Mycobacterium Tuberculosis Detection Using CNN Ranking Approach

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Abstract. The main reason behind the large number of mortality among homo-sapiens is due to Mycobacterium tuberculosis (TB). Majorly, TB can be classified into two categories named as Active and Latent Tuberculosis. Tuberculosis diagnosis is a critical area and needs a high extent of accuracy for working. Minor errors in diagnosis can result in disastrous repercussions. The ultimate goal of this paper is for detecting TB at right time and help combat the increasing number of cases by early treatment. In this paper, we implement CNNs of different configurations on a dataset for binary classification and mainly focus on the objective function value obtained from different CNN models with an LVCEL, MVA, and TT. The objective function can be a useful tool for physicians and our medical community for correctly identifying a TB patient. Experimental evaluation of the best architecture shows that a maximum objective function value of 6.503, with a validation accuracy score of 0.9671 and an AUC of 0.9733 in the Receiver Operating Characteristics (ROC) curve is achieved to correctly identify whether TB is present or not.

Keywords: Convolution neural network (CNN), Artificial neural network (ANN), Deep Learning, Image Recognition, Machine Learning, Biomedical imaging

1 Introduction

A major reason behind death among human beings is due to Tuberculosis. Tuberculosis is a dangerous contagious infectious and chronic disease that usually attacks our lungs and requires complex treatment. Tuberculosis is caused by infectious bacteria named Mycobacterium tuberculosis. According to stats, India is on top where most peoples are suffering from Tuberculosis(TB) and every year 480,000 deaths are recorded between 2006 and 2014 and India faced the loss of $340 Billion US dollars in the economy[1,2]. The reason behind these such large numbers was the lack of good healthcare infrastructures and poor resources and this reason is not acceptable as TB is curable and can be prevented. Majorly Tuberculosis can be classified into two areas i.e. Latent TB and Active TB. Chest X-rays [3] help to detect tuberculosis as there will be many abnormal findings that can be directly diagnosed by the physician by using Chest X-ray images.

An unsupervised neural network (restricted Boltzmann machine) was used to create a time-aware recommendation system to recommend movies to users [4]. Generative models [5] also play an important role in the field of machine learning. The medical and computer vision are major fields that are getting most of the contributions from Machine learning and Deep learning [6, 7]. Similarly, Normal machine learning algorithms like the Random Forest, Decision Tree, Naive Bayes, etc. have been used to detect credit card fraud [8]. Tweets can be analyzed through Natural Language Processing (NLP) to classify them into sentiments (positive or negative) via machine learning algorithms. The tweets were web-mined from Twitter [9]. So machine learning and deep learning are important sectors and they are contributing almost in every field. In this paper, we have discussed performance metrics achieved by different architectures where CNN and ANN models are used for training the dataset. All 15 architectures gave different maximum accuracy, minimum loss, and training time. All these parameters have been used for calculating the objective function value of every architecture and then we activated the neural network and evaluated the intermediate activation in CNN architecture with Keras. By the real-time deployment of tuberculosis automatic diagnosis, we achieve high accuracy by which we can save time using computing power to detect a tuberculosis patient. The rest of the paper is organized as follows:-2. *Related Work*, 3. *Methods and Data* 4. *Experimentation and Results*, 5.*Conclusion and Future Work*. We evaluated different CNN architectures and calculated the objective function value for every architecture and selected the ideal architecture that achieved the highest objective function value for the particular tuberculosis dataset used in section 4.

2 Related Work

Nowadays as many fields are getting a major contribution from machine learning and deep learning techniques and work for medical workers are getting easier and convenient. Diseases like Tuberculosis and Pneumonia are diagnosed by Chest X-ray images and these images are used by CNN architectures for the detection of these diseases. Chhikara *et al.* (2020) used the Chest X-ray images (CXR) for evaluating the performance of pre-trained models like Xception, ResNet, and Inception for detection of pneumonia by implementing some preprocessing processes like gamma correction and filtering [10]. Accuracy of 82.09% was achieved by Hooda *et al.* for classification among a TB patient from a normal person by using deep learning technique for classifying CXR images [11]. For classification among normal and TB patients, Nguyen *et al.* [12] used a DenseNet pre-trained model on a dataset provided by Shenzhen (CHN) and Montogomery County (MC) databases [13] by achieving AUC of 0.94 and 0.82 respectively. Similarly, Lopes and Valiati performed TB detection using X-ray images on the same dataset of CHN and MC and achieved an accuracy of 80% on different pre-trained CNN models for classifying TB into positive and negative cases [14]. Yadav *et al.* achieved an accuracy of 94.89% by using transfer learning techniques for classification among CXR images [15].

