Screening of chest X-Rays for Tuberculosis using Deep Convolutional Neural Network

R.Rohith, S.P.Syed Ibrahim

Abstract— Tuberculosis is a life-threatening disease that mainly affects underdeveloped as well as developing nations. While lethal it is often resistive to antibiotics and the safest way to treat a patient is to detect the disease's presence as soon as possible. Various techniques have been developed to diagnose tuberculosis and radiography of the chest is one of such methods that works well for over a decade.. Though an effective method still the success depends on the medical officer who examines the chest X-rays. Thus ,this paper proposes an approach for detecting X-ray abnormalities using deep learning. The systems output is assessed on two open Montgomery and Shenz en chest X-ray datasets and accuracy of 84 percent is achieved.

Keywords— Image augmentation, deep learning, radiography

I. INTRODUCTION

Tuberculosis, a pandemic that is responsible for the deaths of almost one fourth of the population, is caused by Mycobacterium Tuberculosis. While our immune system may suppress this bacilli, it does still not kill it. These bacilli do have the potential to stay dormant and damage the lungs and other parts of the body. This global pandemic not only affects humans but also has a deleterious effects on economy of a country. According to reports children are more vulnerable and also has a higher fatality rate relative to adults. Another study indicates that about one in five cases go untreated. Thus, the diagnosis of TB is a significant step in the treatment of this disease. There are varieties of TB, and the most perplexed type is the latent tuberculosis where the symptoms remains inert and the major reason for this disease's higher fatality. The other forms of tuberculosis are active TB and military TB. Active TB most commonly regarded as the primary stage spreads in the host or to others and shows symptoms. Though primary still the patient should be isolated to restrain spreading of bacteria to other inmates. The symptoms include incessant coughing, dwindled appetite, soaring temperatures, grappled breathing etc. Detection of tuberculosis in children is a strenuous task and it is one of the major challenges. Another interesting fact is that HIV positive patients are most likely to develop active TB. Military TB is the most periled as well as rarest of the types. The bacteria in this stage gets access directly to the blood stream and this is a swift process. This is more lethal than any other types.

Manuscript received on August 24, 2020.
Revised Manuscript received on January 28, 2021.
Manuscript published on January 30, 2021.
R.Rohith, School of Computer Science and Engineering Vellore Institute of Technology-Chennai
S.P.Syed Ibrahim, School of Computer Science and Engineering Vellore Institute of Technology-Chennai

If failed to identify the chances of patient dying is cent percent. The aghasting fact is that it does not exhibit any symptoms as the active TB and also don't show up in X-Rays. This tends to be normal. Tuberculosis along with HIV makes a deadly couplet.

The ability to retaliate the bacilli by immune system will be enfeebled by HIV thus granting easy access to Tuberculosis bacteria to spread across the body. Certain TB also develops a resistance towards drugs and it is literally uncurable. This type of TB familiarly called as drug resistant TB. Treatment is very ineffective and fatality is high. This paper consists of Basic Detection Technique in Section 1, followed by the existing approaches in tuberculosis detection in Section 2 with a preview of the techniques used in this paper followed by the proposed and experimental approach to tuberculosis detection. The experimental production is attached and the paper ends with future works and references.

II. FRAMEWORK FOR TB DETECTION IN X-RAYS

2.1.1 Pulmonary Tuberculosis Radiological Presentations on X-Rays

An individual with any of these irregularities are most likely to be prone to active TB.These patients should be isolated immediately and sufficient treatment is to be done to overcome this killer disease.Isolation of these patients is also important to restrain spreading to others.The abnormalities include:

2.1.2 Lung Consolidation

The lung vaccum jammed with fluids makes it difficult to breathe.This overts in X-rays.The perplexing issue is that these can be any fluids or even contents of stomach or cells.So the presence of TB cannot be confirmed with consolidations as other relative bacterial diseases also share the same characteristics.The high correlation in these diseases makes it difficult for medical officers to uphold tuberculosis presence

2.1.3 Pulmonary Cavitation

There will be a deformity in lung shape and size.Even the diameter of the lungs changes and this is more often identified only in Chest X-rays.Any change or irregularity in shapes and sizes of the lungs may lead to tuberculosis and is one of the important factors in tuberculosis detection.This condition is known as pulmonary cavitation.

