagnosis mechanism for better identification of lung tuberculosis and reduction of casualties. Numerous digital image processing and classification techniques have proved strong in the detection of lungs nodules, tuberculosis and other lungs illness including cancer. However, assessing the existing approaches we have came to a conclusion that there is still a need of more accurate classification scheme for the identification of lungs tuberculosis in presence of many false-positive outcomes. This research work aims for an automated segmentation approach and multi-feature analysis to detect lungs tuberculosis using artificial neural network to reach better accuracy, and hence reduing the number of false-positives, for which we proposed Enhansed Split Erode Dialate Merge Process (ESEDMP) scheme and presented our results.

Keywords: Lungs Tuberculosis; Computed Tomography; Image Segmentation; Binary Features; Texture Features; Artificial Neural Network.

1. Introduction

TB (Tuberculosis) is known as a silent killer which is produced by a bacterium known as Mycobacterium tuberculosis. Lungs are most commonly attacked by these bacteria, but it can attack any part of the body including brain, kidney, spine etc. TB is a silent killer and many infected people doesn't show symptoms of it, that is why TB is categorized as: 1) LTB1 i.e., latent TB and 2) TB disease. It is highly recommended to treat TB properly otherwise, it can be fatal [1].

Several researchers over the past two decades have been working on the same problem and tried to improve and provided their solutions. Schilham introduced a computer algorithm for nodule detection in chest radiographs, which used multi-scale techniques including Guassian filters. Their selection step added some value in nodule detection but segmentation step didn't. Overall, 2 false-positives up to 51% detection and up to four false-positives up to 67% detection of nodules, which was close to 70% detection rate of radiologist [2]. Shen presented a hybrid knowledge-based automated segmentation technique which used Bayesian classification to automatically detect TB cavities. A comparison to non-hybrid techniques was made and the experimental results has shown that their approach has high accuracy with less false positive rate [3]. Jaeger presented an economic model for developing countries with less medical expertise a lung segmentation approach upto 83% accuray within a tuberculosis control program [4].

Melendez presented a MIL-based system which overcomes the draw-backs of famous miSVM technique and after retaining their MIL-based system, it outperformed (0.86 versus 0.79 for $p<0.0001$, 0.91 versus 0.85 for $p=0.0002$) better than supervised approaches which are typically time and labor intensive [5]. Govindan used Zeihl Neelson (ZN) staining, which is a famous manual microscopic diagnosis technique for TB bacteria. Tuberculosis bacilli was segmented and TB-positive & negative cases were identified performed automatically using classification depending upon features of bacilli in ZN image. MATLAB was used as a tool to implement the algorithm [6]. Hogeweg has presented an automatic system which has shown improved efficiency in detection of Pulmonary TB chest radio graphs. The diversity of TB CXRs requires a platform which can be adapted to deal with multiple abnormalities from different populations. Finally, a CAD system was designed to detect textural, focal and shape abnormalities by means of combining several supervised sub-systems [7]. R. Ramya presented an Automatic Tuberculosis Screening Using Canny Edge Detection Method in which they first extract the lung region using a lung nodule Edge detection method. Then for this lung region, they compute a set of texture and shape features, which enable the x-rays to be classified as normal or abnormal using a binary classifier [8]. Philipsen has presented a generalized method which have been applied thoroughly on many chest radiographs. Their method reconstructs an image by normalizing energy bands. Local application and iterative approaches were used whereas iteration was applied on the lung fields from six datasets of different sources having fifty normal and fifty abnormal images [9].

Hina has presented a CAD system which was trained on number of features and was able to classify into normal or abnormal x-ray images. To achieve this goal, first segmentation was applied, then features were extracted and then classification was done. The analysis was performed after setting different parameters on benchmark data sets [10]. Khobragade have presented a simple yet effective lungs segmentation technique. They used intensity and discontinuity-based approach for Lungs ROI detection, then extracted geometrical features along with statistical features which were used in detection of major lungs disease by using feed forward and back propagation ANN-based classification [11]. Poomimadevi presented that in the existing method it was very difficult to examine TB CXRs due to diaphragm and ribs, and cavities were detected using registration based segmentation methods. It is worth to note that registration was applied first prior to lungs ROI segmentation to reduce difficulties in segmentation. Two data sets were used to examine the performance of their algorithm by comparing them to existing methods [12]. Pattrapisetwong proposed an unsupervised learning method for lung segmentation in chest radiographs based on shadow filter and local thresholding. The approach consists of three processes: pre-processing, initial lung field estimation and noise elimination [13].