Another example of machine learning is an interactive visualization tool which was developed by Pasa *et al.* for TB detection where the optimized deep learning architecture achieved an accuracy of 86.82% for Tuberculosis detection [16]. Hernandez *et al.* used CNN model ensembles for TB detection from X-Ray images and gained an accuracy of 86% and the model was based on the automatic classification method of TB [17]. Evalgelista and Guedes [18] approached chest X-ray images by using an intelligent pattern recognition using CNNs for detecting Tuberculosis and gained an accuracy of 88.76%. Ahsan *et al.* used two techniques like image augmentation and without image augmentation for classifying TB datasets by using a pre-trained CNN architecture and gained accuracy of 81.25% and 80% [19]. Chang *et al.* on labeled tuberculosis culture images used transfer learning and achieved sensitivity and specificity of 99% and 98% [20]. Table 1 provides all the summarized details regarding all related works and time complexity is given for best models only.

Table 1. Comparison between various related works

Ref.	**Technique**	**Advantages**	**Disadvantages**	**Time Complexity**
[11]	19-layered CNN architecture for TB detection	Gained High Accuracy and different optimizers were implemented	Dataset used was old and lacked in evaluation metric section	2.581×10^{10}
[12]	Pre-trained ImageNet architectures and Various tunings on the DenseNet model	Tested ImageNet Architecture under different conditions and complete comparison	Connection building between dataset and models were not so good	2.535×10^{13}
[15]	DNN architectures and transfer learning models were implemented on CXR images	Accuracy was high and metric calculations were good and sufficient	The old dataset was used and models were specifically trained on China dataset	1.763×10^{11}
[18]	9 different CNN architectures with two ensembles were used for TB detection	Originality was Maintained in dataset and architectures were good and balanced on parameters	Accuracy was not high and Dataset was small	6.037×10^{8}
[20]	Transfer learning models and CNN architectures were implemented on CXR images and	The metric evaluation was good and the comparison was explained well. Recall and precision were very high.	Dataset was imbalanced and small	1.029×10^{9}

two-stage classification for boosting results

From this section, we can clearly state that Machine Learning and Deep learning techniques are contributing a major part in medical field issues like heart disease detection [21] and malaria detection [22] can be resolved efficiently and can make things convenient and easier for the radiologist. Although many techniques can be implemented on Tuberculosis there are several limitations like in previous implementations we can see that most of the papers were directed towards transfer learning techniques where they have used pre-trained models on various datasets and lack datasets and there was the repetition of datasets where a single dataset was used by many authors and accuracy achievement was high but lacked instability and few of them were performed on small scale and no different conditions were implemented so that we can check the stability of architectures. So many radiologists faced issues regarding the binary classification as there was not enough information or data for tuberculosis detection.

3 Methods and Data

In this section, we will talk about the techniques we have used for classifying tuberculosis using Chest X-ray images of whether a person is suffering from TB or not. We also specify the dataset we have used for detection and also the technology with which we have done the experimentation and computations are also mentioned in this section. This section maps out as follows 3.1 Dataset Used, 3.2 Convolutional Neural Network (CNN) 3.3 Software and Hardware.

3.1 Dataset Used

The Chest X-ray images for Tuberculosis Detection of patients were collected from Kaggle and were deployed by Tawsifur Rahman, Amith Khandakarand, Dr. Muhammad Chowdhury. They collected all the images from various datasets like the NLM dataset, Belarus dataset, NIAID TB dataset, and RSNA CXR dataset and gathered around 7000 images [23]. A sample difference between a positive infective patient and a normal person is shown in Fig.1. Table 2 describes the amount of Chest X-ray images taken for training, validation, and testing of the model.

