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A Novel Deep Convolutional Neural Network for Tuberculosis Detection

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Abstract: ***India accounts for the world's largest number of cases in TB, with 2.8 million cases annually, and accounts for more than a quarter of the global TB burden. Tuberculosis (TB) is caused by the bacterium (Mycobacterium tuberculosis) which most commonly affects the lungs. TB is transmitted from person to person through the air. When people with TB cough, sneeze or spit, the germs are propelled into the air. This paper showcases a methodology which uses a Deep Learning Model (dCNN) for the detection of Tuberculosis in the lungs. The accuracy obtained by the methods for the model is desirable and dependable, which is increasingly productive in contrast to the accuracy shown by other neural networks.***
Keywords: Tuberculosis, Chest X-ray, Neural Network, Deep Learning, Convolution Neural Network, Image Classification, DICOM Images, Confusion Matrix

I. INTRODUCTION

Tuberculosis (TB) is a pulmonary infection that causes damage to the lungs. It also spreads to various parts of the body such as the brain and spine. *Mycobacterium tuberculosis* complex is a set of closely related bacterial species that causes Tuberculosis. It is the primary cause of tuberculosis in humans. TB falls into two different categories. The first category is Latent TB. Here, the germs persist in the body but the immune system prevents the spread of germs. The person shows no symptoms and the disease remains dormant in the body but can become active anytime. The second category is active TB. The person shows clear symptoms as the germs in the body multiply and weaken the immune system.

The primary challenges to control TB in India involve the following: lack of healthcare facilities in rural areas of states; unregulated private medical care resulting in broad unreasonable utilization of first line and second line anti TB medications and the spread of HIV disease. Poorly built environments such as overcrowded homes, poor ventilation, presence of hazards within workplaces, etc, have been identified as contributors to extend exposure to TB.

There is a requirement for effective medical assessment, surveillance, infrastructure and contact tracing in order to terminate the disease. It is of utmost importance to come up with a solution to eradicate the spread of TB in India as it is a potentially life threatening disease to any human being.

The use of AI in healthcare has been monumental in solving a plethora of medical conditions. Medical diagnosis of diseases such as Diabetes and Cardio vascular diseases are carried out with the same precision as human doctors. This is achieved with the help of complex Machine Learning and Deep Learning algorithms, reason being, AI models are able to recognize patterns and are able to create their own logic, but such models need to be repetitively trained to emulate human accuracy. The primary goal of AI in healthcare is to analyze relationships between prevention or treatment techniques and patient outcomes. Deep learning is the preferred methodology in medical image analysis. The usage of deep neural networks is essential in the diagnosis of various medical health conditions especially Tuberculosis.

Neural networks are a set of neurons organized in different layers that are capable of mimicking human functions, in order to derive patterns. Neural networks understand and learn patterns from various sources of information such as images, sound and text after being trained on labeled datasets. The trend of Neural Networks began with the concept of a simple perceptron.Later, deep neural networks were invented which consisted of multiple hidden layers. This was extremely advantageous as the deeper layers of the Neural Network were able to learn more complex features and patterns. Deep neural networks open up new opportunities for combating tuberculosis (TB) which kills more people globally than any other infectious disease. The persistent identification gap is a major reason for the high mortality; more than one third of the estimated 10 million TB cases go undiagnosed and unreported. Chest X-ray (CXR) is the most commonly available diagnosis tool done for a doctor to identify the presence of TB in a human being.

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II. BACKGROUND

A Neural Network or perceptron is a model that is modeled after the human brain. The main goal of a neural network is to perform tasks like classification, object detection, segmentation, etc. The various layers in the Neural Network consist of units called neurons which are similar to the biological neurons in the human brain. The various neurons in each layer are interconnected and are responsible for performing a particular function. A connection between two neurons is assigned a weight and each individual neuron has a bias quantity. The output of a neuron is shown in equation 1 below:

$$Y = \sum(Weight * Input) + Bias - (1)$$

Where, Y refers to the summation of the product of weights of the respective node and input to that node with its bias value for all of the layers in the neural network. A more advanced version of the Neural Network is the Convolutional Neural Network, also known as CNN. The only addition in this network is the convolution and pooling layers. CNN's are widely used for image classification tasks. The elements of a Neural Network are as discussed below:

1) *Input Layer:* In this layer, the input is fed to the neural network which is given to the subsequent layers for computation purposes.
2) *Hidden Layers:* The hidden layer is the second layer of a Neural Network. The objective of the hidden layer is to perform mathematical computations on the input, weight and bias of the respective neurons. This is followed by an activation function which computes a probability to be passed as output. The activation function can vary depending on the application.
3) *Output Layer:* This layer outputs the result of the Neural Network.

