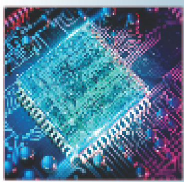

Sharif Abbas et al. LGURJCSIT 2022

SSN: 2521-0122 (Online)
ISSN: 2519-7991 (Print)

LGU Research Journal of
Computer Science & IT

doi: 10.54692/lgurjcsit.2022.0604383
Vol. 6 Issue 4, October – December 2022

Deep learning to predict Pulmonary Tuberculosis from Lung Posterior Chest Radiographs

Hanan Sharif [1], Faisal Rehman[1], Naveed Riaz[2], Awais Salman Qazi[3,4], Rana Mohtasham[1,3*], M husnain[1]
[1]Department of computer science Lahore Leads University, Pakistan,
[2]School of computer science National University of Sciences & Technology, NUST, Pakistan,
[3]Department of computer science Lahore Garrison University, Pakistan,
[4]Department of Computer Science, University of Management and Technology, Lahore

Email: ranasabh@hotmsil.com

ABSTRACT:

Tuberculosis is one of the most dangerous health conditions on the globe. As it affects the human body, tuberculosis is an infectious illness. According to the World Health Organization, roughly 1.7 million individuals get TB throughout their lifetimes. Pakistan ranks fifth among high-burden nations and is responsible for 61% of the TB burden within the WHO Eastern Mediterranean Region. Various methods and procedures exist for the early identification of TB. However, all methods and techniques have their limits. Most currently known approaches for detecting TB rely on model-based lung segmentation. The primary purpose of the proposed study is to identify pulmonary TB utilising chest X-ray (Poster Anterior) lung pictures processed using image processing and machine learning methods. The recommended study introduces a unique model segmentation strategy for TB identification. For classification, CNN and Google Net. Other systems based on deep learning are used. The best accuracy attained by the suggested method utilising Google Net on merged datasets was 89.58 percent. The recommended study will aid in the detection and accurate diagnosis of TB.

KEYWORDS: Chest X-ray, Medical imaging, Deep learning, Segmentation

1. INTRODUCTION

Since tuberculosis is an infectious illness, it can impact the human body. In most cases, microorganisms known as Mycobacterium are to blame for an individual's tuberculosis. This bacterium infects the lungs in addition to causing harm to other regions of the body [1]. The most frequent symptoms are coughing, fever, weight loss, night sweats, and sputum containing blood. Latent TB is when an infection has not shown itself clinically and typically does not cause any symptoms. It is possible that TB will not be recognised at an early stage since there are no symptoms associated with it. It'd result in the death of more than 10% of the world's population. According to the World Health Organization, 510,000 new tuberculosis cases are diagnosed yearly [2]. Pakistan is responsible for 61% of the total TB burden in the WHO Eastern Mediterranean Region [2], ranking fifth on the list of high-burden countries. The World Health Organization says that the number of people with tuberculosis (TB) in Pakistan goes up yearly.

Tuberculosis is still a dangerous illness in both developed and developing nations. TB is mainly transmitted via the air when infected individuals cough, sneeze, and discharge infectious microorganisms. Tuberculosis is a deadly illness that affects individuals with HIV and other conditions. 90% of the world's population is afflicted with tuberculosis. Early diagnosis or identification of tuberculosis is curable, and the proportion of patients who survive may increase. Numerous studies describe various methods for detecting the presence of TB in patients. Public datasets are used to identify TB with the appropriate clinical information. The Chest X-ray data collection includes lung pictures from healthy and tuberculosis-infected patients. Different chest X-ray image databases provide images of varying sizes (number of pixels). However, for the correct diagnosis of tuberculosis in a specific region or country, datasets are provided by hospitals or government institutes of the respective nations. For tuberculosis to be found automatically, there are a lot of essential steps that use machine learning and image processing.

Most tuberculosis research focuses on tuberculosis detection via chest x-ray radiology images. These images have produced new results and computed data for computer-aided screening and detection. However, some work requires specific conditions to achieve the highest level of performance.

Recent work on the detection or diagnosis of TB using machine learning approaches has a wealth of information on the tools, models, and datasets. Using chest X-ray image collections to identify TB is the basis of the proposed study. Instead of a model based on the approaches employed in the proposed study, the suggested research is based on segmentation thresholding techniques. The area of interest and classification results were obtained by segmenting the pictures.