Table 2. Dataset distribution and splitting of images taken into training and testing.

	Tuberculosis	**Normal**
Training	2800	2800
Testing	350	350
Validation	350	350
Total	3500	3500

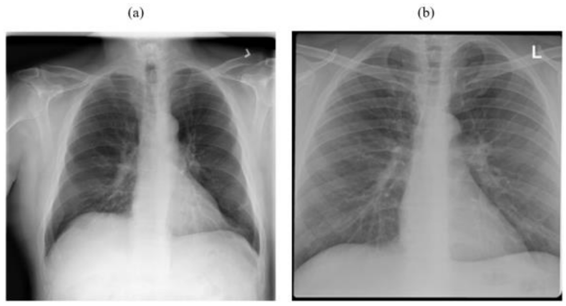

Fig 1. (a) Chest-X Ray of a normal person, and (b) of a tuberculosis positive patient.

3.2 Convolutional Neural Network (CNN)

Convolutional Neural Network [24] is the backbone of deep learning and machine learning technique and CNN is a commonly used framework model which was proposed by *Yan LeCunn* in 1998 and it changed the approaches for the training of models. There are many applications of CNN architectures decoding paddy crop disease detection [25], COVID-19 detection [26], facial recognition [27], nuclei segmentation [28,29]. CNN's are composed of 4 main types of layers – Convolutional, Max-Pooling, Flattening, and Full-Connection. The main objective of Convolutional layers is to extract features by using feature detectors i.e. are known as kernels which are in form of a 2-D matrix. From convolutional neural networks, we can state that it must be related to the convolutional theorem.

So, mathematically we can explain the convolutional layer in terms of the convolutional theorem and that can be defined as

$$(x * y)(a) \triangleq \underbrace{\int_{-\infty}^{\infty} x(\Psi)y(a-\Psi)d\Psi}_{x(a)*y(a)} \tag{1}$$

Where the two functions are $x(a)$ and $y(a)$ of a continuous variable x. For better training and execution of the model, the architecture needs to be more heavy and rich in parameters.

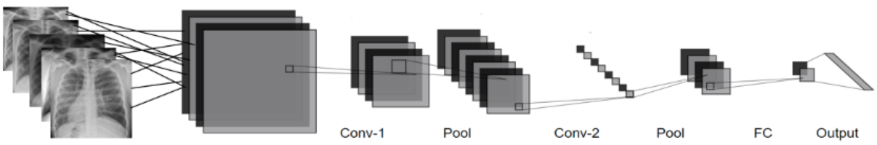

Fig. 2. Convolutional Architecture of a 2- layered CNN model.

After the implementation of max-pooling, Flattening that is the conversion from 2-D matrices kernel into the vertical 1-D array is fed into an ANN after which all connection reflects the Fig 2. Shows a 2 layered full CNN connection.

Various CNN architectures trained for this machine learning analysis Python 3 with the Keras and TensorFlow were used with a jupyter notebook. Hardware workstation is with Intel i5 8^{th} generation and 16 GB RAM.

4 Experimentation and Results

In this section, we elaborate everything regarding experimentation performed on the dataset through different CNN and ANN architectures that contains different parameters and we selected the best model based on stability and reliability for classification among TB patient from the normal person. We divide this section as 4.1 Experiments and Analysis, 4.2. Result of Selected Architecture.

4.1 Experiments and Analysis

We implemented different regularization conditions in different CNN architectures for finding the best model. For the different implementations, we had various parameters such as the number of Convolutional layers and Artificial layers, Batch Normalization, Dropout, and regularization parameters like L1, L2, input sizes of images, kernel sizes, pooling matrix sizes, and feature detection and analogize all the architecture based on Objective Function Value obtained from different architectures and Objective Function Value is based on maximum validation accuracy, least validation cross-entropy loss and training time. The best model was evaluated on Objective Function Value which can be expressed as