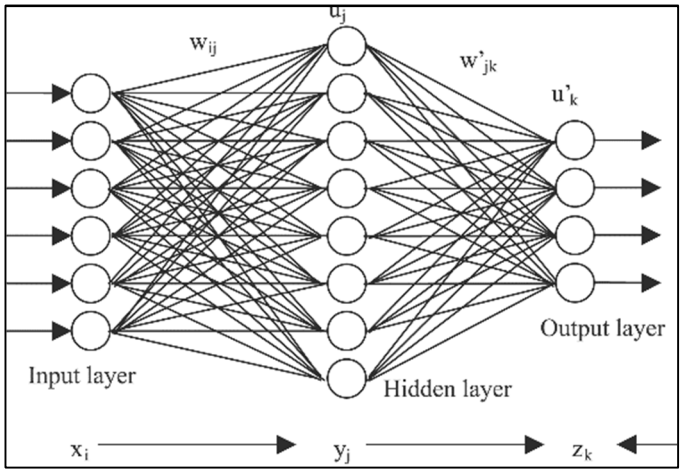

Fig 1: Layers of a Neural Network

Figure 1 highlights all the layers of a neural network which are interconnected to form a Neural Network. Tuberculosis detection technique using CNN is a wide researching area and several ideas have been put forth by multiple researchers. In [1] the authors suggest a Transfer Learning approach for Tuberculosis Detection in Medical Imaging. The authors in [2] speak about two experiments that were carried out. The first experiment attempts to create a massive, real-world and labeled X-ray image dataset to carry out TB testing that is automated. The second research experiment focused on constructing effective and efficient predictive models, in particular, deep convolutional neural networks (CNN) to classify the images into several categories of manifestations of TB. Asma Abbas and Mohammad M. Abdelsamea talk about an effective way to classify lung chest x-ray images of into two categories viz. Tuberculosis infected lungs and healthy lungs.

This is accomplished by implementing a Transfer Learning model known as AlexNet, a pre trained Convolutional Neural Network (CNN) [3]. The authors in [4] proposed a CNN model capable of classifying CXR images into TB positive and negative with an overall accuracy of 94.73% using the Adams Optimizer. A Validation Accuracy of 82.09% and a loss of approximately 0.4013 was achieved. Deep Learning was suggested by authors in paper [5] for classifying distinct X-ray images of possible Tuberculosis infected patients. Three different models with different hyper parameters are used for classification on three different datasets. Out of the course, medium and fine-tuned models, the fine-tuned model achieved the best accuracy of 92.8%.Authors in paper [6] mentioned that if a large amount of labeled data is available, a deep CNN can be trained as an end to end network. But, this was only true for a time series classification [6].The authors in [7] studied ImageNet classification using AlexNet, a deep neural network.

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Paper [8] talks about using a multi scaled image of a lung. This image is given to a CNN for classification into a variety of classes to overcome the drawbacks of traditional patch based algorithms in identifying healthy and infected lungs. In [9], a CNN technique that uses patches was implemented for classifying the tissue of the lung.[10] recommended employing shape and texture features to detect pulmonary abnormality. The features were classified using a Support Vector Machine. The approach achieved an area under the ROC Curve equal to 0.934.Authors of paper [11] proposed a pleural effusion detection algorithm. A Random Forrest algorithm can be used to compute the abnormality score of pleural effusion. This indicates how extreme the case is. Paper [12] carried out Tuberculosis detection using the first ever deep CNN. Gao Huang et.al proved that the usage of class activation maps (CAMs) were useful for visualizing CNN's [13]. [14] Emphasizes on the use of publicly available datasets like Montgomery and Shenzen datasets. The authors of [15] stated that original mapping optimization is easier than residual mapping optimization. This is demonstrated by utilizing a residual network to solve a variety of problems in image classification.

