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Machine Vision based Computer-Aided Detection of Pulmonary Tuberculosis using Chest X-Ray Images

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Abstract- **Tuberculosis (TB) is a lethal disease and developing countries are struggling to overcome this health hazard especially in rural areas and faced globally. Therefore, serious measures are required to reduce this global health hazard. Millary and pulmonary are the most common types of tuberculosis occurring globally. X-ray is the preliminary method to detect tuberculosis; however, the diagnosis is quite often subject to human error. In contrast, the chances of curing Tuberculosis depend on its timely and accurate diagnosis. Therefore, an intelligent machine learning algorithm is developed in this study to assist the clinician in an accurate TB identification in x-ray images. The proposed method pre-processes the X-ray image, enhances its quality and extracts the features of each class which are further passed on to a Deep Convolutional Neural Network-based design for the X-ray image classification, followed by the identification of the tuberculosis type i.e. Millary, Cavitary, Healthy. The classification accuracy for the developed method resulted in 88% and 89% for millary and cavitary TB diseases in X-ray images.**

Index Terms-- **Deep Convolutional Neural Networks, Machine Vision, Tuberculosis, X-Ray Imaging.**

I. INTRODUCTION

Tuberculosis (TB) is a globally acknowledged lethal and dangerous disease, and is ranked higher than the human immunodeficiency virus/Acquired immunodeficiency syndrome (HIV/AIDS) [1], which causes bad health and has more than 1.4 million deaths per year [2]. Almost a third of world population being affected by TB and it is expected that about 5-10% of the population may as well develop the active TB during their life [3]. TB is considered as one of the most contagious diseases and a problem for public health worldwide.

TB is an infectious and contagious disease, the air droplets made via coughing or sneezing when breathed by a healthy person could cause TB. The bacteria are easily spread from an infected to another person, which occurs 95% of the time in the form of Koch's bacillus or bacillus Mycobacterium tuberculosis (M. tuberculosis). These bacteria have a rod-shaped aerobic bacillus structure which measures as 2μm to 6μm long and 0.3 to 0.6μm wide approximately. The main key characteristic of the M. tuberculosis is its acid-fast bacillus because the bacterium resists to acid in decolourization in laboratory testing which is also called staining process According to [1], the pulmonary tuberculosis is the most common type of the tuberculosis diseases which appears in approximately 80% of the overall cases. Since the lethal disease could be prevented only through timely diagnosis and proper treatment. Therefore, if early diagnosis is not performed due to unawareness, and ineffective susceptibility test, then the patients rely on a multi-drug resistant state called MDR_TB in which the bacteria gets resistant to drugs.

In practice, different tests are employed for the detection of TB including Tuberculin Skin Testing (TST) or Mantoux test, Chest Radiograph, Diagnostic Microbiology, TB Interferon-gamma release assays. Since these tests may not be completely accurate or maybe expensive, thus it is important to develop a faster, more accurate and cheaper solution. Besides, the process of detecting TB using CT or X-ray images are mainly acquired by visual means which are handled by the radiologists. The detection is based on radiologist experience and knowledge. In this regard, the computer-aided diagnosis (CAD) techniques and procedures can prove to be useful in medicine to further assist the doctors in diagnosing medical images. This paper addressed on TB detection, particularly two classes, millary and pulmonary by a CAD system.

The process of TB detection is achieved via manual examination of the X-rays or CT images by a clinician. The manual examination is subject to errors and misdiagnosis, especially when the X-rays or CT images are examined via naked eye. Consequently, due to the inaccurate prediction and the error in identification of the irregularities; the clinician is often unable prescribing accurate identification and subsequently medication. This highlights the importance of accurate detection of the irregularities as treatment dosage and medicine prescription is highly dependent. This lays the foundation for the development of a technique that performs an accurate detection of Pulmonary TB, and hence it will be used by the concerned clinician for the accurate identification of pulmonary TB.

II. LITERATURE REVIEW

Various methods have been presented in the literature to diagnose pulmonary tuberculosis. However, still, most of the underdeveloped or developing countries employ the sputum smear microscopy for tuberculosis diagnosis due to its low-cost and fast test procedures and accurate results. The World Health

Organization (WHO), in 2011 began a diagnostic test for TB which was referred to as Microscopic Observed Drug Susceptibility (MOD). MOD is a low cost, identification-based method for M. tuberculosis (MTB), the bacteria growth requires about 7–10 days which is from a sample known as sputum. The shape of bacteria is called morphology and the bacteria are used on the characteristic S-shaped, colonies in the culture evidence the presence of TB.