This paper is divided into six sections. The introduction provides a comprehensive overview of the diagnosis of pulmonary TB using an anterior chest radiograph of the lungs. The second portion includes a review of the relevant literature, while the third section discusses the suggested technique. The fourth portion includes experimental specifics; the fifth section provides findings and discussion; and the last section provides suggestions for the future.

2. LITERATURE REVIEW

The global spread of tuberculosis is a gradual but steady threat to human health. At least 400 years ago, the human body was hit by this lethal illness. Clinical data is combined with machine learning and image processing methods to provide a diagnostic framework for studying and treating illness. Recent work on TB detection by Jaeger Stefan et al. [3] Described a computer-aided diagnosis system for tuberculosis screening and obtained performance close to that of human specialists via graph cut-based segmentation with the lung model for extracting the lung area. Unfortunately, the new chest X-ray datasets have a reliability problem because of the model base segmentation.

Deep learning methods, such as convolutional neural networks and associated models, were used by Lakhani et al. [4] to develop a system for the automated classification of pulmonary TB using chest radiograph datasets. CAD4TB was used to create an automated method for spotting tuberculosis in medical data. The paradigm developed by Maduskar et al. [5] evaluates the accuracy of a computer-aided diagnostic system's automated reading in comparison to human specialist's interpretations of the same data from actual patient's medical records.

Multiple instance learning was introduced by [6] to evaluate several pattern classification algorithms for TB diagnosis (MIL). Since the multiple instances learning-based method optimises computer-aided detection without specific data, it is much more accessible. The MIL accuracy guide uses educated guesses in place of a fixed set of decision values.

When fed digitised chest X-ray pictures, the system developed by Becker et al. [7] may automatically diagnose TB using deep learning methods. People's past TB records were looked through for patterns of a disease to test how well deep learning could detect and classify, but only a few datasets were used.

To better understand how well a computer-aided detection system for TB performs in the private sector of Pakistan, Zaidi et al. [8] established a framework for doing so. First, chest x-ray data sets were examined from various regions of Pakistan. The classification outcomes were then generated.

Using deep transfer learning for classification, Gao et al. [9] created a system for identifying drug-resistant TB. A more severe illness occurs when the tuberculosis-causing bacterium can resist treatment. So, the framework for computed tomography (CT) learned through transfer learning was used to find patients who were becoming resistant to their medications early.

Cao et al. [10] outlined a strategy to enhance TB diagnosis in the underprivileged Chinese community by developing novel deep-learning algorithms and mobile health technology.

To choose the most useful characteristics for tasks like object identification and picture retrieval, Vajda et al. [11] developed a system. Chest X-ray image datasets were employed in the developed framework. In addition, the area under the curve (ROC) and diagnosis accuracy were used in the TB diagnostic system (ACC) performance assessment.

3. PROPOSED METHODOLOGY

The suggested technique employs machine learning and image processing to identify TB. The suggested approach uses pre-processing, segmentation, feature extraction, and classification methods. The suggested approach aims to provide a framework for the most precise TB detection using deep learning [12] to extract characteristics and classify them. Figure 1 is a diagram of the suggested method, which shows the steps that need to be taken.

The data collection process, data reduction, and feature extraction using deep learning are the components of the system for identifying TB. The suggested approach concludes with presenting classification outcomes, which are attained using two deep learning classification methods. The parts of the technique we suggest are broken down and explained in more detail below.

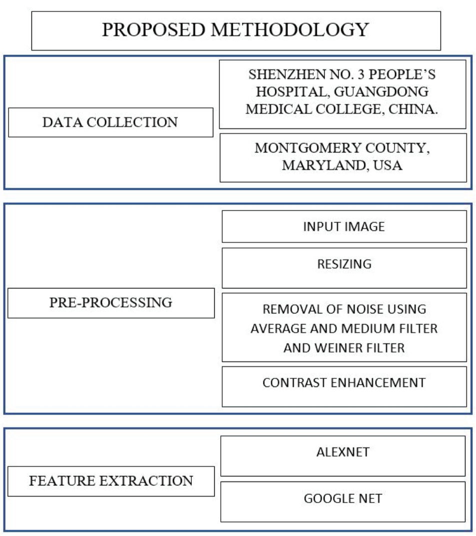

Figure 1: Proposed Methodology

3.1. *Feature extraction and labelling*

In deep learning , the convolutional neural network (CNN) [12] is used as a classification method since it can analyse the signal, and images in a supervised manner [13] [14] [15] [16]. Convolutional neural networks use a multilayer network to recognise the visual pattern of the pixel pictures with little pre-processing. The convolutional neural network architecture learns from training and testing pictures by extracting features to classify the provided datasets. Several models of varying complexity are used to train a convolutional neural network. The datasets are classified with the highest possible precision using these models. The following convolutional neural network models are used in the datasets for the suggested approach. Their designs are explained in more detail in the next section.