Joykutty presented a new approach to identify tuberculosis in chest radiographs. The strategy incorporates a three phase procedure of accurate identification of tuberculosis. First, the lung segmentation using adaptive thresholding is used to segment chest radiographs which have diverse illumination. Then features were extracted and the input image was converted to a set of features having relevant details and in last KNN was used for normal or abnormal classification of the image. Four performance evaluation criteria were used, namely: accuracy, sensitivity, specificity and area under the ROC curve. The simulation results have shown 4% more progress than other TB detection system [14]. Melendez proposed to embed MIL classifier into their AL framework to decrease the uncertainty and reduce labeling effort. A new instance selection method was developed which uses the MIL problem definition with means of one-class classification. Hence adapting meaningful ROIs instead of manual expert labeling which is considered more accurate in given application domain. The main optimization was to perform single iteration as contrary to existing active learning methods. The developed MIL-based CAD system was tested with and without AL framework. It is important to note that the system proposed was to detect textural abnormalities in TB. Finally, the results have shown that AL method has improved MIL-based classification [15]. Soltaninejad has shown their Concave hull algorithm was improved and yet shown over segmentation. Here they introduce Adaptive Concave Hulls, combine it with Adaptive Median Filtering, and finally apply an Active Contour Model to make the results much more robust and eliminate the over segmentation and under segmentation problem. Their technique is especially useful for automated detection of Juxtapleural pulmonary nodules that are attached to the chest wall. Experimental results demonstrate the improvements achieved by their new algorithm [16].

According to comprehensive survey by Hooda, TB has spread over the world and needs to be eradicated using appropriate medication, diagnostic procedures, and screening techniques. Computer-aided diagnostic (CADx) systems with an artificial intelligence component are said to be important for widespread tuberculosis screening. Research on the development of CADx systems began four decades ago, and to date, many CADx systems have been developed. There hasn't, however, been a presentation of an impartial survey that highlights the developments in these systems. Their study closes this gap by compiling the developments and providing an extensive overview of CADx systems for tuberculosis detection that have been created to date, with an emphasis on their fundamental ideas [17].

Many healthcare facilities employ chest x-ray imagery as a method of early screening for tuberculosis (TB). One key area of deep learning research is the automatic identification of tuberculosis based on chest x-ray images. A thorough analysis of the most recent deep learning models by Kotie, suggested for the automated identification of tuberculosis from frontal chest x-ray pictures. Pre-trained CNN and convolutional neural networks (CNN) are the most widely utilized deep learning techniques in this context. Different datasets, feature extraction, preprocessing, and classification methods applied to the suggested models and performance assessment metrics reviewed [18].

Yadav claimed that the automatic, quick, and trustworthy identification of lung illnesses from medical images is a significant potential of deep learning approaches. Convolutional neural networks, in particular, have achieved encouraging outcomes in the diagnosis of disease. Despite this, the effectiveness of these supervised models is highly dependent on the availability of substantial amounts of labeled data, which can be costly and time-consuming to gather, particularly for new diseases. Consequently, they suggested using a deep unsupervised framework to categorize lung diseases from X-ray and CT scans of the chest. Within this approach, multiple-layer generative adversarial networks (Lung-GANs) are introduced, which use only unlabeled data to learn interpretable representations of lung disease images. They trained a stacking classifier and a support vector machine using the lung attributes that the model had learned. [19].

Recently, survey performed by Bansal, the quantity of research on using machine learning techniques to the analysis of chest X-ray images for screening about pulmonary problems has increased dramatically during the last ten years. In particular, there has been a noticeable interest in tuberculosis testing. This heightened awareness coincides with the extraordinary advancements in deep learning (DL), mostly based on convolutional neural networks (CNNs).

Finally, in another survey by Al-Qaness the conclusion highlights the urgent need for more technical development in this field in order to close gaps in the delivery of healthcare and enhance patient outcomes. The main objective is to open the door for more accurate, effective, and easily available diagnostic instruments in the fight against lung disorders, while highlighting the critical role that technology plays in contemporary healthcare [20].

2. Materials and Methods

2.1 Background

Lung abnormalities in human cause different diseases especially in third world countries like Pakistan where health is major subject on which work has to be done. There is lack of latest medical technologies in Pakistan which is one of the major factors due to which these diseases are not diagnosed well in time and cause severe damages. Human eyes could not detect the abnormalities in human anatomy directly. Most of the time X-rays and Radiographs are used to diagnose the diseases. But as the last decision is to be made by the medical practitioner; human eye error factor could not be ignored. Delay in diagnosis of such disease causes complications and death in the extreme cases.

