A Deep Learning Approach for Tuberculosis Diagnosis from chest X-Rays: A Survey

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Abstract

Deep Learning has been on the rise for various applications that includes but not limited to autonomous driving, industries and medical imaging. Medical Imaging is one of the best data sources having ability to assist in diagnosis of diseases, rehabilitation as well as in treatment. The power of deep learning is that it can automatically learn from data and classify the images with good accuracy that has led to path-breaking applications. The clear view and a structured approach of applying deep learning in the health domain in order to assist in diagnosis and treatment of diseases in accurate and precise manner is the beneficial aspect of technology. The various aspects to utilize deep learning for diagnosis of Tuberculosis (TB) are important in building of appropriate Computer Aided Diagnosis (CAD) system. In this paper, a comprehensive overview of deep learning based Convolutional Neural Network (CNN) models implemented specifically on Tuberculosis (TB) diseases. The chest X-rays are the most economical and commonly used imaging technique, is the dataset considered in review. The transfer learning utilization for detection of disease is explored with classification performance analysis. The future challenges with the application of deep learning models and the new directions of research needed in this field to achieve the practical performance requirements, are discussed.

Keywords

Deep Learning, tuberculosis, chest X-rays, transfer learning

1. Introduction

Deep learning is inspired by the human brain's deep structure and its algorithms use computational methods to learn features of data. Deep learning makes use of neural networks to extract important feature representations directly from data. Deep learning approach based Convolutional Neural Network (CNN) algorithms that can learn from data images automatically, is reckoned effective on medical images [1]. Tuberculosis (TB) is among top infectious diseases as reported by W.H.O and is the major cause of deaths worldwide. Detection at an early stage of this infectious disease is highly needed. The Chest X-Rays are commonly utilized in detection of TB as it is economically viable but its manifestations rely on texture and geometric features so the accurate diagnosis requires highly experienced medical staff [2]. Therefore, there is a high need for an automated screening system to assist medical staff in the decision making process. Artificial intelligence helps indevelopment of such high impact automated screening systems. The automated TB screening can be achieved by CNN models as they give higher accuracy as compared to other methods [3]. The CNNs are made up of various layers, i.e., convolution, pooling and fully connected layers A CNN takes a picture and runs it through the network layers, producing a final class. These network layers learn the features of the image.

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Filters at various resolutions are implemented on image and convolution with previous image is done and output is fed to the next layer [5]. The simple and complex features are learned efficiently by layers. The max pooling layer functions to convolve the features of the last layer. The last layers are fully connected and soft max layers. Feature extraction is a simple task with deep learning and learned features helps to train a classifier [6]. The several approaches for training a deep learning network are used: such as training from scratch, transfer learning and semantic segmentation [8]. The transfer learning approach is mainly utilized. The training parameters tuning is also important to get the better results [9]. Data augmentation helps in improving the performance with smaller datasets. Dropout regularization is highly impactful in improving the performance of CNNs. Batch normalization makes the training of the network more efficient. CNNs consist of various parameters which are adjusted throughout the training phase, with the help of large amount of calculations. The Graphical Processing Unit(GPU) is suitable for parallel processing and helps to speed up calculations during the training phase. MATLAB and Python programming languages are generally used to implement deep learning.

2. Deep Learning: An Overview

There are various approaches to train the deep learning network are training from scratch, transfer learning and semantic segmentation to pre-train the network [10]. The training composed of accessing data and preprocessing data next is configuring network layers, training the network and tuning the parameters to achieve good performance of the system. The workflow is shown in figure 1.