$$Objective\ Function\ Value = \frac{MVA}{TT + LVCEL} \tag{2}$$

All information regarding the all different 15 CNN architectures with their maximum validation accuracy, least validation cross-entropy loss, and training time in seconds are included in Table 4, and Table 3 contains all the meaning of abbreviations used in Table 3. Structure-based on minimum LVCEL, maximum MVA of every architecture is shown in Fig. 3. Fig. 4 plots the training time of every architecture Fig. 5 plots the training accuracy and plots the validation cross-entropy loss of each architecture concerning each epoch. From Table 4 we observed that architecture 9 performed poorly concerning MVA and LVCEL as it had the least objective function value of 0.8400. Architecture 9 was the most time-consuming. It took 3045 seconds for the training of the model. This might happened due to Dropout as when Dropout is implemented it reduces the trainable training data parameters which may lead to a drop in accuracy which leads to a fall in objective function value and restricted the model from building a relationship with the dataset. We also noticed that training time was heavily impacted by the change in image input shapes. We can say MVA, TT also depends on input sizes as in architecture 1, 3, 4, 7, and 8 where image size was (64, 64) which reduced the training time, and thus we can conclude that TT depends on IS. We can also say TT is inversely proportional to the number of layers as More number of layers the computational work increases and training time will increase and if the architecture is not heavily parameterized then TT will be less load will increase on training the neural network increases when an intensive task is performed. Architecture 2, 5, 10, and 12 performed very well but they took training time higher than the architectures which were fed with (64, 64) images but their performance was noticeable as accuracy gained by all these architectures were greater than 97%. Architectures like 13, 14, and 15 were implemented with L1 and L2 regularization conditions they all were very heavy architectures but they also gained high accuracy without taking much training time. So L1, L2 reduced the training time of the architectures which were much heavier and rich in parameters when compared with other architectures. Architecture 11 had a very minimum validation loss as it was balanced architecture in terms of CL and AL layers but the time took for training was higher but the relationship between model and dataset was very good. Architecture 6 was simple but due to Dropout and Batch Normalization performance was decreased and architecture was moderate when compared to all other CNN architectures. Fig. 4 changes excessively when there increase or decrease in the layers of CNN architectures and there is an impact on TT of CNN and ANN architecture but there is not an extreme change in LVCEL and MVA.

However, the maximum objective function value was obtained by model 4 which was 6.503 and the minimum objective function value of 0.84 was obtained by model 9. By this, we can conclude that normal and small CNN and ANN architectures perform more stable and better with good accuracy and high objective function value. The model will either overfit or underfit if we implement more features and layers. So for further consideration, we have taken model 4 as an ideal architecture to evaluate model performance on the tuberculosis dataset in the next section.

Table 3. Abbreviations are used in Table 3.

Abbreviation	Meaning
CL	The number of CNN Layers in an architecture.
AL	The number of ANN Layers in an architecture.
L1	Level 1 regularizations
L2	Level 2 regularizations
BN	Batch Normalization
DO	Dropout
IS	Input Size of image (64x64 or 128x128)
FD	Feature detected in a convolutional layer, layer-wise.
KS	Kernel Sizes for each convolutional layer, layer-wise.
PS	Pooling Sizes followed by every convolutional layer are always assumed to be a square matrix.
TT	Time taken in seconds to train the model.
LVCEL	Least Validation Cross-Entropy Loss achieved during training.
MVA	Maximum Validation Accuracy was achieved during training.

Table 4. Performance of 15 different CNN architectures on various parameters.