Radiologists always considers many factors while identifying TB, like de-shaped morphology of the lung’s airways, patient’s age and anatomical structure before producing the final conclusion/report. There is a list of world class 2D & 3D image viewing software available to inspect CT Scans like Vitrea ® Enterprise Imaging (a propriety paid solution used by BVH) and an open source application MITK provided by German Cancer Research Center Division of Medical Image Computing. But still automated identification of the TB is not present, consequently, it doesn't provide any solution for the problem addressed in this research work.

2.2 Digital Image Processing

Digital Image Processing is a fundamental field of Computer Vision. Advancements in the development of state-of-the-art digital imaging devices has led to tremendous increase in not only the improvement in diagnostics but also the powerful visualization capabilities, which aids medical practitioners for better diagnostics. Digital Image Processing plays an important role in our daily life and it ranges from remote sensing, medical, education, and several other industries like monitoring and control. Hence, a huge volume of imaging data is being produced on daily basis, which needs an automated procedure to be examined, which is otherwise not possible manually. Thus, there is a need of an automated process, without or least human involvement for the processing of such huge volume of imaging data.

2.2.1. Digital Image Processing Process

Digital Image Processing is an iterative process, which can be categorized into three levels.

1. Lowest Level

At lowest level, raw image data is being studied, thus manipulating the original contents of the image by applying pre-processing techniques like: noise removal, compression, filtering, or enhancement. Hence, the input is an image and so is the output, also produced as an image.

2. Middle Level

At middle level, segmentation or edge detection and linking techniques are used. Here, like in step mentioned above, the input is an image and so is the output, also produced as an image.

3. Highest Level

At highest level, the segmented objects are labelled to produce some semantics of the image, which can be used for image representation or further processing. Thus, the input is an image, but the output is a higher-level representation of semantic data.

Now, the highest-level semantic data obtained from the image processing is used widely in knowledge representation and decision making.

2.2.2. Medical Image Processing Process

Medical images are of complex nature and must be processed differently depending on the type, shape and medical situation of organs presented in the image. Typically, three types of tasks are performed:

1. Pre-processing / Filtering

It ranges from noise reduction, filters, brightness, contrast, and other enhancements

2. Segmentation

Isolation of organs or region of interests (ROIs)

3. For the identification of medical conditions and/or events

Comprehension / Registration

4. Quantitative and/or qualitative analysis of the abnormalities and/or events found

It is very important to understand that the qualitative analysis must be performed by medical practitioners as it is ill suited for computer vision systems for various reasons. However, the quantitative analysis is best suited for computer vision systems, such as calculating the volumetric information of a tumor or the size of a fractured bone, dimensions of damaged muscle etc.

Thus, the combination of both quantitative and qualitative analysis, builds a power binding and hybrid tool which might otherwise doesn't produce better results.

2.3 Methodology

2.3.1. Proposed Methodology

The proposed methodology consists of three steps as depicted in (**Figure 1**):