3.1.1. *AlexNet*

Alexnet (CNN) is a convolutional neural network model. With a decrease in the top 5 mistakes from 26% to 15.3%, Alexnet performed much better than its competitors and generated a trustworthy classification result [17]. The second highest rate among the top five is around 26.6%. Graphics processing units may enable a reliable classification result with fair training and testing data (GPU). Each network design has eight layers, with convolutional layers making up the first five and fully linked layers rounding out the stack. Alexnet's filter layers, ReLU activation, data segmentation [18], and momentum augmentation make up Alexnet's filter layers, while the network's 11x11,5x5,3x3 convolutions and dropout make up Alexnet's network architecture. There is a schematic of Alexnet shown in Figure 2.

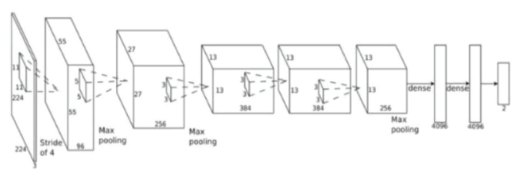

Figure 2: AlexNet Architecture

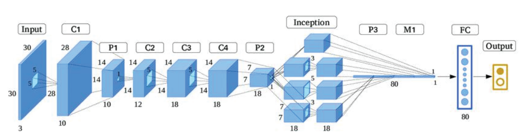

Figure 3: Google Net Architecture

3.1.2. *Google Net*

The Google Net network has already been trained using convolutional neural networks. A 22-layer deep convolutional neural network is used as the network architecture; however, the number of parameters is reduced from 60 million to 4 million [17]. Its performance was so close to human levels that the challenge organiser had them analyse it, and it placed in the top five with an error rate of 6.67 percent. As can be seen in Figure 3, Google's network architecture is shown in a diagrammatic form. It relies on a series of convolutions with tiny centres to limit the range of variables. Batch normalisation, picture distortion, and root-mean-squared corrections (RMSprops) were all included. The unique components are implemented in an inception module, thus the name.

4. EXPERIMENTAL DETAILS

4.1. Data Collection

The suggested technique makes use of datasets that are accessible online. These are two different datasets, and both databases include the standard digital chest X-ray pictures for TB produced by the National Library of Medicine [19].

The initial set of data was collected at the Shenzhen No. 3 People's Hospital, affiliated with the Guangdong Medical College in China. The second data set comes from Montgomery County in the state of Maryland in the United States.

The healthy people and the TB patients have normal and aberrant images on their chest X-rays. These images can be seen in both datasets. The United States of America dataset has a pixel spacing of 0.0875 mm in both the vertical and horizontal dimensions. The CXR represents the anterior and posterior ribs and the lung section taken from the pictures using the area of interest (ROI) approach. This is the case for both datasets. Table 1 gives a more detailed description of the datasets based on several factors and more information about the datasets themselves, which will be discussed in more detail below.

4.2. Pre-processing

After collecting both datasets, the next phase is data preprocessing. The preprocessing steps consist of the resizing and dimension changing, noise removal, and contrast enhancement of the chest X-ray images. Preprocessing is a very important phase before going to the segmentation phase because the percentage oferrors and bad performance is high. So, the pre-processing was performed on both datasets with different techniques in MATLAB.

Table 1: Dataset Description

Dataset Name	Shenzhen - China	Montgomery Country - USA
Image count and Details	Total 662 Normal Lung X-Rays (0) 326 Affected Lung X-Rays (1) 336	Total 138 Normal Lung X-Rays (0) 80 Affected Lung X-Rays (1) 58
Size	3k x 3k	4020 x 4892 4892 x 4020
Format	Portable Network Graphic	Portable Network Graphic
No. of grey levels	12 bits	12 bits

The pre-processing phase can be seen in Figure 1, which explains the processes carried out during this phase. The graphic indicates that the process begins with the images entered and then modifies the size and dimensions of the images based on the many circumstances necessary in the subsequent phase. The noise initially present in the images is removed to obtain clean images for subsequent processing. During the region of interest (ROI) extraction phase, the image's brightness is a big part of how regions of interest are found.