2.1.4 Nodular opacity

Growth of lessions or nodules in the form of tuber.This is a reliable evidence for tuberculosis and the patient should be treated immediately.

Even this issue has its own challenge because cancers also develop tumors. This is the most common abnormality observed in most of the X-Rays.

2.1.5 Pleural effusion

This condition is the accumulation of fluids in pleural area.The fluid accumulates with respect to the position of the patient during the time when X-Ray is taken.The fluid settles down at the base if patient is in a standard position.

2.1.6 Hilar abnormality

This abnormality is slightly similar to pulmonary caviation but includes vessels,bronchi as well as lymph nodes also.Any deviation in shape,size or depth leads to hilar abnormalities.

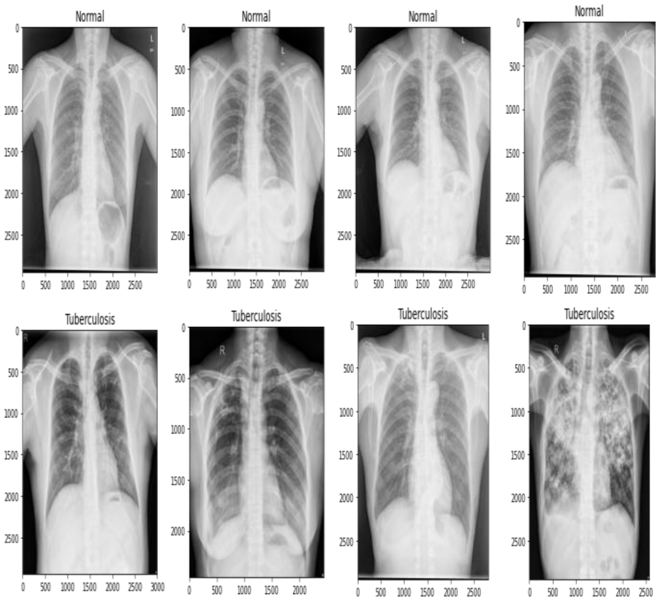

Fig.1.A glimpse of normal abnormal chest X-ray tuberculosis

2.2 Existing work

Though detection is a tedious task due to above mentioned challenges many machine learning as well as deep learning models started to evolve for classifying these X-ray images.Over the years these models and architectures provided astonishing results in image classification.Some of the works are mentioned below.

[1]This paper details about an automated methodology of segmentation of lungs for feature extraction and a linear support vector machine is used for categorizing normal and abnormal tuberculosis classes.With 385 images to classify this method showed a promising result in extracting features as well as classifying.[2]This work has a high correlation with the previous work.The graph cuts for image segmentation is used in segmenting lungs,and different set of features are extracted.The classifying algorithm in this technique is the support vector machine popularly known as (SVM).1000 images are used in development of this model.[3]This presented an integration of systems to detect lung irregularity.This is good in detecting shape abnormality,textural features etc.The classifier used in this method is (LDA) also known as Linear Discriminant Analysis).This overted an improved performance than the previous systems.This[4] work proposed a model in identifying pulmonary cavities in lungs mainly textural features are taken into consideration with segmentation on edges and classified using support vector machine.The succeeding work[5]suggests an approach for pleural as well as pulmonary irregularities.SVM a robust classifier is used in distinguishing classes. Another approach[6] for detecting pleural effusion is to select feature vectors with respect to angles and the random forest classifier is used in categorizing classes. Over past few years deep learning has captivated many researches in the field of image classification.The foremost architecture used in classifying tuberculosis is the AlexNet architecture[7] A similar work[8] with a little fine tuning such as shuffle sampling as well as cross validation is implemented.GoogleNet[9] a faster effective method has a better accuracy than other traditional architectural models.This is quick because it has lesser parameters to learn compared to other architectures.Though ImageNet[10] achieved 89 percent accuracy it took around 1 lakh epochs which is a very slow.The next work[11] used a technique called image augmentation to provide varieties in images.Increase in size increases the performance of a model.[12]With seven convolutional layers and three fully connected layers precision is compared with three optimizers such as Adams,SGD, momentum where adams optimizers gave the best accuracy.Another sought after architecture is the ResNet[13] architecture with features being extracted automatically and provides improved accuracy with a compact model.