S. no.	CL	AL	Regularization				IS	FD	KS	PS	LVCEL	MVA	TT
			L1	L2	BN	DO							
1	2	3	✗	✗	✗	✗	(64,64)	{64,32}	{9,3}	{4,2}	0.1001	0.9700	1181
2	2	4	✗	✗	✓	✗	(128,128)	{64,32}	{9,3}	{4,2}	0.0977	0.9714	2868
3	2	4	✗	✗	✗	✓	(64,64)	{64,32}	{9,3}	{4,2}	0.1324	0.9543	1321
4	**3**	**3**	✗	✗	✗	✗	**(64,64)**	**{64,32,16}**	**{6,3,3}**	**{2,2,2}**	**0.1116**	**0.9671**	**1074**
5	3	4	✗	✗	✗	✗	(128,128)	{128,64,32}	{9,6,3}	{4,4,2}	0.0945	0.9714	2331
6	3	5	✗	✗	✓	✓	(128,128)	{128,64,32}	{9,6,3}	{4,4,2}	0.1150	0.9657	2292
7	4	4	✗	✗	✗	✗	(64,64)	{64,64,32,16}	{6,6,3,3}	{2,2,2,2}	0.1071	0.9686	1120
8	4	4	✗	✗	✓	✓	(64,64)	{64,64,32,16}	{6,6,3,3}	{2,2,2,2}	0.1473	0.9571	998
9	4	5	✗	✗	✗	✓	(128,128)	{128,64,32,16}	{9,6,3,3}	{4,2,2,2}	0.1323	0.9614	3045
10	4	6	✗	✗	✗	✗	(128,128)	{128,64,32,16}	{9,6,3,3}	{4,4,2,2}	0.1124	0.9743	2290
11	5	5	✗	✗	✗	✗	(128,128)	{128,64,64,32,16}	{9,6,6,3,3}	{4,2,2,2,2}	0.0962	0.9629	1706
12	5	6	✓	✗	✗	✓	(128,128)	{128,64,64,32,16}	{9,66,,3,3}	{4,2,2,2,2}	0.0978	0.9743	1982
13	5	7	✗	✓	✗	✗	(128,128)	{128,64,64,32,16}	{9,6,3,3,3}	{2,2,2,2,2}	0.1077	0.9614	1905
14	6	7	✓	✗	✓	✓	(128,128)	{128,128,64,64,32,16}	{9,6,6,3,3,3}	{2,2,2,2,2,2}	0.1304	0.9571	1662

15	6	8	✓	✓	✕	✓	(128, 128)	{128,128,64,64, 32,16}	{9,6,6,3, 3,3}	{2,2,2, 2,2,2}	0.1418	0.9571	1743

(a) (b)

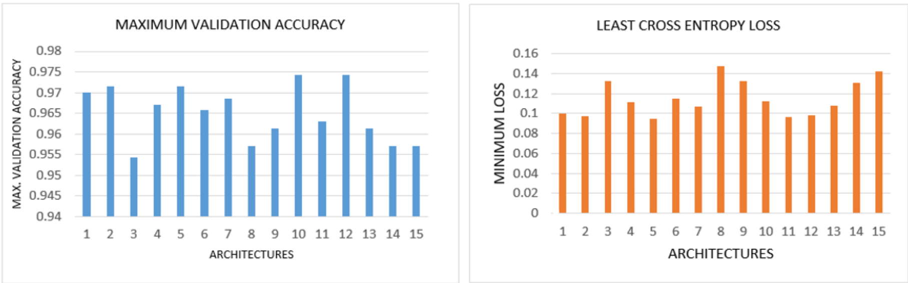

Fig. 3. (a) Maximum Validation Accuracy (MVA) for each architecture. **(b)** Least Cross-Entropy Loss (LVCEL) for each architecture.

Fig. 4. Training Time (TT) for each architecture.

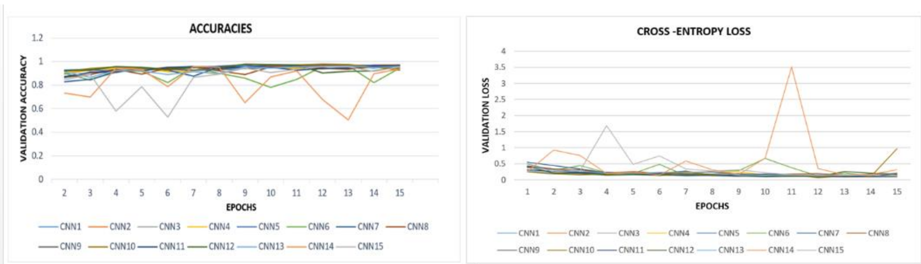

Fig. 5. (L)Validation accuracy training curve for each architecture per epoch. (R) Validation cross-entropy loss training curve for each architecture per epoch.

