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A Survey Paper on Computer Aided Detection of Tuberculosis

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Abstract

Tuberculosis (TB) is a disease that claims millions of lives each year, primarily in impoverished places. Traditional TB screening procedures may not only take longer time, but may also be infeasible in areas with inadequate healthcare infrastructure. Artificial intelligence developments have propelled computer-aided diagnostic systems to new heights. The identification of TB using computer-aided approaches offers various benefits and has the potential to be superior to traditional diagnostic procedures, particularly in poor and middle-income countries where medical specialists and machinery are few. This survey article intends to describe the scientific effort done in computer assisted detection of TB and provides light on future research opportunities.

Keywords: tuberculosis; transfer learning; deep convolution neural network; ensemble learning.

1. Introduction

1.1. What is Tuberculosis?

Tuberculosis (TB) is among the leading causes of death worldwide. It is an infectious disease caused by a specific bacterium known as Mycobacterium tuberculosis. Pulmonary tuberculosis, i.e., tuberculosis of the lungs, is the most common form of this disease, but it can affect any part of the body but nails and hair. Tuberculosis of Bones, Brain, Kidneys, Lymph Nodes, Spine, etc., are tuberculosis variants, to name a few. If not diagnosed early and treated properly, TB disease can prove to be fatal.

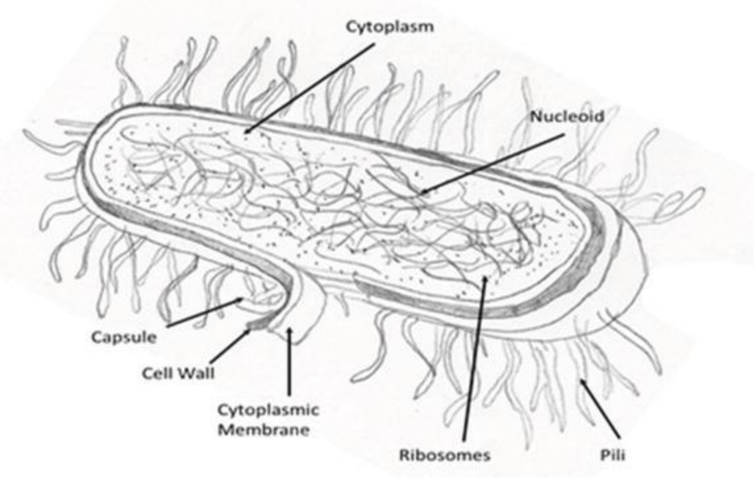

Fig. 1. Structure of Mycobacterium Tuberculosis (Jabir, Rukmana, & Kurniawati, 2017)

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1.2. What are the conventional techniques of Tuberculosis detection?

Broadly, there are two types of techniques for tuberculosis detection, namely skin test-based or blood test-based. Purified protein derivative (PPD) intradermal skin test, also known as the Tuberculin test, Mantoux test, or the TB test, is performed by injecting purified protein derivative into the skin to assess the patient's sensitivity to the tuberculin protein. The size of the reaction patch on the skin estimates disease's the severity level for the patient at that time. The test results take 48-72 hours to show.

Fig. 2. Mantoux test yielding strong positive results (Lisha, James, & Ravindran, 2012)