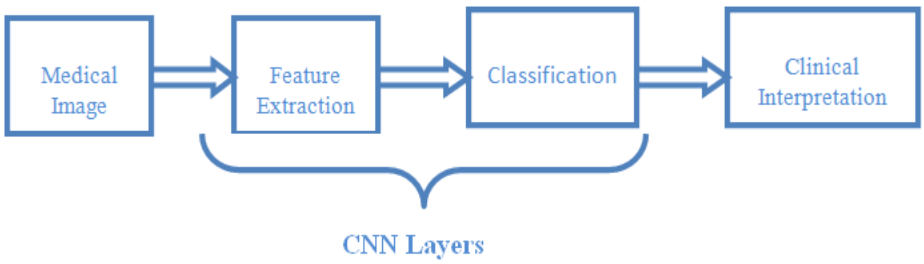

Figure 1: the Deep Learning Workflow

2.1. Convolutional Neural Network

CNN is a feed-forward network and consists of various layers which are given below.

- Convolution layer: This layers outputs a feature map by convolving the input image with a convolution filter. The convolution is controlled by stride. The operation learns the features which are further utilized in classification.
- Pooling layer: This layer performs the pooling operations like average, sum to the spatial dimension of the input. According to its function it is also known as a down sampling layer. The Pooling and convolution layers are used in tandem in the development of network architecture.
- Fully-connected layer: In this every neuron of the current layer is connected to each neuron in the previous layer. The number of classes is determined by the total number of fully connected neurons in the final layer. All neurons are connected, having a specific weight assigned to each connection. This layer establishes a weighted sum of all the outputs from the previous layer to determine aspecific target output.
- Rectified Linear Unit (ReLU): ReLU is an activation function implemented next to the convolution layer. This layer entails mapping the output to the input set and projecting the nonlinearity onto the network. [11].

- Batch normalization: It is done amidst the layers of network to create normalized activation maps for each training batch. It maintains the regularization of the network and increases training efficiency.

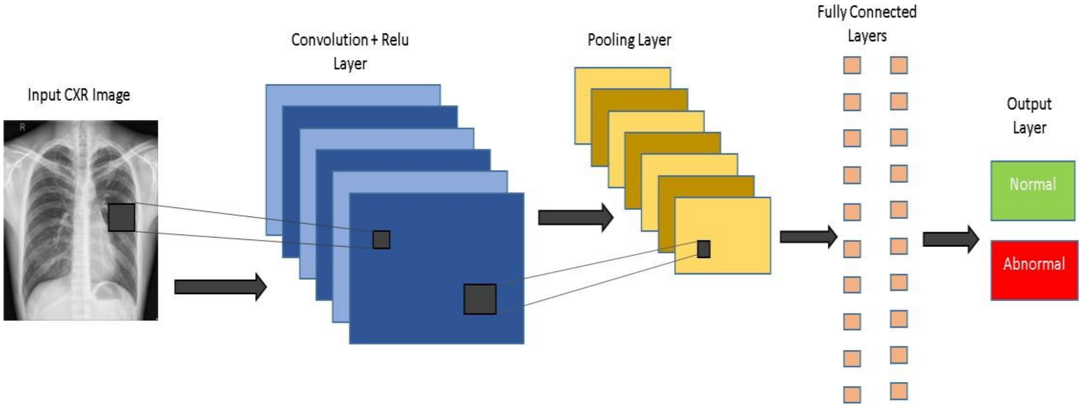

Figure 2: the CNN Architecture

2.1.1. Transfer Learning

Transfer learning is the process in which a pre-trained network's layers are transferred to other networks for fine-tuning and feature extraction. The CNN training is done with large dataset initially and after that small dataset is utilized to train the pre-trained model with fine tuning for efficient performance of CNN model [12]. Transfer learning gives better results than training from scratch. The performance further can be enhanced with optimization of hyper-parameters.

2.2. Classifiers

- Support vector machine (SVM): The SVM process is based on the separation of two classes by determining a hyper plane which maximizes the margin size by optimization and minimizes the miss-classification errors simultaneously [13].
- Soft max classifier: Softmax utilizes logistic regression to deal with multiple class outputs. Each class in the problem is given decimal probabilities[4].