2.3 Deep learning methodology

The hierarchial technique deep learning , a subset of machine learning progressed from the visual cortex of a cat.Over the years this approach proved effective with large datasets particularly in the field of image classification/recognition as well as text analysis.The main advantage of this approach is the automated feature extraction.These models learn features itself through layers.There are some essential information one needs to know before proceeding into the proposed architecture.There are numerous algorithm in deep learning and CNN known as Convolutional Neural Networks is the most widely used algorithm in image classification. Convolutional layers popularly known as the hidden layers are responsible for learning features with the help of filters.The filters may be of varying size.The output of one layer is fed into the input of other layers.Strides are similar to steps that helps filter to move across the input image for feature learning.Maxpooling and average pooling reduces the dimmensions of the image. Dropout layers minimizes overfitting. The fully connected layers categorizes images on unique features followed by softmax to produce desired class.There are numerous activation functions to fire specific neurons.The optimizers adjusts parameters for better model performance.

III. PROPOSED CNN ARCHITECTURE

This part details the proposed architecture in stratification of tuberculosis into normal and abnormal classes.

3.1 Datasets

The open datasets Montgomery and Shenzen amalgamated to form the end dataset. The Montgomery generated by the U.S. National library of Medicine has 138 images whereas Shenzen dataset generated by the same organization in collaboration with Guandong Medical college has around 662 images.

3.2 Pretreatment

Though deep learning do not require a lot of preprocrессing still part of it can be done for better performance of the model.In this model the images are transformed into RGB and the images are rescaled into 128 x 128.The augmentation of images is done inorder to get a large dataset which will play a major role in improvement of accuracy of the system.

3.3 Proposed model

The presented model consists of 9 convolutional layers which learns the parameters using disparate number of filters for different layers and has a kernel of size 3 x 3.The convolutional layers are followed by 3 maxpooling layers to reduce the dimensions of the input that is necessary for faster learning.The maxpooling layer takes the maximum of the value in the kernel thus reducing the dimensions of the input image.These maxpooling layers are followed by 4 dropout layers one in each block.The purpose of this block is to turn down overfitting of the model. These are followed by 1 flatten layer to transform the input into vectors and paves way to the 2 fully connected convolutional layers popularly called as dense layers.The classification of normal abnormal classes is done by the softmax layer.This layer contains the same number of neurons present in the previous fully connected layer.Sigmoid function can also be used for classification.The actrivation function employed in this model is the Relu function known as rectified linear unit defined as y=max(0,x) modifies every negative value into positive and has provided impressive results in the field of image recognition and classification.The main purpose of relu is providing non linearity so that model could have a great adaptability over varieties of data.The idea about the architecture with parameters to be learned of this architecture is given in fig2.The block diagram is depicted in Fig 3.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
conv2d_1 (Conv2D)	(None, 124, 124, 32)	9248
conv2d_2 (Conv2D)	(None, 122, 122, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 61, 61, 32)	0
dropout (Dropout)	(None, 61, 61, 32)	0
conv2d_3 (Conv2D)	(None, 59, 59, 64)	18496
conv2d_4 (Conv2D)	(None, 57, 57, 64)	36928
conv2d_5 (Conv2D)	(None, 55, 55, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 27, 27, 64)	0
dropout_1 (Dropout)	(None, 27, 27, 64)	0
conv2d_6 (Conv2D)	(None, 25, 25, 128)	73856
conv2d_7 (Conv2D)	(None, 23, 23, 128)	147584
conv2d_8 (Conv2D)	(None, 21, 21, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 10, 10, 128)	0
dropout_2 (Dropout)	(None, 10, 10, 128)	0
flatten (Flatten)	(None, 12800)	0
dense (Dense)	(None, 256)	3277056
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 2)	514