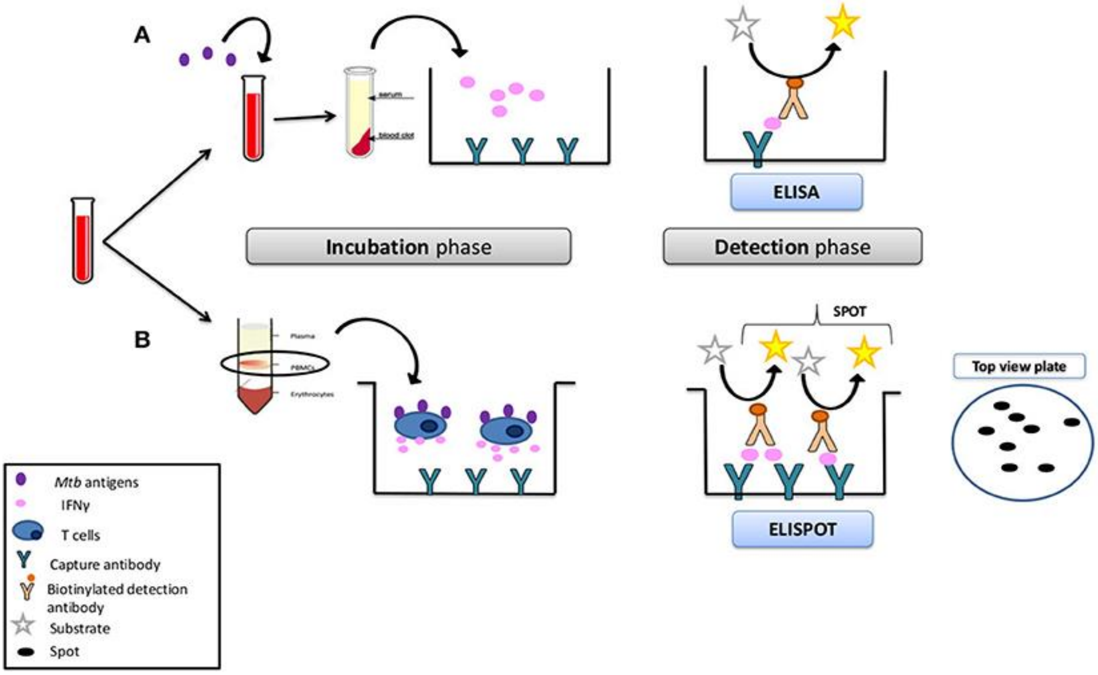

Fig. 3. Interferon gamma-based in vitro assays (IGRA) (Albert-Vega et.al., 2018)

The second category comprises Interferon-gamma release assay (IGRA), also known as the TB blood test. This test analyses the amount of a specific protein known as the interferon-gamma produced by t cells, which are a type of white blood cells. The amount of interferon-gamma found in the bloodstream during the TB blood test is proportional to the severity level of T infection in the patient's body. The most contagious form of TB, i.e., Pulmonary TB can be diagnosed by either of the three techniques, including chest radiography, sputum smear microscopy, or cultivation of Mycobacterium tuberculosis.

1.3. Why Computer Aided detection of Tuberculosis is crucial?

Mitigating the spread of this disease is crucial for decreasing tuberculosis mortality rate. The reproductive rate of the bacterium is very high; hence the early detection of tuberculosis is highly important for efficient patient treatment. Poor healthcare infrastructure in remote areas makes early diagnosis and proper treatment a difficult task. The lack of medical personnel like skilled radiologists can be compensated with computer-aided diagnosis of tuberculosis.

2. Challenges

For starters, there is a scarcity of radiological interpretation skills in many TB-endemic areas, particularly in rural areas. Furthermore, the adoption of a point-of-care (POC) tuberculosis diagnosis tool for distant populations with little or no internet connectivity is difficult. Because TB CXR pictures are frequently of poor quality due to low contrast, deep learning-based systems require a large collection of high-quality training examples. Furthermore, there is a need to combine healthcare data from the country's multiple systems of information, while there is ambiguity about the vulnerable patients' data and other essential facts in electronic databases.

3. Literature Survey

3.1 Deep Learning Based Diagnosis

Hooda et al. (2017) employed Convolution Neural Network based algorithm for binary classifying chest X-Ray images into normal and abnormal. The dataset consisted of Montgomery and Shenzhen publicly available chest X-Ray dataset which is reduced to 224x224 size. The research work implementation is based on a nineteen-layer convolution neural network architecture made up of seven convolution layers, seven rectified linear unit layers, three layers that are totally connected and two dropouts layers. The dataset of 800 images is splitted into train-test with 3/4th data going to train set and the batch size is set to 80 with 300 epochs. Out of Adam, Momentum and Stochastic Gradient Descent optimizers, the Adam optimizer performed the best with validation accuracy of 82.09% and overall accuracy of 94.73%.

Kant & Srivastava (2018) proposed a method to locate tuberculosis bacteria on the microscopic images of sputum slides using 5 layered fully connected CNN. The dataset is inherited from sputum smear microscopy image database. Their approach employed a patch-wise detection procedure, in which 20px X 20px patches from the input picture (a microscope view-held) are distinguished for the inclusion or exclusion of bacilli one by one. Since the number of negative samples were much larger than positive samples, a cascaded architecture is employed where in 1st architecture random negative samples equal in number to positive samples are used for classification and the 2nd architecture is used to segment false positives from actual positives in the output of 1st architecture to get the actual result. The precision and recall values are determined to be 67.55% and 83.78% respectively.

