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Research Article

A Novel Deep Learning Framework for the Detection of Tuberculosis using Chest X-ray Images

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Abstract: Machine learning can play an important role in changing the dynamics of the modern healthcare system. In terms of the diagnosis field, Machine learning algorithms have offered tremendous support to Radiologists, healthcare workers, and other decision-makers. Early diagnosis of TB can stop the further spread and eventually mortality rate due to TB will fall. Currently, the standard method that is used for the diagnosis of TB takes one to four weeks while the rapid test takes 24 hours, so using Radiological images has an advantage over the existing standard method. In this paper, we have proposed a Novel Framework based on the application of Deep Learning to detect Tuberculosis (TB) using Chest X-ray images. In this work, 4200 images have been used to train the deep learning model. The model has achieved an accuracy of 99.41% in classifying Normal Chest X-rays and Tuberculosis (TB) Chest X-rays.

Keywords: Machine learning, Tuberculosis, Deep learning, Chest X-ray, Radiological images.

1. Introduction

Different studies have shown the potential of artificial intelligence-based diagnosis in the medical sphere. Different AI-based diagnostic systems are referred to as expert systems, as they are designed to replicate the decision-making power of health care professionals. These systems are designed and trained on existing clinical data so they can provide different insights. Different techniques of data science including artificial intelligence, data mining, machine learning algorithms, and deep learning methodologies are used to exploit complex clinical data to get useful insights, classification of diseases, therapies, medicine recommendations, etc. Mostly, deep learning technology is used to train expert systems, so that they can classify different diseases using radiological images.

Tuberculosis (TB) is a serious infectious disease caused by the family of a bacterium called Mycobacterium Tuberculosis [1]. TB directly attacks the lungs of the infected patient. Tuberculosis is an asymptomatic disease, but in some cases, symptoms can be coughing and sneezing. The TB-infected patient requires a long course of medication to get healthy again [2]. The mortality rate is quite high. According to the report published by the World Health Organization (WHO), 10 million people around the globe are affected every year by this dreadful disease, out of which 1.5 million people succumb to Tuberculosis. Around one-fourth of the total population has been infected by TB in 2019. Tuberculosis spreads through tiny droplets using air as a medium and infecting different people who come in contact. Tiny droplets carrying infectious bacteria are released via sneezes, and coughs of an infected person.

Currently, available methods for differentiating TB-infected patients from non-infected take up to four weeks while rapid tests can take up to 24 hours. However, the main problem with these tests is to differentiate between patients with active Tuberculosis and those patients who have a history of Tuberculosis. Chest X-ray can be cheap and rapid testing for detecting diseases like Tuberculosis, Pneumonia, and other pulmonary diseases. Although Pneumonia and TB share various common symptoms with other pulmonary diseases so it is difficult for radiologists and decision-makers to diagnose TB just by analyzing Chest radio images. Convolutional Neural Network (CNN) techniques can play a vital role in detecting TB disease more accurately. The available large data in the medical field can help train Deep Learning.

In this paper, we have implemented a deep learning neural network to discriminate between tuberculosis-infected Chest X-rays and normal Chest X-rays.

2. Literature Review

Deep Learning technology has numerous applications in different domains, but for the medical sphere, multiple applications have been proposed for the last decade [3][4]. It can be applied in two main areas i.e., for health management and diagnostic systems [5]. Different experiments have been conducted to detect different diseases. During the pandemic, when Covid-19 breakout out all over the world, Research for creating computer-aided diagnostics has also increased. Different architectures based on the neural network have been proposed to detect Covid-19 using different modalities [3]. Machine learning has also been used for future prediction of cases or other diseases.

Detecting pulmonary diseases with modalities has already remained a challenge from the beginning and different efforts have been made to create diagnostic systems [6]. Detecting Tuberculosis with Chest modalities has been in practice for a long time but it creates a burden for radiologists and other decision-makers so creating an automated diagnostic system is needed.