Total params: 3,758,338
Trainable params: 3,758,338
Non-trainable params: 0

Fig 2.The proposed architecture with parameters to be learnt

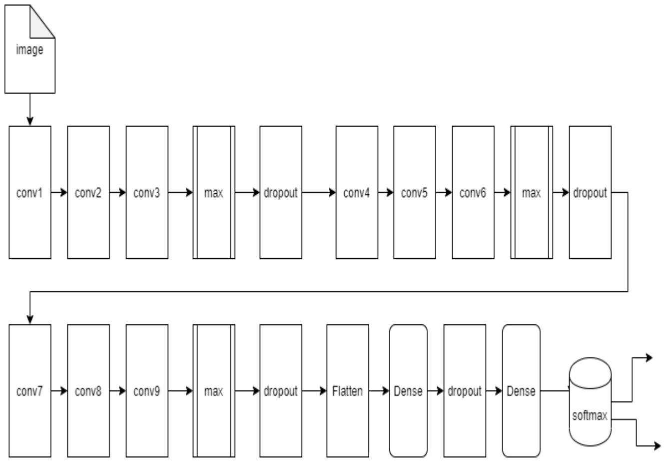

Fig 3.The Block Diagram of this architecture

IV. EXPERIMENTAL RESULTS

The presented model was trained and evaluated in 2104 images and trained for 100 epochs to achieve an accuracy of 84 percent in the validation set.According to the classification report the f1 scores of normal 0.82 is greater than 0.79(abnormal class)expresses that the model is slightly better in finding normal class than the abnormal class.The overall accuracy is 84 percent which is higher than the traditional architectures like AlexNet,ResNet,VGG etc. The batch size is 50.

The optimizers used in this architecture is the Adams optimizer which uses history of gradients to regulate the learning rate.The history of derivaties wielded to measure current update and the second derivative manages learning rate based on density or sparsity of features.The fig 3 and fig 4 shows the training and validation accuracy and loss of this model.This shows that this model performs well with a good accuracy with minimized loss.Another important technique in good performance of this model is due to the image augmentation technique which increased the variety in the dataset and helped the model to learn abnormalities better.

MODELS	ACCURACY
] Xu, T., Cheng, I., Long, R., & Mandal, M. (2013).	82.8%
[11] Rohilla, A., Hooda, R., & Mittal, A. (2017)	80%
[12] Hooda, R., Sofat, S., Kaur, S., Mittal, A., & Meriaudeau, F. (2017, September).	82.09%
Our Model	84%

Table 1:comparison of models.

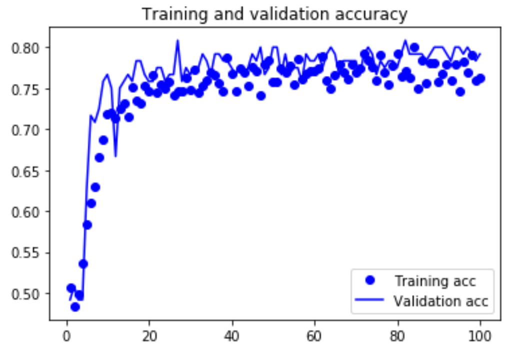

Fig 3 training and validation accuracy

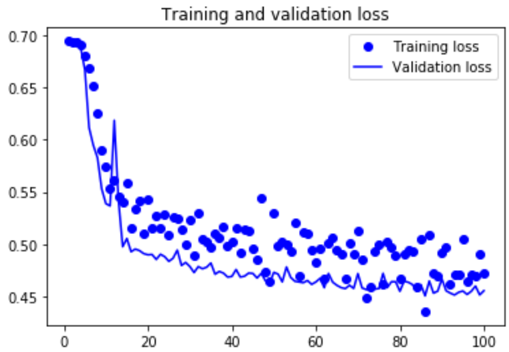

Fig 4 training and validation loss

V. CONCLUSION AND FUTURE WORKS

This paper overted a method in categorizing TB images with good accuracy and minimum loss however more works can be done to improve the performance of the system. More accurate hyper parameters can be tested to improve accuracy of the system. Increasing the epochs can increase efficiency of the system. Decreasing the number of parameters to be learned in each layers can decrease the computing time of the system as result we could get a quicker model with no compromise in accuracy. The model can be trained with higher computation platforms with more epochs and lesser learning rates so that better accuracy relative to radiologist be achieved in the near future.