Lopes & Valiati (2017) proposed three approaches for detection of tuberculosis using pre-trained convolution neural network. The dataset consisted of Shenzhen and Montgomery public datasets as well as DA and DB datasets from National Institute of Tuberculosis and Respiratory Diseases, New Delhi. Firstly, lung regions relevant to detection of tuberculosis are segmented. The first proposal employed GoogleNet, ResNet and VggNet pre-trained architectures for extracting the features from segmented regions and then SVM (both 'rbf' and 'linear' kernel) is employed at output layer for binary classification. The second approach is similar to the first approach except that the images are no longer resized but divided into multiple regions to create a dictionary of visuals characteristics whose elements are used to create a global bag descriptor, transforming the task into a supervised categorization problem with just a single feature vector and matching label for each bag. The last approach created an ensemble classifier by combining all the three SVMs used as claasifiers in GoogleNet, ResNet and VggNet. With an accuracy of 0.782 and an AUC of 0.838 for the Montgomery dataset, GoogLenet provided the best results in the initial proposal. In the Shenzhen dataset, ResNet had the best accuracy (0.834), while VggNet had the highest AUC (0.912). Overall, the third approach had the greatest accuracy and AUC for the Montgomery dataset, which were 0.826 and 0.908, respectively, whereas the first proposal achieved the highest AUC for Shenzhen, which was 0.926.

Liu et al. (2017) tweaked AlexNet and GoogleNet by adding a softmax layer in the output to get predictive score for each category. To solve overfitting and convergence issues, AlexNet is trained using a 7-layer network topology comprising of convolutional layers (5) and two layers which are fully connected, as well as dropout and rectified linear unit layers. On the other hand, the 22-layer network topology that integrates the Inception model, as well as dropout and corrected linear unit, is implemented in GoogLeNet. In order to augment the data, shuffle sampling is utilized and a final classification accuracy of 85.68% is achieved.

Deep convolutional neural networks (DCNN) can effectively detect TB using chest radiography, according to Lakhani & Sundaram (2017), with an AUC of 0.99. Further, in case of any discrepancy among the classifiers, adopting a radiologist-augmented approach increased the accuracy. Two separate DCNNs, AlexNet and GoogLeNet, are utilised to identify the photos as having or not having pulmonary tuberculosis signs. ImageNet is used as both an untrained and a pre-trained network, augmenting with multiple preprocessing techniques, and ensemble learning is performed on the best-performing algorithms. A hybrid model of the AlexNet and GoogLeNet DCNNs produced the best results, with an AUC of 0.99. Pre-trained models have significantly more AUCs than non-trained algorithms.

3.2 m-Health Techniques

Shabut et al. (2018) proposed a TB antigen-specific antibodies detection technique. The authors proposed deploying a mobile-enabled plasmonic ELISA-based scheme using smartphones incorporating machine learning techniques like random forest classifier. The authors achieved an accuracy of 98.4%. Efficient image processing techniques, including clustering and object detection, are used in preprocessing. Further, the system required no virtual plate or guide in detecting samples (wells). Right clusters are selected among the multiple clusters using detecting components, hence detecting wells and surpassing the samples from noise. Furthermore, in real-time, the system can read and classify multiple samples into either class, i.e., positive or negative.

Santos et al. (2019) presented a study that supports clinical decisions using a multiplatform mobile application that calculates a predictive score for tuberculosis meningitis (TBM). This versatile application is compatible with various devices, including mobile phones, tablets, etc., and remote locations having limited or no internet connectivity would also have access to this application. The only disadvantage of this score implementation is the requirement for trained staff. But the speedy diagnosis of TBM through this application certainly compensates for the training cost and time required to train the staff. Increasing access to the score among doctors would save time and resources considerably.