2.3. Training of the Convolutional Neural Network

Before training the training options are selected like learning rate, max epoch, mini-batch, depth, layers, regularization etc. During training the CNN learns the features directly from the image. The layers weights are learned during the training. The network is run and training is monitored. In case of inappropriate results the parameters tuning and Bayesian optimization [21] can be implemented. The learning rate is the most important hyper-parameter which controls the speed of the training. Several optimizers such as RMS prop, Stochastic Gradient Descent(SGD) and Adaptive Moment Estimation (Adam)[6] are there which work to adjust parameters within CNNs. The learning process consists of feeding input data to CNNs, updation of parameters within CNNs and iteration with units of mini-batch. When whole of the training data is used once it is called one epoch. Data is generally shuffled and allocated to different groups for each epoch when using mini-batch learning.

2.4. Performance Metrics

CNN models can be evaluated efficiently and directly with statistical methods. Classification accuracy of the model is calculated. The confusion matrix can be utilized to know the performance of the created model. On the test datasets, Receiver-Operating-Characteristics(ROC) curve [6, 27] and Area-under-Curve(AUC) [1] are determined. Contingency tables, sensitivity and specificity [1] measured for performance analysis of the model. The recall, F1-score which combine precision and recall [23] w.r.t positive class metrics measures of the baseline model determined for comparison of different architectures.

3. Related Work

In [1] researcher proposed the CNN-based TB screening system utilizing pre-trained CNN AlexNet. One extra convolution layer added to deal with high resolution medical images. The resized images used in training to increase the performance efficiency. The parameter learning rate is tuned in decayed mode with stochastic gradient optimization. The entire training process, from feature extraction to classification is presented. The AUCs for three real-world datasets for the automatic TB screening CAD system based on deep CNN were calculated. The initial layers learn low level features and high level features were learned by higher layers during training. Data augmentation and transfer learning is utilized to improve the performance measures. The performances on KIT, Montgomery and Shenzhen datasets are compared. In [2] author demonstrated the three different proposals for TB detection utilizing pre-trained networks such as Resnet and Googlenet as features extractors and then support vector machine(SVM) classifier is trained with the extracted features of images. In the first proposal resized images and in the second sub-regions of image are considered for extracting features. The last model ensembles the trained classifiers. The findings show that ResNet gives stable accuracies as compared to other CNNs. In [3] the author proposed the Deep CNN (DCNN) approach based on automated TB disease classification. In this, the ensemble model of AlexNet and GoogleNet is utilized to increase the performance measures. The both post processing and preprocessing data augmentation techniques such as random cropping, mirror images, mean subtraction, rotations are applied to the dataset. The Stochastic Gradient Descent Optimizer is considered during tuning of the training parameters. Ensemble approach is utilized which is based on the implementation of different weighted averages of the probability scores provided by the classifiers of both the CNNs. In [4] the author presented the automatic TB detection system with region of interest features learning approach and CNN VGG-Net is considered and accuracy about 80% was achieved. In[5] researcher presented the method of classification of TB disease using CNN AlexNet and GoogleNet.The focus is mainly on the optimization techniques for improve the performance of the network. The decay learning rate with iterations and weights of dropout and ReLU layers are implemented to avoid over-fitting during training. The improvement in accuracy from 53.02 to 85.68% was achieved using shuffle sampling technique. In [6] the author developed a generalized model for medical image classification based on decision tree approach. The accuracy of 81.25% and AUC of 0.99 with VGG- Net was achieved utilizing the data augmentation, Adam optimizer, sigmoid activation function and SVM classifiers. In [7] demonstrated the transfer learning on medical imaging for TB detection using improvement in training weights. The impact of varying weights on learning is evaluated by performance metrics and AUC 0.99 with ResNet-50 is achieved on Shenzhen dataset. In [8] the author applied data augmentation on region of interest on image and HAAR and LBP features are utilized on ResNet CNN. In [9] the author emphasized on modality specific learning for generalization utilizing large X-rays dataset. The various CNN such as VGG-16, InceptionV3, ResNet and DenseNet-121 for TB detection is used. The evaluation reveals that DenseNet-121 gives the best result with AUC 0.92 and accuracy 0.897. In [11] the significance of using ReLU activation for the purpose of object recognition as compared to the binary units and the several aspects of deep learning and recent clinical studies are demonstrated. In [12] authors emphasized that better generalization performance can be achieved on initializing with transfer weights after considerable fine tuning on a new task. In [13] author demonstrated pre-trained deep CNN model and support vector machine for feature extraction and classification for good results. In [14] author demonstrated the several aspects of deep learning and recent clinical studies. In [15] author presented the performance of the model improved with larger dataset and fine tuning of hyper-parameters. In [16] demonstrated pre-trained deep CNN model for extraction of feature of input gives good results. In [17] the feasibility of CNN utilizing larger dataset with learning set of low-level features including Scale Invariant Feature Transform (SIFT), GIST, PHOG and SSIM. In [18] the ResNet CNN model by transfer learning the pre-training weights extracted from the ImageNet to detect tuberculosis manifestations. In [19] author utilized textural features as descriptors to categorize into TB or non-TB cases and able to detect this disease with statistical features in the image histogram. In [20] author presented a statistical interpretation method for detecting tuberculosis. In [21] author demonstrated the Bayesian classification for detection of TB. In [22] author provided a textural and geometric feature-based classification of tuberculosis manifestations. In [23] author proposed thetwo- stage classification method and achieved boost up in the recall value. To perform identification and detection different sub-models are implemented. The performance analysis demonstrated that resizing the dataset, normalization of data leads to faster convergence. In [26] author demonstrated thevarious deep learning based CAD tools for detection of TB diseases available commercially such as T-x net, CAD4TB etc. Considering the above literature review, the several techniques utilized and CNN algorithm used for TB disease detection with the performance achieved are summarized. Table 1 belowshows the datasets used by authors in research papers of review and Table 2 shows the summary of works carried out for TB Detection using deep learning with CXRs.