Table 2: Results

Dataset	No. of images	Training	Testing	Classification	Classes	Accuracy
Shenzen, China	662	600	62	Google Net	2	0.9045
		600	62	AlexNet	2	0.8492
Montgomery, USA	138	100	38	Google Net	2	0.8433
		100	38	AlexNet	2	0.8433
Full Data Combine datasets	800	716	84	Google Net	2	0.8958
		716	84	AlexNet	2	0.8625

5. DISCUSSION AND RESULTS

Deep learning methods were used during the experiment to look for signs of TB. In the study that has been proposed, we have made use of convolutional neural networks (CNN) and the various models that are available for them to extract features and carry out classification. In the course of our experiment, we made use of CNN in combination with AlexNet and Google Net.

In order to eliminate bias, we first create a balanced division of the normal and affected images. Table 2 presents the results of these classifiers' accuracy tests.

Accuracy and error rate were used as the primary metrics for determining how well the convolution neural network and its models performed. Both models have the same level of accuracy, which is 83.33%, with an error rate of 0.1667. Both models also have the same error rate. When run via Google Net, the dataset pertaining to China achieves an accuracy of 90.45% with an error rate of 0.0955. When applied to pooled datasets, Google Net achieves the greatest accuracy possible, which is 89.53%, with an error rate of 0.1042 percent.

The combined accuracy graph for the United States and China datasets shows the varying degrees of accuracy achieved by employing the Google net classifier. Both the smooth training accuracy of the combined datasets, which begin at The starting point for the training accuracy of the dataset is 90%. 20%, and the validation accuracy, which begins at 89.58% and is also the ultimate accuracy of the combined datasets, start from the same point. The graphs of the two dataset's degrees of accuracy are shown in Figure 4.

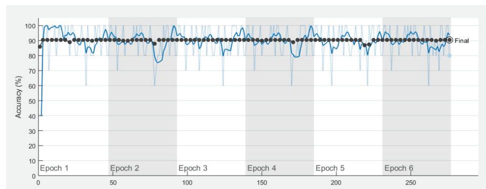

Figure 4: Combined Dataset – Accuracy Graph

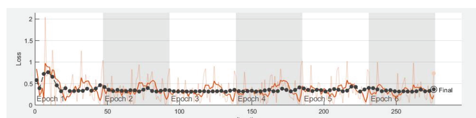

Figure 5: Combined Dataset – Loss Graph

The combined datasets have a loss of 0.4% regardless of whether the accuracy graph shows an increase or a reduction. Roughly speaking, the smooth training loss starts at 0.8%, and the validation loss is 0.5%. As seen in Figure 5, the training deficit starts to accumulate at a rate of 0.9%.

6. CONCLUSION

Tuberculosis is a highly contagious illness that affects millions of individuals every year all over the globe. Different strategies for the early diagnosis of TB are being implemented by medical professionals and research scientists in response to the alarmingly rapid pace at which tuberculosis is spreading, especially in countries that are economically developing. When using linear regression classifiers, the accuracy of the Montgomery, USA dataset is 86.86%, whereas the accuracy of the Shenzhen, China dataset is just 85.86%.

According to the WHO study, Pakistan is one of the most severely impacted by tuberculosis. To accurately diagnose TB disease in Pakistan, the framework described above must be used, with the help of knowledgeable people and data sets from Pakistan's most affected areas. Because of this, automated detection would be advantageous for medical research and TB sufferers, particularly in Pakistan.

REFERENCES

[1] R. Roy Chowdhury et al., "A multi-cohort study of the immune factors associated with M. tuberculosis infection outcomes," Nature, vol. 560, no. 7720, pp. 644–648, Aug. 2018, doi: 10.1038/s41586-018-0439-x.

[2] "No Title," [Online]. Available: https://www.who.int/publications/i/item/978924 003 7021.

[3] S. Jaeger et al., "Automatic Tuberculosis Screening Using Chest Radiographs," IEEE Trans. Med. Imaging, vol. 33, no. 2, pp. 233–245, Feb. 2014, doi: 10.1109/TMI.2013.2284099.

[4] P. Lakhani and B. Sundaram, "Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks," Radiology, vol. 284, no. 2, pp. 574–582, Aug. 2017, doi: 10.1148/radiol.2017162326.