According to a reported survey [4] regarding automatic testing for detecting TB employing chest radiographs, TB screening has been a major challenging task to handle and an open area for research to counter the problem. The Resonance Imaging which includes methods such as ultrasound diagnostic, (MRI) and X-ray imaging are imaging techniques that have a great yield in computer-aided diagnosis (CAD). Thus, CAD offers an improvement in the field of biomedical image processing with an effective merger of an artificial intelligence-based algorithm (AI) and image processing combined with radiological based image processing. Many techniques have been introduced for the segmentation of lung [5, 6]. Scientists and researchers have worked on the classification of abnormal and normal CXR using texture features [7, 8].

Generally, the quality of X-rays plays an important role in the detection process. The X-ray is used to generate a two-dimensional shadow which is a raw data with no meaningful information detailing. The shadow, which is created by the rays passing through soft tissue, may generate an incomplete picture. This may result in providing small details regarding the irregularities present in the lung lobes at the upper lobes. The segmentation of this upper lobe region is an important procedure for medical imaging analysis and classification, especially for the radiological evaluation and computer-aided diagnosis.

During the process of image segmentation, image is divided into a group of pixels, each sharing similar characteristic, features or some properties. In other words, the image segmentation technique segments the regions of similar features together [7]. The region-based methods are considered as the most effective and fast [8]. Particularly, snakes or active counter (AC) were used in [7-9] which accurately segments the ROI (region of interest). Another method involves microscopic images to detect and segment TB [10]. It involves an adaptive threshold-based segmentation whereas parameters such as colour, morphological, and size filters are used to eliminate any noise data set in the (R-G) Segmented image in Binarization based TB detection system was also proposed [11] which is based on binarizing the set edges and lines of the ribs, followed by the use of gradient vector flow model for performing segmentation and K-means classification for TB detection. In [12] a method proposed as TB Ziehl-Neelsen Stained Tissue Slide Images was presented for the detection of tuberculosis which suggested active shape model for texture analysis. Followed by Multilevel Image Enhancement for the auto-detection of the tiny nodules which helped in obtaining detail information on pulmonary tuberculosis. In their approach, the following image processing techniques were applied i.e. (i) Repeating a smoothing-sharpening technique for the improvement of X-ray images of lung (ii) Diagnosis of the indeterminate nodules using Bayesian classifier. The proposed technique successfully experimented on the lung X-ray images [13]. An automatic system was developed to detect TB by an automatic screening of Posterior Chest radio-graphs [14]. The authors in [15] have discussed an efficient coarse-to-fine dual scale technique for the cavitary detection in chest radiographs. Their method first uses the Gaussian-based matching (GBM), followed by the local binary pattern for the detection of cavities. In the end, gradient orientation features are used at the coarse-scale. The coefficient of variation for circularity, gradient inverse and Kullback-Leibler divergence techniques are applied.

Similarly, a wavelet transform was used in [16] on the CXR images to achieve a low-frequency component, a high frequency. Approximately, profiles of thirty lines were obtained from a CXR image of a patient with TB. These profiles line contained the 2^{nd} rib, up to the 5^{th} rib. These profiles were used to represent Daubechies coefficients. The statistical analyses on the clustering were used to determine whether the features were enough for identification of TB in a CXR image. In [17], an important and complex method was presented which combines advanced geometrical and textural features with the aim of TB cavitary detection. First, a technique is employed to extract and classify the feature, (SVM), the Gaussian model-based template matching (GTM), the LBP (local binary pattern) and the histogram of the oriented gradients (HOG), extract cavitary candidates from CXR images. Afterwards, the extracted features are refined more by using image enhancement techniques such as Eigenvalues of the Hessian matrix (HIE) and the active contours snake-based technique (ACS). In the last step of the algorithm, the improved form of the cavitary is then broken down which reduces false positives by making use of the classification technique. The authors proposed an interesting approach to locate the focal opacities of TB using CXRs. The method focuses on an extracting of rib lines initially. After locating the ribs accurately, Morphological operations (opening) and a seed growing method are applied to the binary CXR image to locate the focal opacity. X-ray based TB detection has been performed before via deep learning and the x-ray images of the lungs were multi-level enhanced. Then, TB was classified through back propagation neural networks [18]. The methods discussed are novel and interesting; however, some methods fall short in terms of accuracy and were time-consuming. Limited researchers detected and studied the full spectrum of TB detection (i.e. military, cavity and Healthy). Nonetheless, making use of the development of advanced computational system and state of the art laboratory, a method for the detection of cavitary, millary TB and healthy lungs is proposed in this study.