1. Prepare Training Dataset
2. Automated Image Processing
3. Multi-Feature Analysis and Classification Results

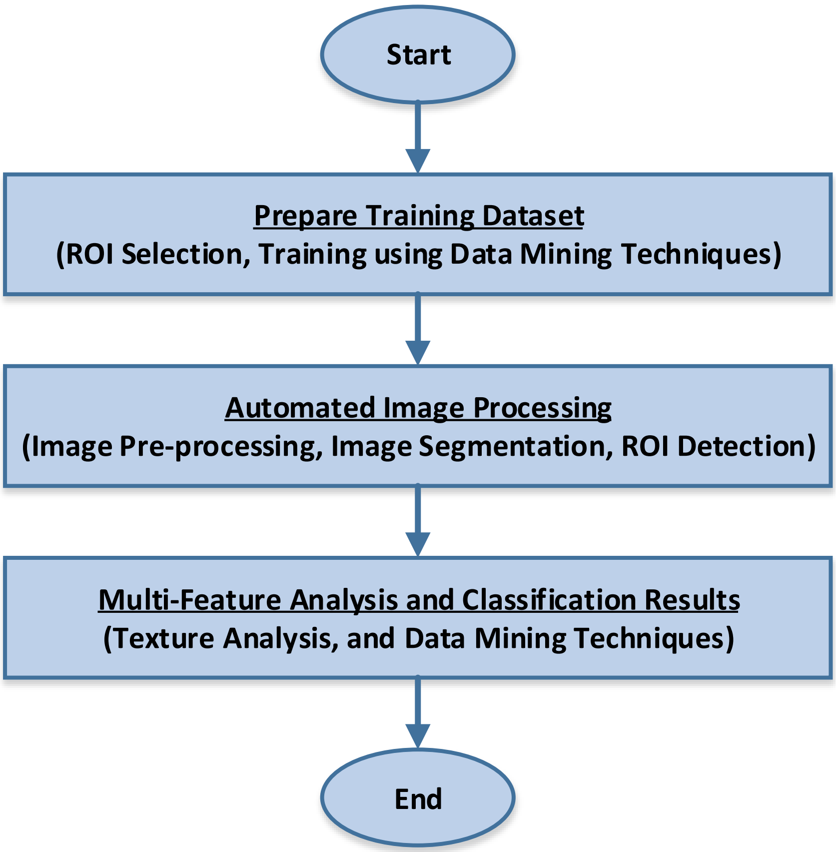

Figure 1. Proposed Methodology

2.3.2. Anatomical Feature Extraction Method using ESEDMP

Anatomical feature extraction method consists of following steps:

1. Set Image to NULL.
2. Let Processes be the list of process.

[Note: A process takes an image and optional set of parameters as an input and returns an image as an output after performing a process over it]

3. Add LoadGrayImageProcess in Processes with Filename as a parameter.
4. Use IPGrayMatrix to get the Mean of the image.
5. Add BinarizationProcess in Processes with Mean as a parameter.
6. Add ErosionProcess in Processes with 3 as a parameter.

[Note: Erosion will be applied 3 times]

7. Add DilatationProcess in Processes with 3 as a parameter.

[Note: Dilatation will be applied 3 times]

8. Add NeighbourExtractionProcess in Processes with Four points as a parameter.
9. Add NegativeProcess in Processes with Mean as a parameter.
10. For Each Process in Processes
    call Perform ( ) [Note: To process image and save resultant image in the list of image results]
11. Clear Processes List.
12. Set Image to first image result.
13. Add BlackMaskingProcess in Processes with last image result as a parameter.

[Note: Last image result was obtained from NegativeProcess]

14. Add SplidErodeDialateMergeProcess in Processes with 0 as foreground and 255 as background.
15. For Each Process in Processes
    call Perform ( ) [Note: To process image and save resultant image in the list of image results]
16. Use IPConverter to obtain Image Objects.
17. Label Each Image Object Automatically.
18. Use Gray-Level Filtering to Extract Anatomical Features.

It is pertinent to mention that ESEDMP is a modular scheme and can be extended easily to accommodate different processes like noise removal, image contrast, etc. The resulting images obtained from ESEDMP are used in labelling and feature extraction process. Finally, these features are provided to an Artificial Neural Network for classification.