III. PROPOSED METHOD

A. The detection of Tuberculosis consists of the following steps:

1) *Input Dataset:* Dataset was obtained from Kaggle, which is one of the biggest sources of datasets for the AI community. The dataset set contains chest X-ray images of Tuberculosis positive and negative patients. The training dataset is used to train the CNN and to predict the presence of Tuberculosis in it whereas; the test dataset is used to check the efficiency of the model by giving unseen inputs to the neural network to check its performance.
2) *Image Processing:* DICOM images have both, the image and the relevant patient information which is associated with it which is not important with respect to the training of the CNN and thus, the DICOM image is first converted to a JPEG or PNG image format and then given as an input to the model. The DICOM image is a greyscale image having only two dimensions and the value ranges between 0-255. The images will be of different dimensions and thus they are reshaped into one unique size of 800x800 pixels and then finally flattened.

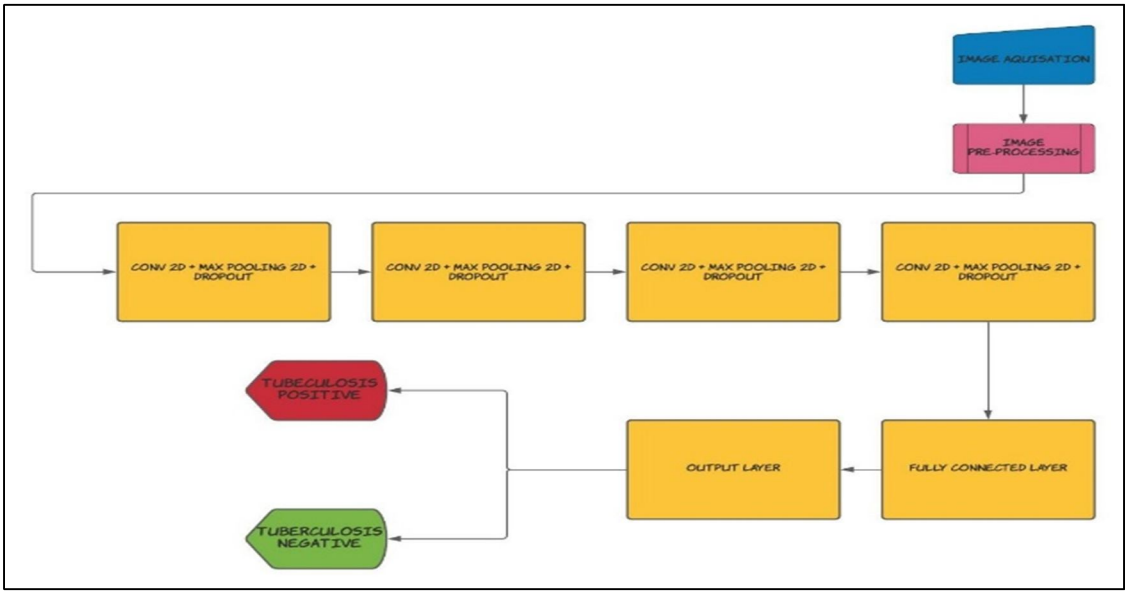

Fig 2: Proposed Method

B. The Proposed Method Is Divided Into A Series Of Steps As Shown In Figure 2 And Each Step Is Explained In Detail Below

1) *Image Acquisition:* The dataset of Chest X-ray is acquired from Kaggle. The X-rays here are used in .png format
2) *Image Pre-processing:* The DICOM image is a grayscale image having only two dimensions and the value ranges between 0-255. The images will be of different dimensions and thus they are reshaped into one unique size of 800x800 pixels and then finally flattened.
3) *dCNN Model:* dCNN stands for Deep Convolutional Neural Network. The model consists of 14 layers which include four Convolutional layers, four Max Pooling layers and four Dropout layers along with a fully connected layer and an output layer.