The study has been conducted to investigate the age-specific impact of Bacillus Calmette-Guérin (BCG) vaccination [7]. The study aimed to find the accuracy of AI-based diagnostic systems to detect Tuberculosis disease using Chest X-rays. 2075 individuals participated in this experiment, three algorithms were used and in parallel sputum test is also used. Abnormality scores for all three algorithms were found to be highly correlated with the sputum bacillary load test [8]. [2] has proposed a novel architecture based on VGG and Proposed CNN, this system can classify Pneumonia, Lung Cancer, Tuberculosis, Lung Opacity, and Covid-19. The model has been trained on more than 25,000 Chest X-ray images of different classes. [1] has used different augmentation techniques for the preprocessing of the dataset which further enhances the validation and learning rate of the algorithm. The model can classify the TB images from other normal Chest X-ray images with an accuracy of 99.1%. [9] has a proposed Machine Learning model that extracts optimal features from tuberculosis-infected Chest CT-Scan images and selects the most suitable hyperparameters of the classifier. A genetic algorithm helps choose the best features to enhance the learning rate has been used. The genetic algorithm is further connected to the support vector machine. [10] has used two types of approaches, In the first approach ResNet-50 is combined with a support vector machine and in the second approach GoogleNet-50 is combined with a support vector machine. Both the models have been trained and tested on two different datasets and have performed well. An overall accuracy of more than 95% has been achieved by the model.

[11] has proposed an ensemble method to differentiate Tuberculosis Chest X-ray images from normal Chest X-rays and Covid-19 Chest X-rays. The model has been evaluated on different parameters. [12] has proposed CNN architecture and has achieved an accuracy of 85.68%. Pretrained model VGG-19 has been used for the automatic detection of Tuberculosis, In [13], the images were preprocessed then important features were extracted, these steps were followed by enhancing the Chest X-ray images, and the Seagul Algorithm for the optimization of features was used and concatenated with the previous steps. In the end, the model is evaluated on different parameters.

[14] used 5 different pre-trained models namely Inception V3, VGG-16, VGG-19, Xception, and ResNet, all the models were trained and tested on a common dataset. After comparing the performance of these models VGG-16 has overperformed the other four models. [15] has carried out an experiment to test the feasibility of Deep learning-based detection of Tuberculosis. It has studied the patterns of Tuberculosis in the Chest X-ray of TB-infected patients. [16] has proposed an ensemble method that detects Tuberculosis using X-ray images of the lungs, Deep features, and hand-crafted features were extracted using a pre-trained deep neural network and Gabor filter respectively. Also, two publicly available datasets namely Montgomery and Shenzhen were used to evaluate the proposed model. The k-fold Cross-validation method is used to validate the proposed model. [17] has used deep learning to differentiate tuberculosis-infected and normal CT-scan images.

Explainable AI or Interpretable Machine learning is the other domain that can be proven to help full for making automatic diagnostic systems. [18] proposed a method of detecting Tuberculosis and Crohn's disease and also can provide explainability for the case. The XG-Boost method is used for the classification while the SHAP model can provide explainability. These models are essential as they can provide a Global explanation of the disease as well as an explanation for the particular disease. The Deep Fused Linear Triangulation method is a technique used to establish a relation between Chest X-ray images, it pacifies the similarities and differences between different classes. [23] has used the advanced FLT method to highlight the TB-infected area in CXR without Segmentation.

3. Materials and Methods

This Section discusses in detail the Material that is used to carry out the experiment and the detailed methodology of the experiment and the proposed architecture.

3.1. Dataset Description

The dataset used to experiment consists of 3500 Tuberculosis Chest X-ray images, 700 Normal Chest X-ray images, and 4200 total Chest X-ray images. Initially, we picked the dataset from Kaggle, the link is given in the table. Images are merged and shuffled to remove any biases if exist. The overall description of the dataset is given in Table 1. The dataset was collected from secondary sources although it can be upgraded by retrieving data from primary sources of geographically diverse locations to make data more diverse so that the generalization capability of the model can also be increased with a variety of datasets. Table 1 shows the number of images of each class and the reference from where the dataset is retrieved. The Tuberculosis images were kind of hazy from within the bronchitis of the lung whereas Normal lungs' x-rays were visible. More description of the features was extracted by the model. A few Tuberculosis Lung X-ray images and Normal Chest X-ray images are selected randomly from the dataset and are added below in Figure 1, just for reference purposes. The Ground Glass opacity is visible in images**.**