3. Results

3.1 ESEDMP Results *(Figure 2) represents the ESEDMP results below:*

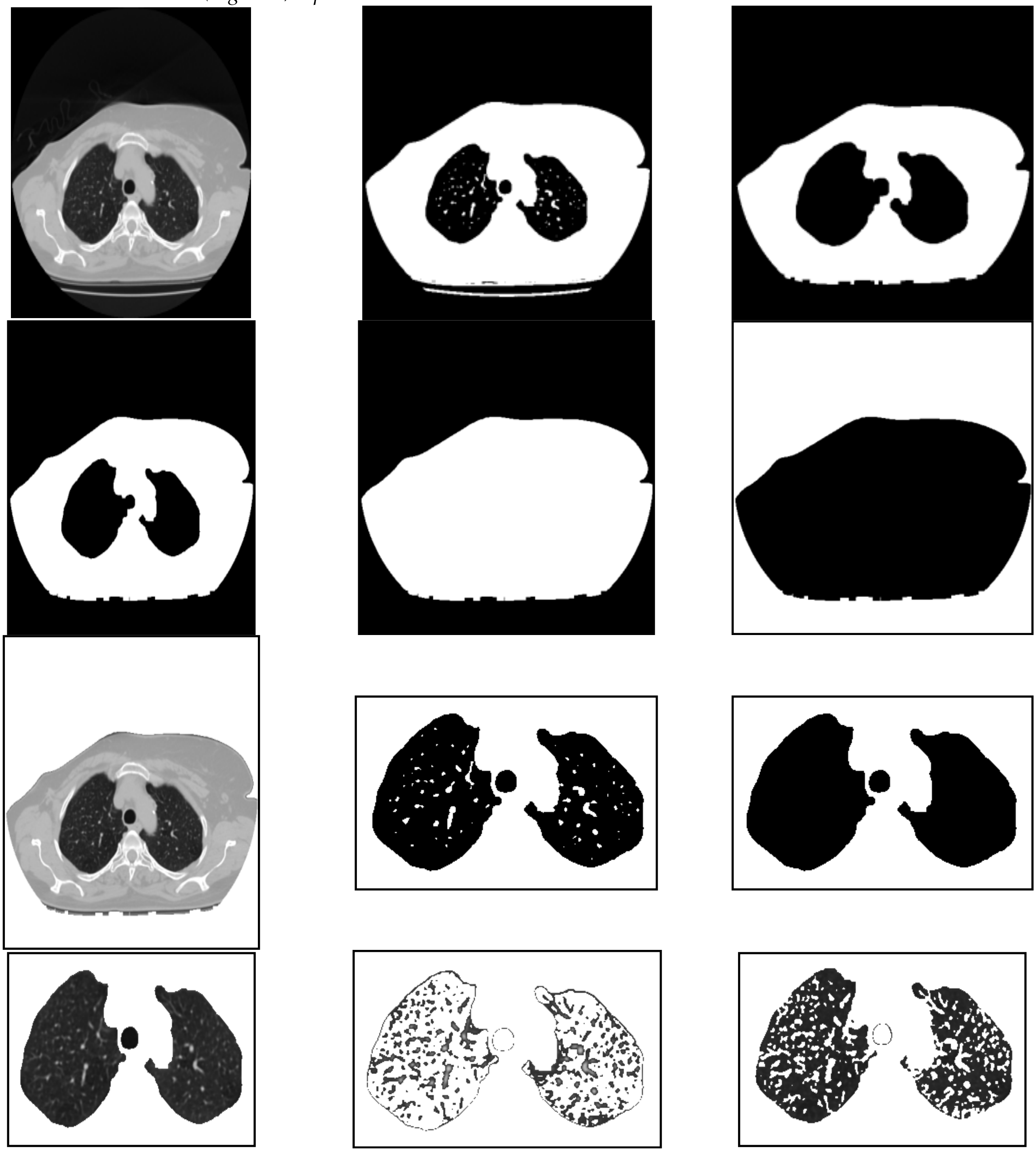

Figure 2. ESEDMP Results

3.2. Artificial Neural Network based Classification Results

The multi-feature classification results are shown below in (Figure 3).