Alcantra et al. (2017) proposed two major developments for early detection of tuberculosis which consisted of constructing an X-Ray picture library, annotation software, and computer algorithms to categorise images into distinct TB semblance. As per the authors, there existed no real-world large scale annotated data for multiple TB manifestations and computational system based on mobile device platform dedicated to early diagnosis of tuberculosis. The dataset involved 4761(453 normal images and 4248 abnormal images) chest X-ray images of tuberculosis patients, each with a full TB screening description in a close collaboration with clinical and research scientists. Furthermore, the authors created web-based annotation software to evaluate chest radiography, locate key contents, label them, as well as retrieve the labelled contents for the purpose of further research and education. For classification, multiple regions of interest are extracted from mobile device captured X-Ray images and global as well as local features are further retrieved after resizing the regions into 227x227 size and then fed into Convolution Neural Network. An accuracy of 89.6% is obtained for binary classification (Normal/Abnormal) from GoogleNet architecture while 62.07% accuracy is achieved for multi-class classification into various manifestations.

3.3 Image Processing combined Deep Learning Approach

Rahman et al. (2020) proposed a technique for efficient detection of tuberculosis through chest radiographs using deep Convolutional Neural Networks with a transfer learning-based approach. The authors reliably detected TB from the CXR images using data augmentation, image preprocessing, image segmentation, and deep-learning classification techniques. They compared the performance of a group of different CNN models used for the classification of TB or no TB CXR images. The ChexNet model performed best among the group of deep CNN models for the datasets. The ChexNet model is deployed without image segmentation as a preprocessing step. In the second category, image classification is followed by image preprocessing. DenseNet201 outperformed the group of models for the segmented lung images. They reported three standard metrics obtained for their experiments: classification accuracy, precision, and recall. For the no-segmentation category, 96.47%, 96.62%, and 96.47% are the values obtained for the classification accuracy, precision, and recall for the detection of TB, respectively whereas the values for the detection post image segmentation are 98.6%, 98.57%, and 98.56%, respectively. Image segmentation could significantly improve classification accuracy to a huge extent. The authors included explainability in their experiments to build user trust. The Score-CAM explainability technique strongly suggested the role of lung segmentation in taking the classification decision from the lung portion of the chest radiographs, unlike the original x-rays, where features outside the lung region might be responsible for the classification.

Mundai et al. (2020) incorporated deep learning algorithms post image enhancement techniques like Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF). The authors used EfficientNet-B4, ResNet-50, and ResNet-18 to train the TB images dataset and significantly improve the TB detection accuracy. Moreover, in comparison to the previous works, their proposed idea achieved better results in terms of standard metrics like AUC and accuracy. Using an image enhancement system to pre-process the TB images facilitated better learning of the model through a tested pre-trained network. Classification accuracy of 89.92% and an AUC value of 0.948 are achieved on the Shenzhen dataset.

4. Future Scope

A more current version of GoogLeNet is trained on around 1,30,000 dermatological photos to identify carcinoma and has obtained results comparable to human specialists (Esteva et.al, 2017). This shows that any artificial intelligence-based computer aided diagnostic system can be made trustworthy enough if it has been trained on a very large dataset. We recommend the same for tuberculosis detection as well. If the models are deployed after training on at least over one lakh images, we can expect considerably reliable results.

More transfer learning models such as VGG16, ResNet50, EfficientB0 etc. with an ensemble topmost layer can be employed to detect tuberculosis more accurately because it is an established fact that ensemble learning based models that work on maximum vote classification strategy attain higher accuracy than traditional models in complex situations most of the time, if not always. By using image processing techniques, the chest radiography pictures will be fine-tuned, resulting in improved categorization with higher accuracy. This is due to the fact that more distinct characteristics may be recovered from clean data, hence enhancing discriminator capacities. Also, it is noteworthy that the m-health based diagnosis has higher impact provided it is scaled to remote areas. It is recommended to bring in more investment and research in this aspect to provide accessible and affordable healthcare to all, specifically to tuberculosis patients. Drug-sensitive microscopy of sputum smears for tuberculosis is primarily a three-stage method that involves slide preparation, observing closely on various sections of slide, and attempting to find bacilli. It should be considered to fully automate the process of scanning for bacilli in the slides. The conventional method not only takes a lot of time but also has chances of human error which can be eliminated via automation.

5. Conclusion

The exhaustive literature review and future scope of research in computer aided detection of tuberculosis reveals that the mobile health-based diagnosis combined with artificial intelligence models has the potential to not only significantly reduce the burden of healthcare professionals involved in diagnosis and treatment process, but also can highly decrease the unnecessary delay in detection caused by lack of adequate manpower and infrastructure. Therefore, many lives can be saved every year.

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