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Table 1: Dataset Information

Class	Number of Images	Reference
Tuberculosis	3500	https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset
Normal	700	
Total X-ray images used for the experiment: 4200		

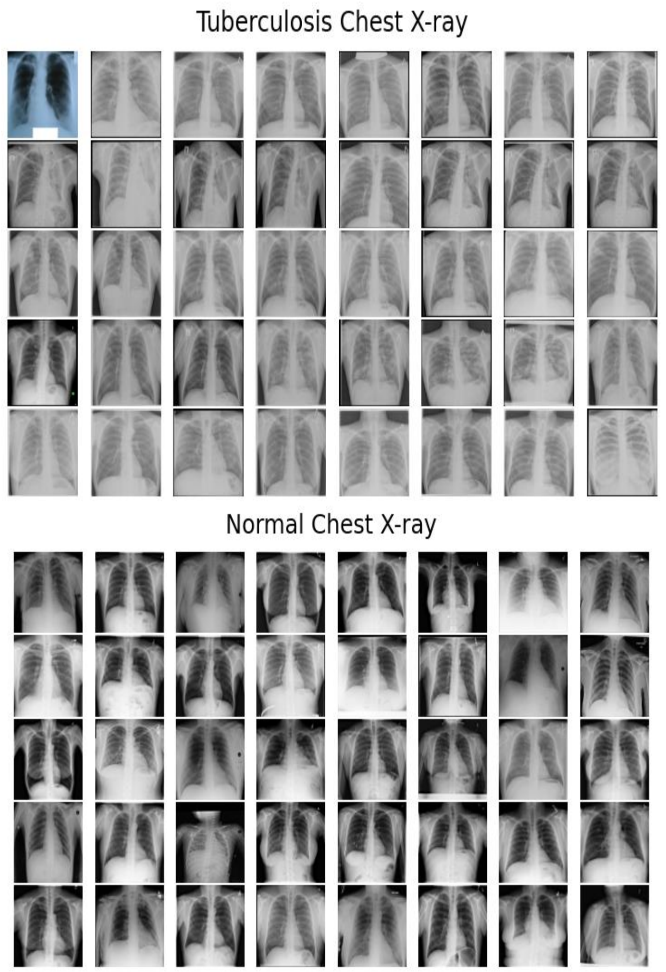


Figure 1: Random Chest X-ray images from the dataset

3.2. Research Methodology

This section deals with all the information related to the process of how the experiment is carried out. The first step is to fetch data. We collect 4200 TB infected images and Normal Chest X-ray images. The next step is to preprocess the data, both classes of images are shuffled and resized to 512x512 pixels. The dataset is then divided into two parts training and testing data. We split the data into 80% for training and 20% for testing, from 20% training data some part is used for testing and some part is used for validation of the model. Validation is performed during the training of the model; The Model is validated on data other than training data so that it should not overfit itself by seeing training data again and again. After Data preprocessing, Training data is fed to the proposed model, A novel CNN based architecture is proposed with a sufficient number of layers so that the model can extract and learn features from the dataset Detailed description of the layers of the model is given in section 3.3. The model is then trained using 50 epochs and training data is given in batches of size 25 during training. Layers are added after a few runs to fine-tune the model to train it for distinguishing TB from normal chest X-rays. Other than Convolutional layers few other layers were also used like dropout to avoid the problem of overfitting, the dense layer is also used at the end. The activation function at each layer has been used to add nonlinearity in the model. Adamax optimizer has been used to enhance the learning rate. In the last step trained model is tested over the testing data. Different evaluation parameters have been used to evaluate the performance of the Deep learning model. The workflow of the experiment is given in Figure 2.