REFERENCES

1. jaeger, s., karargyris, a., antani, s., & thoma, g. (2012, august). detecting tuberculosis in radiographs using combined lung masks. in 2012 annual international conference of the ieee engineering in medicine and biology society (pp. 4978-4981). ieee.
2. jaeger, s., karargyris, a., antani, s., & thoma, g. (2012, august). detecting tuberculosis in radiographs using combined lung masks. in 2012 annual international conference of the ieee engineering in medicine and biology society (pp. 4978-4981). ieee.
3. hogeweg, l., mol, c., de jong, p. a., dawson, r., ayles, h., & van ginneken, b. (2010, september). fusion of local and global detection systems to detect tuberculosis in chest radiographs. in international conference on medical image computing and computer-assisted intervention (pp. 650-657). springer, berlin, heidelberg.
4. xu, t., cheng, i., long, r., & mandal, m. (2013). novel coarse-to-fine dual scale technique for tuberculosis cavity detection in chest radiographs. eurasip journal on image and video processing, 2013(1), 3.
5. karargyris, a., siegelman, j., tzortzis, d., jaeger, s., candemir, s., xue, z., ... & thoma, g. r. (2016). combination of texture and shape features to detect pulmonary abnormalities in digital chest x-rays. international journal of computer assisted radiology and surgery, 11(1), 99-106.
6. maduskar, p., philipsen, r. h., melendez, j., scholten, e., chanda, d., ayles, h., ... & van ginneken, b. (2016). automatic detection of pleural effusion in chest radiographs. medical image analysis, 28, 22-32.
7. hwang, s., kim, h. e., jeong, j., & kim, h. j. (2016, march). a novel approach for tuberculosis screening based on deep convolutional neural networks. in medical imaging 2016: computer-aided diagnosis (vol. 9785, p. 97852w). international society for optics and photonics.
8. liu, c., cao, y., alcantara, m., liu, b., brunette, m., peinado, j., & curioso, w. (2017, september). tx-cnn: detecting tuberculosis in chest x-ray images using convolutional neural network. in 2017 ieee international conference on image processing (icip) (pp. 2314-2318). ieee.
9. szegedy, c., liu, w., jia, y., sermanet, p., reed, s., anguelov, d., ... & rabinovich, a. (2015). going deeper with convolutions. in proceedings of the ieee conference on computer vision and pattern recognition (pp. 1-9).
10. deng, j., dong, w., socher, r., li, l. j., li, k., & fei-fei, l. (2009, june). imagenet: a large-scale hierarchical image database. in 2009 ieee conference on computer vision and pattern recognition (pp. 248-255). ieee.
11. rohilla, a., hooda, r., & mittal, a. (2017). tb detection in chest radiograph using deep learning architecture. icetetsm-17, 136-147.
12. hooda, r., sofat, s., kaur, s., mittal, a., & meriaudeau, f. (2017, september). deep-learning: a potential method for tuberculosis detection using chest radiography. in 2017 ieee international conference on signal and image processing applications (icsipa) (pp. 497-502). ieee.
13. he, k., zhang, x., ren, s., & sun, j. (2016). deep residual learning for image recognition. in proceedings of the ieee conference on computer vision and pattern recognition (pp. 770-778).

AUTHORS PROFILE

R.Rohith currently pursuing Masters degree in computer science Big data analytics at VIT Chennai has received his Bachelors degree at Sri Venkateswara college of engineering.He is a highly motivated individual who is a data science fanatic and wishes to take forth his career in the field of data science.He has received certain certifications in the field of data science,machine learning as well as deep learning.He is also a EC-Council Certified Ethical Hacker and also a EC-Council certified Security Analyst.He also has participated in various hackathons and has been part of many impressive projects.

S.P. Syed Ibrahim has received his Bachelors, Masters and Ph.D. in Computer Science and Engineering. He is working as a Professor for the past 7 years at VIT Chennai. He is a recipient of VIT Researcher award for the last 7 consecutive years. He has also received a Best Faculty Award from VIT for the year 2016 and EMC academic alliance award for the year 2013. With 13 years of teaching experience, he has published more than 75 research papers in Journals and Conferences. He has provided guidance for more than 50 M.Tech. students project and currently guiding 4 Ph.D scholars. He has delivered more than 100 invited talks in the International Conferences, workshops. He has organized five short term courses on data analytics for students from universities abroad and also organized DST sponsored national workshop on data science research. He was a founder coordinator for a data analytics research group in VIT and during his tenure he had introduced M.Tech CSE with specialization in Big Data Analytics in the year 2013, a first of its kind in India.