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C. *L2 Regularization was applied to fully connected layers to optimize the model. the dcnn model consists of the following layers and their description is given below*

1) *Input Image:* The input image passed to dCNN model and is resized to 224x224 to match the standard input of the model.
2) *Convolution Layer:* The convolutional layer is responsible for extracting important features from the image. This is done with the help of filters. The filter slides over the image and performs the convolution operation thus obtaining high level features.
3) *Non-linearity ReLU:* ReLU stands for Rectified Linear unit for a non-linear operation. The ReLU function is given by the expression:

$$f(x) = max(0,x)$$

Where *f(x)* is the maximum of the range of values between 0 and x. This is an activation function whose responsibility is to introduce non linearity in the image. This is done by preserving the non-negative values of the image.

4) *Max-Pooling Layer:* The convolved feature map is passed to the pooling layer. The main function of pooling is to reduce the dimension of the convolved feature. The sliding window is passed over the convolved image and the most important features are extracted.
5) *Dropout:* To eliminate the problem of overfitting, Dropout is used. Neurons are randomly dropped from layers to enhance the performance.
6) *Flattening Layer:* The pooled features maps are flattened into a single vector of values that are passed as input to the Fully Connected Layer.
7) *Fully Connected Layer:* The Fully Connected Layer is similar to a normal Artificial Neural Network consisting of input, hidden layers and an output layer. The flattened features are passed in as input and the neural network performs the necessary operations to compute the output.

IV. EXPERIMENTAL ANALYSIS

The said method is simulated in Google Colaboratory using Python 3. The model was trained over 528 images (268 TB positive and 260 TB negative) and validated over 67 images (34 TB positive and 33 TB negative). The model training is as shown below:

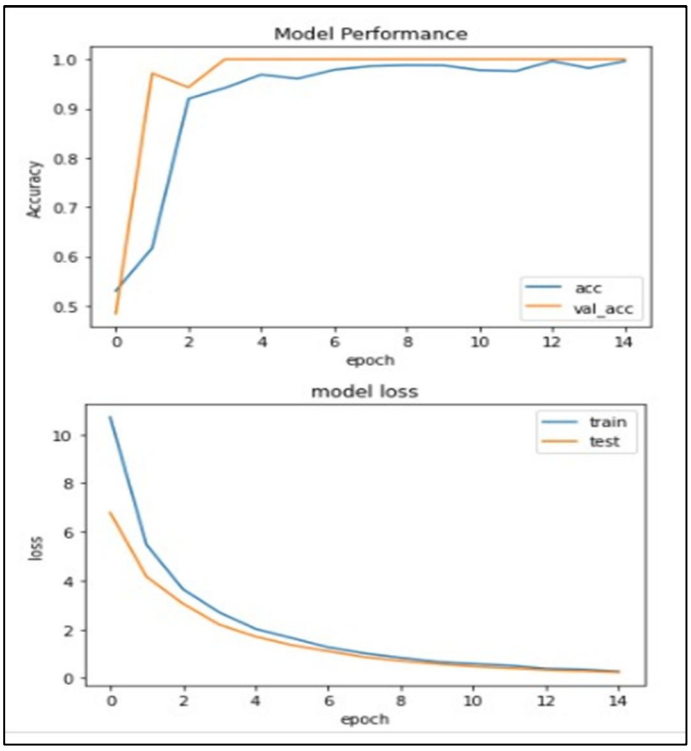

Fig 3: Model Performance Graph

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The following table shows the accuracy (model performance) achieved by this model:

Table 1: Accuracy rates

Dataset	Accuracy
Training Set	99.60%
Validation Set	100%

As shown in Table 1, a training accuracy achieved was of 99.60% was obtained and a validation accuracy of 100% was obtained. The model was tested over unseen data and the results are visualized using a confusion matrix as shown below:

Table 2: Confusion Matrix

	Predicted -ve	Predicted +ve
Actual -ve	33	0
Actual +ve	0	34

As seen from the confusion matrix, accuracy obtained for the test dataset was 100% as it was able to correctly classify all the images present in the test dataset.

V. CONCLUSION

The implementation of the neural network is done for predicting whether or not a person is diagnosed with Tuberculosis wherein the real time dataset was collected from Kaggle. Google Colab with scikit learn, keras, tensorflow is used for the implementation in Python Language. dCNN type of neural network is used for the prediction of Tuberculosis from the input Chest X-ray images. Test images are compared against the training images to detect the disease. The result thus obtained provides a fine accuracy which enables the medical practitioners to rely on this device considerably. The training set accuracy of 99.60% and test set accuracy of 100.00% was achieved. To fine tune performance, more data and deeper network can be constructed. Further work on segmentation of Tuberculosis as stage 1 and stage 2 can also be done to detect the level of threat and a suitable diagnosis can be answered.