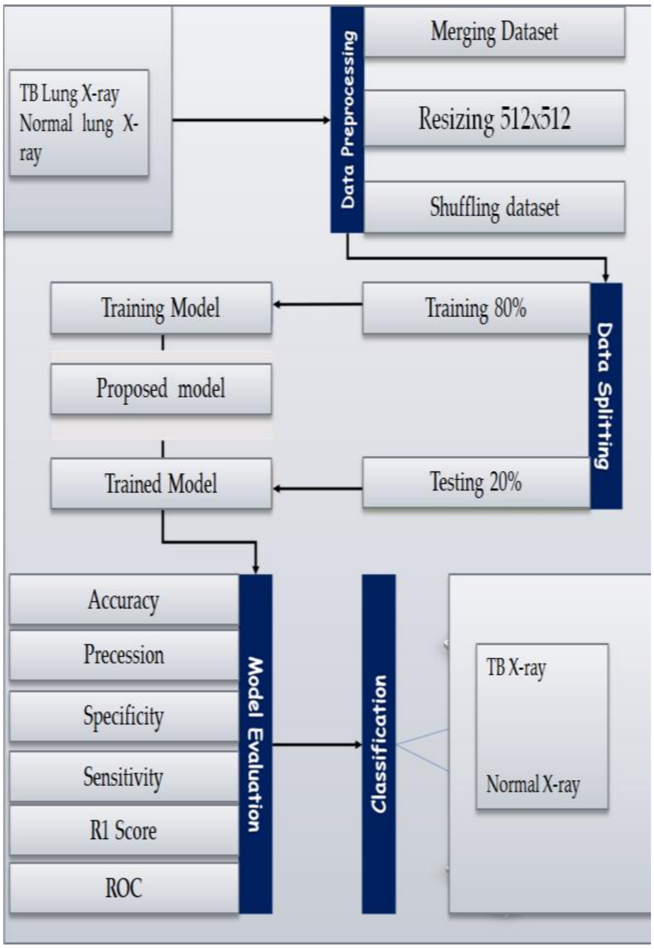


Figure 2: Flow Diagram

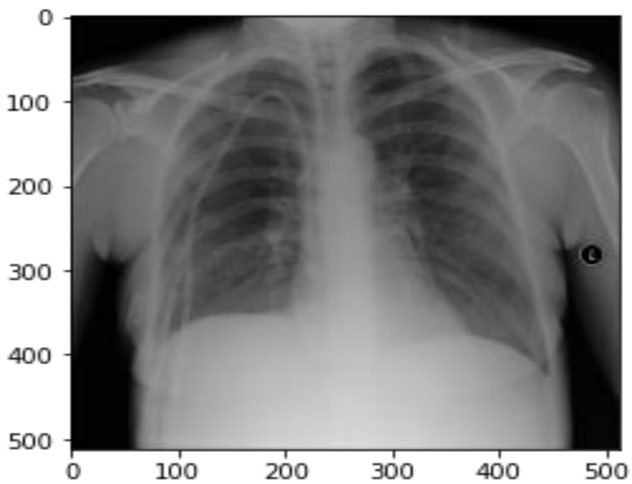


Figure 3: Resized Chest X-Ray Image Sample (512 x 512)

3.3. Parameter Tunning

The images in the datasets are not of the same resolution. So, images were scaled to a fixed size of 512x512 pixels. The dataset used was randomly split into 80% and 20% for training and testing. To train the model 50 epochs were conducted to avoid the overfitting problem with a batch size of 25. The preprocessed image is given in Figure 3.

3.4. Proposed Framework

The proposed model consists of one input layer which accepts images of size 512x512 and two convolutional layers, each followed by Batch normalization, Leaky ReLU, and Max pooling layer. After two convolutional layers followed by subsequent other layers, the flattened layer is added so that the feature map can be converted into the 1-dimensional matrix and to further feed the output of the flattened layer into the Dense layer. After two dense layers and a dropout function, SoftMax is added to predict the output from the learned features. Activation functions are added at appropriate places to add non-linearity.

4. Experiment Evaluation and Results

4.1. Implementation Environment

The whole experimental work was carried out on Jupyter Notebook provided by Google's Colab environment. 10 GB RAM and TESLA K-80 GPU were used to carry out the whole experiment.