Table 1

Different Datasets for Tuberculosis

Sr.no.	Dataset	Image size	Number of Images	Type of Image
1.	Montgomery [24]	4020*4892	138	Frontal
2.	Shenzhen [24]	NA	662	Frontal
3.	KIT [1]	NA	10,848	NA
4.	JSRT [25]	2048*2048	247	NA

Table 2

Brief of research carried out for Tuberculosis Detection utilizing Deep Learning with Chest X-rays Imaging.

Sr.	Author's name	Year	Dataset	Algorithm	Processing Technique	Accuracy
1.	Hwang et al.[1]	2016	• KIT • Montgomery • Shenzhen	• AlexNet	• data augmentation transfer learning from lower convolutional layer • decaying learning rate	82.6% 83.4%
2.	Lopes et al.[2]	2017	• Montgomery • Shenzhen	• GoogleNet • ResNet • VGG-Net	• CNNs as feature extractors • Support vector machine as classifier • Image processing on datasets	82.8%
3.	Lakhani et al[3]	2017	• Montgomery • Shenzhen	• AlexNet • GoogleNet	• DCNN approach • Ensemble model of AlexNet and GoogleNet implemented on average of weights of classifier	85.68%
4.	Hooda et al[4]	2018	• JSRT • Montgomery	• AlexNet • GoogleNet • VGG-Net	• Softmax classification • Modified CNN	82.09%
5.	Liu et al.[5]	2017	• Shenzhen	• AlexNet • GoogleNet	• Decaying learning rate and weights • shuffle sampling technique for data augmentation	85.68%
6.	Ahsan et al.[6]	2017	• Shenzhen	• VGG-Net	• CNN reapplied on augmented images	81.25%
7.	Nyugen et.al.[7]	2019	• Shenzhen • Montgomery • NIH-14	• Inception • ResNetV2 • Dense Net	• Varying weights technique	
8.	R.S. Gorakhvi[8]	2019	• Shenzhen • Montgomery	• ResNet-18	• Data augmentation with the help of HAAR and LBP features and cropped ROI. • Data generated with augmentation used along with the original dataset for training	81.33%
9.	Alcantara et al.[9]	2017	• BMC • BUMC	• GoogleNet	• Supervised training using larger dataset • Fine tuning the CNN for smaller datasets • ROI based feature extraction • SVM Classification	89.6%
10.	Liu et al[10]	2019	• Pulmonary Chest X-ray abnormalities	• Self- designed CNN	• Hyper parameter optimization • Masked algorithm used on the dataset to remove noise	87%