III. MATERIALS AND METHADOLOGY

The methodology consists of machine vision-based techniques to classify three classes of Chest X-ray, pulmonary, millary and healthy. To achieve this, a dataset was created. The dataset was self-generated and was collected by hospitals with patients' consent. A total of 300 images were initially collected. The images were scanned under a controlled environment and then uploaded to the dataset. Since these images were not enough for training the classifier; therefore, several augmentation techniques were applied to increase the data set for each class (i.e. normal, millary tuberculosis and cavitary tuberculosis). Data Augmentation was applied to the original data set to create more images of the specific form. Consequently, the augmented dataset was used to train the classifier so that the algorithm becomes more robust and accurate. The employed augmenter library sets up a pipeline for each folder/class of images with different probabilities and degree of rotation, zoom, flip from left to right, and applying random distortion.

The augmented dataset was split into three sections namely, training data, validation and test data. Image generator was set to augment the data on the fly for each epoch in the model training to increase model robustness for generic data. It was designed to set rotation type, rescale value, zoom range, shear range, width shift range, horizontal flip measure and height shift range for each train, validation and test data. The image augmentation stage was followed by the development of the Convolutional Neural network (CNN) model for image classification in a multiclass problem. These have different layers each with a different number of filters to learn the patterns of images in a better way. This trains the model on the training. After training the model, its performance is evaluated on test data, using different performance metrics such as confusion matrix, error rate accuracy for each class etc.

Deep learning generates hierarchical features from images. These features are generated automatically and are from a feature of a lower level and enhance it to a higher level. The enhancing of lower-level feature to the higher level provided better classification in deep learning algorithms [19]. The CNN consists of Neurons which have weights and biases, The CNN consists of few layers mainly the convolutional layer, pooling layer and Fully Connected (FC) layer [20]. These layers mostly consist of four different types as shown in Fig. 1. In the input layer, the image data was presented to the network. The input image is generally presented in matrix form. The matrix is present in a square matrix having equal rows and columns but in the input layer the matrix is reshaped into a single column and the rows is increased. The column number will be changed to the number of training models. Suppose there is an image of dimension 28 x 28 =784, it is converted into 784 x 1 before feeding as an input to the network.

In the next step, the Convo layers also called convolutional layer features were extracted. The features in the x-ray are the different features occurring in the area of the lungs. The suggested features for two classes of TB are the web-shaped widely spread structure for millary tuberculosis and the round holes shaped cavities for cavity tuberculosis.

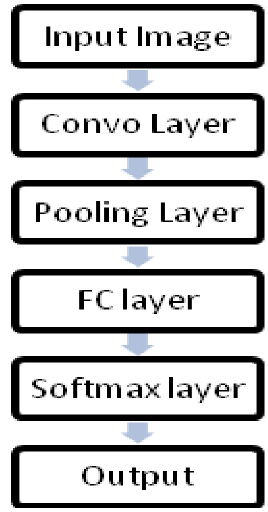

FIGURE 1: CNN Layers

Firstly, a fragment of the image is passed to the Convolution layer to perform the function and to calculate the dot product between receptive fields and the filter. A single integer of the output volume is the result of the operation. Subsequently, the filter slides over the next receptive field of the same input image by a stride and perform the same operation again. The convolutional layer also consists of ReLU activation. ReLU activation changes all negative values to zero. Next, pooling layer is used to reduce the dimensional volume of input image after convolution as shown in Fig. 2. It is used between two convolution layers.

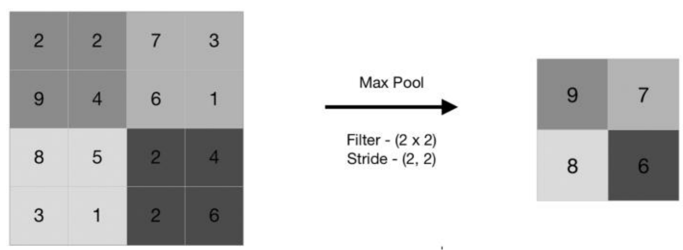

FIGURE 2: Pooling layer

The fully connected (FC) layer includes weights, biases, and neurons which are shown in Fig. 3. Neurons from one layer to another layer are connected by the FC layer. It is used for image classification.