4.2 Result of Selected Architecture

We selected architecture 4 as the model performance was excellent and achieved the highest objective function value. An evaluation metrics we calculated the confusion matrix and calculated the sensitivity, specificity, precision, F1 score, and MCC i.e. Mathew Correlation Coefficient.

$$\text{Sensitivity} = {}^{\text{TP}}/_{(\text{TP} + \text{FN})} \tag{3}$$

$$\text{Specificity} = \text{TN} / (\text{FP} + \text{TN}) \tag{4}$$

$$Precision = \text{TP} / (\text{TP} + \text{FP}) \tag{5}$$

$$F1\,Score = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN}) \tag{6}$$

$$\text{MCC} = \frac{\text{TP x TN} - \text{FP x FN}}{\sqrt{((\text{TP} + \text{FP}) * (\text{TP} + \text{FN}) * (\text{TN} + \text{FP}) * (\text{TN} + \text{FN}))}} \tag{7}$$

Where TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative respectively. See Fig. 6 illustrates the confusion matrix and ROC of the selected model where testing was done on 700 images where TN=339 TP= 335 FN = 11 FP = 15. From equations 3, 4, 5, 6, and 7 we calculated $Senstivity = 0.9576$ $Specificity = 0.9682$, $Precision = 0.9686$, $F1 - Score = 0.9631$, $MCC = 0.9258$. All five metrics are above 90% this indicates that our model was accurate and performed excellently in diagnosing the positive TB cases and negative TB cases. Moreover, the ROC curve is illustrated in See Fig. 6 where the area under the curve (AUC) was found to be 0.973355 which is very good. These metrics are excellent and are comparable with various architectures based on Tuberculosis detection using Chest X-ray images. Table 5 shows the accuracy and time complexity comparison of best architecture with various other works (best architectures) related to CXR images.

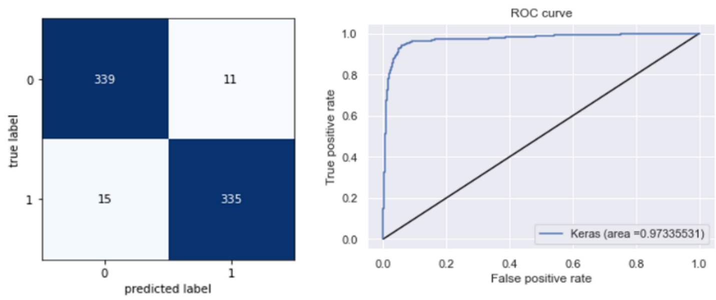

Fig. 6. (L)The confusion matrix for architecture 4 (see Table 3). (R**)** The receiver-operating characteristics (ROC) curve for 4th CNN architecture. The AUC of the ROC curve was found to be 0. 973355 units

Table 5. Accuracy and Time Complexity Comparison of our Architecture with various other models

Ref.	Author Name	Accuracy	Time Complexity
[11]	Hooda *et al.*	82.09%	2.581×10^{10}
[16]	Pasa *et al.*	86.82%	8.950×10^{10}
[18]	Evalgelista and Guedes	88.76%	6.037×10^{8}
[20]	Chang *et al.*	98%	1.029×10^{9}
-	**Architecture 4**	**96.71%**	$\mathbf{3.226 \times 10^{8}}$

5. Conclusions and Future Work

In this paper, we make a best effort to find out the best approach for tuberculosis detection using Chest X-ray Images by comparing all the 15 different CNN and ANN architectures based on performance and we selected an ideal model based on maximum objective function value which is easy to train and detect tuberculosis faster and more reliable manner. The metrics of selected architecture compared to other ones are simpler as if architecture gets complex the training time gets increased drastically but accuracy and loss were not changing much as compared to TT. We admit architecture 4 performed best and can gain more stability and accuracy if we do small adjustments and experimented upon more.

Future work of Tuberculosis detection through various algorithms as there are already many papers on Transfer learning we can create efficient and stable CNN architectures by user method. There can also be the implementation of many conditions on any model for finding the best suitable condition for training and executing our model. So tuberculosis is a sensible case and can give better outcomes via various algorithms under different conditions and can give the better result of diagnosing tuberculosis patients and normal peoples.

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