4. Conclusion

This paper reviews deep learning methods used in several papers on TB screening, based onchest X-Ray Imaging. The performances of several CNN algorithms are analyzed and observed that performance of CNNs are highly reliable for detection and classification of TB disease. It is observed that deep learning success depends on labelled public datasets. It is also seen that the speed and accuracy of the network improves by data augmentation and optimization. The fine practical settings also aid in improvement of the model performance. A comprehensive review helps the researchers in choice of the suitable algorithm and to setup the appropriate framework for their research. Although these researches provide good accuracy, still the new directions in standardized framework specifically for medical images and computer vision is needed. The study of literature describes the deep learning methods surpassing the state of art in medical image domains. Finally, on the basis of tuning parameters we suggest that optimization usage is most helpful in improving the performance easily. In future, the deep learning based diagnosis tool available worldwide for TB disease will leads to more efficient, very low cost and fast results having the techniques within the deep learning software for image visualizations.

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5. References

[1] S. S. Hwang, H.-E. Kim, J. Jeong, and H.-J. Kim, "A novel approach for TB screening based on deep convolutional neural networks," 2016, doi: 10.1117/12.2216198.

[2] U. K. Lopes and J. F. Valiati, "Pre-trained convolutional neural networks as feature extractors for TB detection," Computers in Biology and Medicine, 2017, doi: 10.1016/j.compbiomed.2017.08.001.

[3] P. Lakhani and B. Sundaram, "Deep learning at chest radiography: Automated classification of pulmonary TB by using convolutional neural networks," Radiology, 2017, doi: 10.1148/radiol.2017162326.

[4] R. Hooda, A. Mittal, and S. Sofat, "An Efficient Variant of Fully-Convolutional Network for Segmenting Lung Fields from Chest Radiographs," Wireless Personal Communications, 2018, doi: 10.1007/s11277-018-5777-3.

[5] Y. Cao et al., "Improving TB Diagnostics Using Deep Learning and Mobile Health Technologies among Resource-Poor and Marginalized Communities," 2016, doi: 10.1109/CHASE.2016.18.

[6] M. Ahsan, R. Gomes, and A. Denton, "Application of a convolutional neural network using transfer learning for TB detection," 2019, doi: 10.1109/EIT.2019.8833768.

[7] Q. H. Nguyen et al., "Deep Learning Models for TB Detection from Chest X-ray Images," 2019, doi: 10.1109/ICT.2019.8798798.

[8] R. S. Ghorakavi, "TBNet:Pulmonary TB Diagnosing System using Deep Neural Networks," ArXiv190208897 Cs, Feb. 2019, Accessed: Jul. 15, 2020. [Online]. Available: http://arxiv.org/abs/1902.08897.

[9] M. F. Alcantara et al., "Improving TB diagnostics using deep learning and mobile health technologies among resource-poor communities in Perú," Smart Health, 2017, doi: 10.1016/j.smhl.2017.04.003.

[10] X. Liu, H. Lei, and S. Han, "TB Detection from Computed Tomography with Convolutional Neural Networks," Advances in Computed Tomography, vol. 08, no. 04, pp. 47–56, 2019, doi: 10.4236/act.2019.84005.