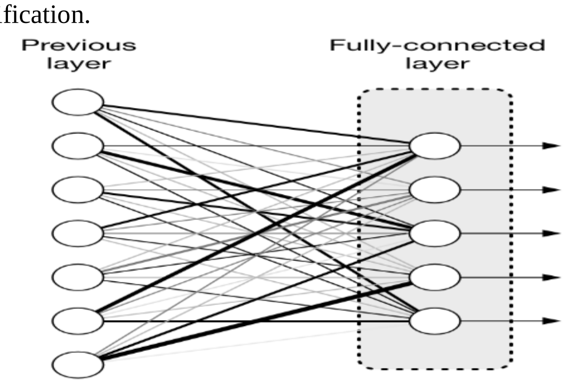

FIGURE 3: Fully Connected Layer (FC)

Softmax layer appears at the last of the all layers of the CNN and just after the fully connected layer. For binary classification Logistic is used and for multi-classification softmax is used since there are multiclass such as normal millary tuberculosis and cavity we have used the softmax layer. Finally the output layer contains the label which is in the one-hot encoded form. The output layer comes as the output from all the before process and after the output layer, the final layer/Process of CNN is performed in which the image is classified on the base of the trained model. Keras is the function used for the classification. The algorithm was implemented using the Keras to classify the image and the state of tuberculosis whether normal, millary or cavitary tuberculosis.

IV. EXPERIMENTATION

The experimentation stage makes use of different techniques to detect and classify the state of tuberculosis. The method firstly receives an input x-ray image and the input image is pre-processed as per the demands using image processing techniques. As a result of the pre-processing stage, the input image becomes simplified and ready for further processing. The region of interest (ROI) is extracted and then further techniques are applied. Finally, the processed image is fed to the classifier to perform the classification of the image. The classifier is developed using multiclass Deep Convolutional Neural Networks (DCNN) which is trained using 3500 data sets for each of the class i.e. negative tuberculosis, Millary tuberculosis and Cavitary tuberculosis. The stage is discussed in the followings. Image acquisition is the preliminary step to accurately detect tuberculosis.

In this study, the X-ray images are collected specifically of the pulmonary region which is classified by the radiologist into three different classes.. The second step involves arranging the image in a suitable manner which increases the data and information which is useful for further information extraction (i.e. features). The pre-processing involves augmentation techniques which are previously discussed. The feature extractor module is designed to extract the main suggested features of the given class which are (i) Web shaped structure for Millary (ii) Round cavities for cavitary and (iii) Normal Chest X-ray for Normal Condition. Figure 4 represents x-ray images of healthy lungs, millary tuberculosis and a cavitary respectively. The algorithm was trained using the extracted features of the augmented dataset. The image classifier uses KERAS library of the DCNN to classify the image. The algorithm classifies the results into the classes such as Millary TB, Cavitary TB and Normal. Image classification is performed by the usage of deep convolutional neural networks which pass the test image through various filters and then classify it respective to the trained data.

The training set validation and accuracy of the trained models were generated as shown in Fig. 5, according to which, the validation and training are reaching the desired accuracy.

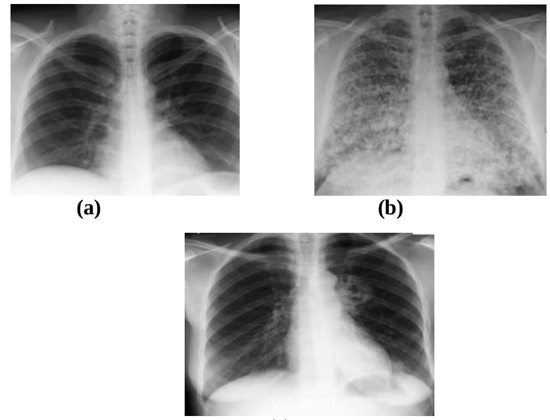

FIGURE 4: (a) Healthy (b) Millary Tuberculosis X-ray (c) Cavitary Tuberculosis X-ray