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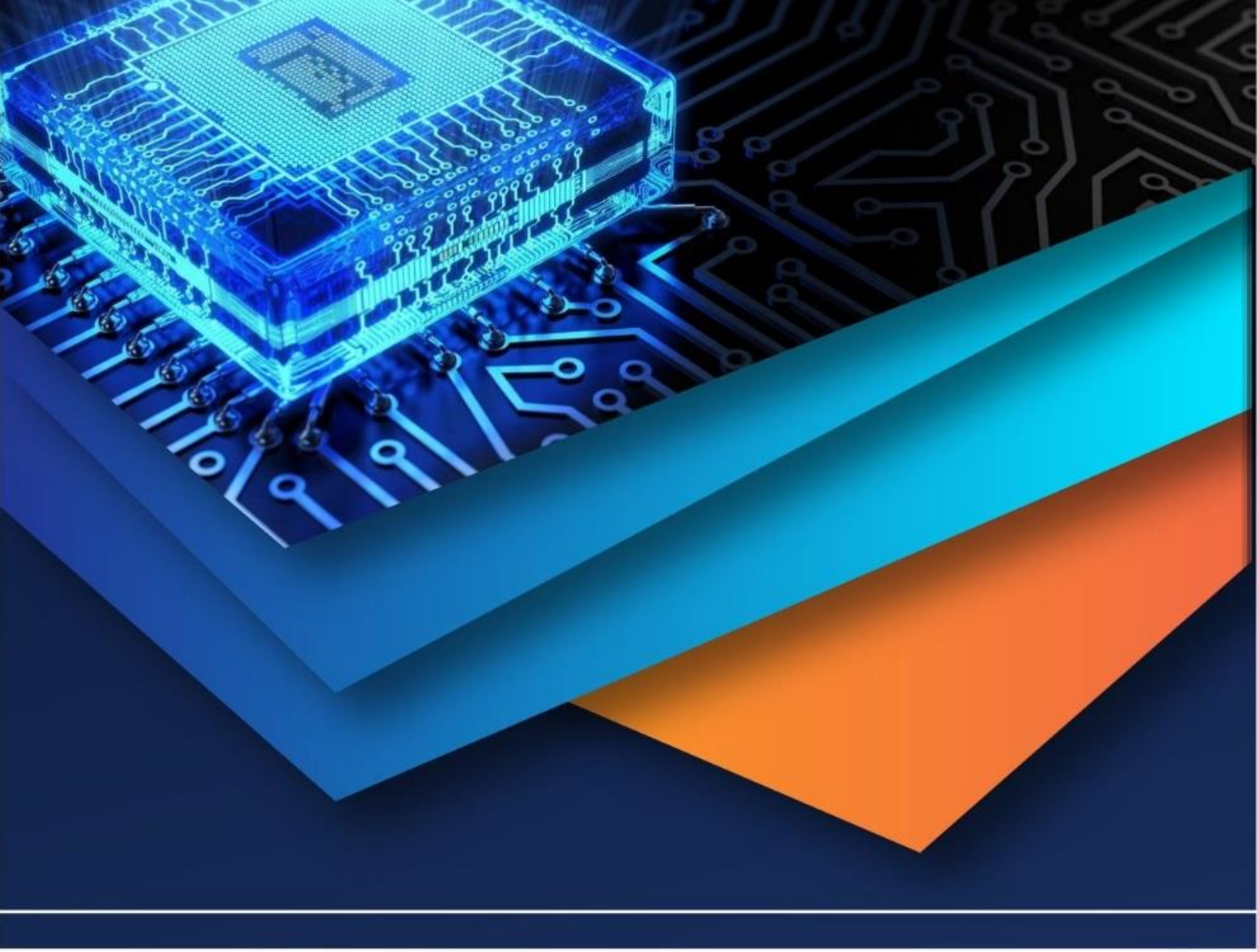

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