[11] V. Nair and G. E. Hinton, "Rectified linear units improve Restricted Boltzmann machines," in ICML 2010 - Proceedings, 27th International Conference on Machine Learning, 2010, pp. 807–814.

[12] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, "How transferable are features in deep neural networks?," in Advances in Neural Information Processing Systems, 2014, vol. 4, no. January, pp. 3320–3328.

[13] N. Cristianini and J. Shawe-Taylor, An Introduction to Support Vector Machines and Other Kernel-based Learning Methods. Cambridge University Press, 2000.

[14] K. Yasaka, H. Akai, A. Kunimatsu, S. Kiryu, and O. Abe, "Deep learning with convolutional neural network in radiology," Japanese Journal of Radiology. 2018, doi: 10.1007/s11604-018-0726-3.

[15] R. Shen, I. Cheng, and A. Basu, "A hybrid knowledge-guided detection technique for screening of infectious pulmonary TB from chest radiographs," IEEE Transactions on Biomedical Engineering,

2010, doi: 10.1109/TBME.2010.2057509.
[16] C. Qin, D. Yao, Y. Shi, and Z. Song, “Computer-aided detection in chest radiography based on artificial intelligence: A survey,” BioMedical Engineering Online. 2018, doi: 10.1186/s12938-018-0544-y.
[17] R. N. Rohmah, A. Susanto, and I. Soesanti, “Lung TB identification based on statistical feature of thoracic X-ray,” 2013, doi: 10.1109/QiR.2013.6632528.
[18] Z. Z. Qin et al., “Using artificial intelligence to read chest radiographs for TB detection: A multi-site evaluation of the diagnostic accuracy of three deep learning systems,” Scientific Reports, 2019, doi: 10.1038/s41598-019-51503-3.
[19] Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen, and H. Greenspan, “Chest pathology detection using deep learning with non-medical training,” 2015, doi: 10.1109/ISBI.2015.7163871.
[20] J. Ma, Y. Song, X. Tian, Y. Hua, R. Zhang, and J. Wu, “Survey on deep learning for pulmonary medical imaging,” Frontiers of Medicine. 2019, doi: 10.1007/s11684-019-0726-4.
[21] R. H. Abiyev and M. K. S. Ma’aitah, “Deep Convolutional Neural Networks for Chest Diseases Detection,” Journal of Healthcare Engineering, 2018, doi: 10.1155/2018/4168538.
[22] D. S. W. Ting, P. H. Yi, and F. Hui, “Clinical applicability of deep learning system in detecting TB with chest radiography,” Radiology. 2018, doi: 10.1148/radiol.2017172407.
[23] H. Abe, H. MacMahon, J. Shiraishi, Q. Li, R. Engelmann, and K. Doi, “Computer-aided diagnosis in chest radiology,” Seminars in Ultrasound, CT and MRI, 2004, doi: 10.1053/j.sult.2004.02.004.
[24] S. Jaeger, S. Candemir, S. Antani, Y.-X. J. Wáng, P.-X. Lu, and G. Thoma, “Two public chest X-ray datasets for computer-aided screening of pulmonary diseases.” Quantitative imaging in medicine and surgery, 2014, doi: 10.3978/j.issn.2223-4292.2014.11.20.
[25] J. Shiraishi et al., “Development of a digital image database for chest radiographs with and without a lung nodule: Receiver operating characteristic analysis of radiologists’ detection of pulmonary nodules,” American Journal of Roentgenology, 2000, doi: 10.2214/ajr.174.1.1740071.
[26] Qin, Z. Z., Naheyan, T., Ruhwald, M., Denkinger, C. M., Gelaw, S., Nash, M. ... & Kik, S. V. (2021). A new resource on artificial intelligence powered computer automated detection software products for tuberculosis programmes and implementers. Tuberculosis, 127,102049.