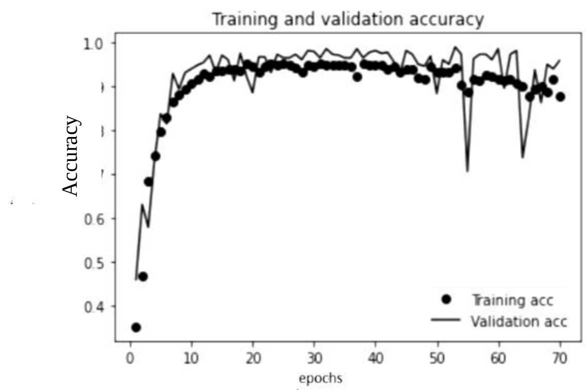

FIGURE 5: Validation and training accuracy

V. RESULTS & DISCUSSION

The tuberculosis detection was performed by using the PYTHON IDE. The images resolutions were 600 x 600; the input images were taken from x-ray machines and then given to software for classification. The developed algorithm is a combination of image enhancement, machine learning and classification using a multi-class DCNN. The confusion matrixes were used for checking and evaluating the accuracy of the classifier. The developed method has experimented on different X-ray images for the detection of tuberculosis and results were generated. The experiments were repeated with different conditions. The database had data points exceeding three thousand and the execution time for the developed algorithm was within ten seconds.

During testing, the image is taken and provided to the algorithm to apply image pre-processing techniques and image enhancement to upgrade the image representation. The algorithm resulted in accurate results and the accuracy rate of the algorithm was 88% for a cavity, 89% for millary and 89% for the normal state on 120 images as shown in Tab. I. This matrix represents the total number of detections done by the algorithm.

TABLE I: Multiclass Evaluation Matrix

	Cavitary	**Millary**	**Normal**
FP	1.00000	0.000000	13.000000
FN	13.000000	1.00000	0.000000
TP	27.000000	39.000000	40.000000
`TN	79.000000	80.000000	67.000000
TPR	0.675000	0.975000	1.00000
FPR	0.012500	0.000000	0.000000
FNR	0.325000	0.025000	0.000000
ACC	0.883333	0.891667	0.891667

For this test, a total of 120 test subjects were used.This approach was successful in the identification of three classes, Normal, Millary TB and Cavitary TB. To explain the accuracy of the proposed method, analysis were done comparing the proposed method and the already accepted methods which are discussed in Xu T et al. [15] and Betsy et al. [21] are limited to a certain class or type of tuberculosis while the developed method detects both common types of TB such as millary and cavitary which is shown in Tab. II.

TABLE II: Comparison Of Different Methods

S No	**Reference**	**Methods**	**Remarks**
1	[15]	Gaussian based Kullback Lieber divergence.	Detects Only Cavitry Tuberculosis
2	[21]	KNN Classifier	Detects Millary Tuberculosis
3	Developed method	Deep Convolutional Neural Networks	Detects Millary and Cavitry Tuberculosis

As further explained in Fig.6, the developed method overall accuracy is 94%, compare to other established methods having 64% and 80% for [15] and [22].

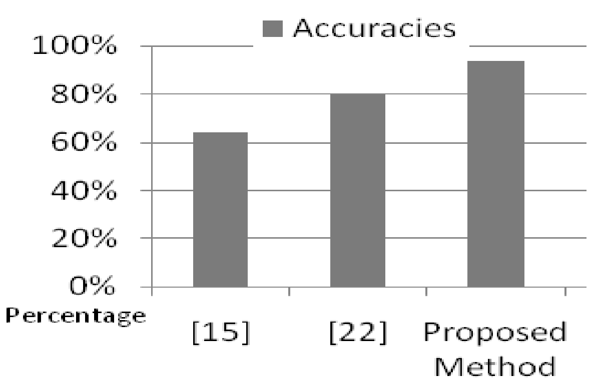

FIGURE 6: Comparison Graph

The results presented for developed method indicate better performance thus, the effectiveness of the proposed method more efficient and accurate. Other methods [15] and [21] are limited to a certain class or type of tuberculosis while the developed method detects both common types of TB such as millary and cavitary and also is more accurate.

VI. CONCLUSION

Machine Vision-based systems are employed to detect to diseases at early stages and further saving important human lives. In this study, a system was developed to assist healthcare workers to detect tuberculosis at an early stage and avoid cause fatalities, therefore, a data set of 120 image sets were tested which resulted in an accuracy of 88% for a cavity, 89% for millary and 89% for the normal state. Therefore it is concluded that the approach accomplished the desired aim to detect tuberculosis and types of tuberculosis millary and cavitary. It was observed that the proposed method results are promising and computationally efficient.

In future, experimentation on lungs damage accurate identification in consultation with the radiologist for the identification tuberculosis bacteria is in progress.

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