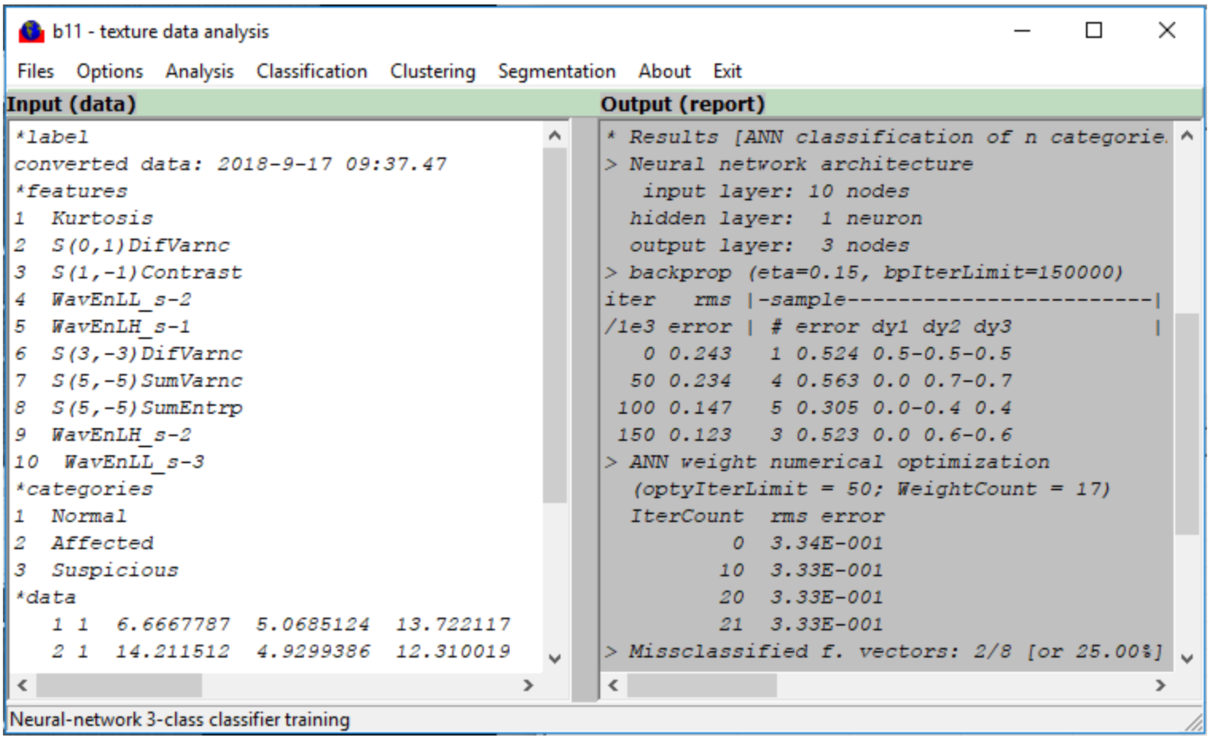

Figure 3. Artificial Neural Network based Classification Results

4. Discussion

4.1 Tools

1. Mazda Software
   MaZda is used for ROI selection
2. B11 Software
   B11 is used for Feature Selection/Reduction & ANN Classification

4.2 Dataset and Features Vector Space

- Dataset details
  03 types of images (Normal, Affected, Suspicious)
- 50 images of each Type
  i.e. 50 x 03 = 150 images dataset
- 04 non-overlapping ROIs for each image
  i.e. 150 x 04 = 600 ROIs for dataset
- Texture / Co-occurrence Matrix Features
  11 Co-occurrence Matrix Features
  04 Dimensions: (0, 45, 90, 135) degrees
  05 Pixel Distances: (1, 2, 3, 4, 5)
  i.e. 11 x 04 x 05 = 220 Texture / Co-occurrence Features
- Histogram Features
  09 Histogram Features
- Total Features: Texture / Co-occurrence Features + Histogram Features
  i.e. 220 + 9 = 229 Features for each ROI
- Total Features Vector Space
  Total 600 x 229 = 137400 Features

4.3 Feature Selection / Reduction

B11 software is used for feature selection/reduction technique. POE + ACC Feature Selection/Reduction Technique was applied. 229 Texture / Co-occurrence + Histogram Features were used and reduced to 10 best features.

- Reduced Feature Vector Space
  Total 10 Reduced Features for each ROI

Total 600 ROIs

Total Reduced Features = 600 x 10 = 6000 features

i.e. 137400 features were reduced to 6000 best optimized features only.

4.4 Classification Results

The overall mis-classification was reported 0.25 i.e., 25% which means the overall classification accuracy obtained was 75%.

5. Conclusions

Lungs Tuberculosis (TB) also called pulmonary tuberculosis is highly infectious disease and it spreads easily by air droplets from a cough or sneeze of an infected person. Pakistan is a third world country and there is a high rate of people in poor living conditions; such as homelessness, over-crowding, poor sanitation as well as poor nutritional conditions. Lack of awareness is another prime factor which leads to the deadly state of health. There are number of international and governmental efforts to reduce the infectious disease, but lack of experienced doctors is another reason behind large number of casualities. Identification of TB needs highly intensive and careful observation of radiographs (including X-Rays and CT-Scans). Thus, due to a large number of pa-tients and very less number of experienced, over-burdened doctors, leads to poor diagnosis and results in more casualties sooner or later. Under such critical situation, there is a dire need of standard computer aided diagnosis mechanism for better identification of lung tuberculosis and reduction of casualties. Numerous digital image processing and classification techniques have proved strong in the detection of lungs nodules, tuberculosis and other lungs illness including cancer. However, assessing the existing approaches we have came to a conclusion that there is still a need of more accurate classification scheme for the identification of lungs tuberculosis in presence of many false-positive outcomes. This research work aims for an automated segmentation approach and multi-feature analysis to detect lungs tuberculosis using artificial neural network to reach better accuracy, and hence reduing the number of false-positives, for which we proposed Enhansed Split Erode Dialate Merge Process (ESEDMP) scheme and presented our results.

As the ROI selection and labelling is a manual and time intensive process, the next phase of this research work will be to develop an automated labelling technique for ROI selection and applying deep learning techniques for better performance and classification results.

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