[5] ""P. Maduskar, M. Muyoyeta, H. Ayles, L. Hogeweg, L. Peters-Bax, and B. van Ginneken, 'Detection of tuberculosis using digital chest radiography: automated reading vs. interpretation by clinical officers,' Int. J. Tuberc. Lung Dis., vol. 17, no. 12, pp. 16."

[6] J. Melendez et al., "A Novel Multiple-Instance Learning-Based Approach to Computer-Aided Detection of Tuberculosis on Chest X-Rays," IEEE Trans. Med. Imaging, vol. 34, no. 1, pp. 179– 192, Jan. 2015, doi: 10.1109/TMI.2014.2350539.

[7] "A. S. Becker et al., 'Detection of tuberculosis patterns in digital photographs of chest X-ray images using Deep Learning: feasibility study.,' Int. J. Tuberc. lung Dis. Off. J. Int. Union against Tuberc. Lung Dis., vol. 22, no. 3, pp. 328–335, Mar. 2018."

[8] "No Title," doi: doi: 10.1038/s41598-018-30810-1.

[9] "'L. Gao, E. Zhu, and C. Qian, "A Framework for Tuberculosis Drug Resistance Classification Based on Deep Transfer Learning," pp. 0–4, 2018.'"

[10] B. S. Riza, C. Science, U. P. Utama, C. S. Faculty, O. Thresholding, and H. S. Value, "Comparison of K-Means Clustering and Otsu Thresholding Methods in the Detection of Tuberculosis Extra Pulmonary Bacilli in the HSV Color Space," vol. 16, no. 3, pp. 227–238, 2022.

[11] S. Vajda et al., "Feature Selection for Automatic Tuberculosis Screening in Frontal Chest Radiographs," J. Med. Syst., vol. 42, no. 8, p. 146, Aug. 2018, doi: 10.1007/s10916-018-0991-9.

[12] H. Sharif, F. Rehman, and A. Rida, "Deep Learning: Convolutional Neural Networks for Medical Image Analysis - A Quick Review," in 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2), May 2022, pp. 1–4, doi: 10.1109/icodt255437.2022.9787469.

[13] N. Riaz, S. I. A. Shah, F. Rehman, and M.J. Khan, "An Intelligent Hybrid Scheme for Identification of Faults in Industrial Ball Screw Linear Motion Systems," IEEE Access, vol. 9, pp.35136–35150, 2021, doi:10.1109/ACCESS.2021.3062496.

[14] N. Riaz, S. I. A. Shah, F. Rehman, S. O.Gilani, and E. Udin, "A Novel 2-D Current Signal-Based Residual Learning With Optimised Softmax to Identify Faults in Ball Screw Actuators," IEEE Access, vol. 8, pp. 115299–115313, 2020, doi: 10.1109/ACESS.2020.3004489.

[15] H. Sharif, F. Rehman, and A. Rida, "Deep Learning: Convolutional Neural Networks for Medical Image Analysis - A Quick Review," in 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2), May 2022, pp. 1–4, doi: 10.1109/ICoDT255437.2022.9787469.

[16] F. Rehman, S. I. A. Shah, S. O. Gilani,

D.Emad, M. N. Riaz, and R. Faiza, "A Novel Framework to Segment out Cervical Vertebrae," in 2019 2nd International Conference on Communication, Computing and Digital systems (C-CODE), Mar. 2019, pp. 190–194, doi: 10.1109/C-CODE.2019.8680994.

[17] G. Wu, H. Zhang, Y. Li, and B. Zhang, "A contour extraction algorithm of palmprints based on corner point features," in 2012 IEEE International Conference on Automation and Logistics, Aug. 2012, pp. 501–505, doi: 10.1109/ICAL.2012.6308255.

[18] F. Rehman, S. I. Ali Shah, N. Riaz, and S.O. Gilani, "A Robust Scheme of Vertebrae Segmentation for Medical Diagnosis," IEEE Access, vol. 7, pp. 120387–120398, 2019, doi: 10.1109/ACCESS.2019.2936492.

[19] O. Gozes and H. Greenspan, "Deep Feature learning from a Hospital-Scale Chest X-ray Dataset with Application to TB Detection on a Small-Scale Dataset," in 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jul. 2019, pp. 4076–4079, doi: 10.1109/EMBC.2019.8856729.