4.2. Performance Evaluation and Results

This section deals with the performance evaluation and the results obtained during the training and testing of the model.

4.3. Model Description

The model consists of different Convolutional layers which extract the features from the training data, Maxpooling layer after each convolutional layer has been used to reduce the dimensions of the feature map obtained as an output of the Convolutional layer. A different dense layer has been added and the ReLU activation function has been used to add non-linearity to the model. Flatten layer has been added to convert the multidimensional matrix into a single dimension array so that it can be fed to a dense layer, then Dropout is added in which a few learned features are dropped to avoid overfitting the model. The whole data has been sent to the architecture 50 times which is termed an epoch to train the model. Adamax optimizer has been used.

A detailed description of the layers of the architecture has been given in Table 2. Parameters and output obtained from each layer have been added in the description table.

- **Optimizer:** *Adamax*
- **Loss:** *categorical_crossentropy*

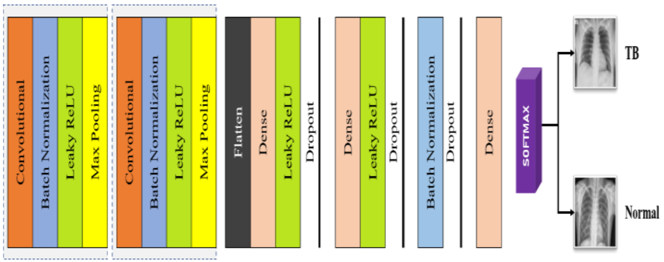


Figure 4: Proposed Architecture

Table 2: Model Description

Layer (type)	Output Shape	Parameters
conv2d_5 (Conv2D)	(None, 127, 127, 32)	416
batch_normalization_7	(None, 127, 127, 32)	128
leaky_relu_11	(None, 127, 127, 32)	0
max_pooling2d_5	(None, 63, 63, 32)	0
conv2d_6 (Conv2D)	(None, 61, 61, 256)	73984
batch_normalization_8	(None, 61, 61, 256)	1024
leaky_re_lu_12	(None, 61, 61, 256)	0
max_pooling2d_6	(None, 30, 30, 256)	0
flatten_2 (Flatten)	(None, 230400)	0
dense_8 (Dense)	(None, 256)	58982656
leaky_re_lu_13	(None, 256)	0
dropout_7 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None,	32896
leaky_re_lu_14	(None, 128)	0
dropout_8 (Dropout)	(None, 128)	0
batch_normalization_9	(None, 128)	512
dropout_9 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 2)	258

Experiment Evaluation

The model has been tested on different parameters, Evaluating the performance of the model can signify its strength of the model and can form a basis for further improvement. The model has been evaluated by finding Precession, Recall, Specificity, F1-Score, and Accuracy. All the evaluating parameters have been calculated using the Confusion matrix given in Figure 4. The result of the parameters is recorded in evaluation table 3. Precision, Recall, Specificity, and F1-Score for detecting tuberculosis-infected Chest X-rays are 100%, 99%, and 100% respectively. While for detecting Normal Chest X-ray precision is recorded as 93%, Recall 100%, Specificity 100%, and F1-Score also 100%. The overall Accuracy of the proposed model is 99.41%.

Graph representing how the accuracy of the model is increased through training is given in the Accuracy curve also it contains the accuracy curve of testing. Another Graph represents the loss during training and testing of the model. Figure 5 contains the Accuracy curve and the loss curve of the model.

Table 3: Classification Performance

Experiment Type	Label	Precision	Recall	Specificity	F1-Score	Support	Overall Accuracy
Binary Class	Tuberculosis	100%	99 %	100%	99 %	140	**99.41 %**
	Normal	93%	100 %	100%	100%	28	

Comparative Analysis

Different researchers have proposed different techniques and architectures to enhance the accuracy of the existing diagnostic system. The comparison of the existing technique with our proposed technique is given in Table 4.

After comparing with existing State of Art our model has achieved good accuracy. But we cannot say which model has outperformed the other model because every model has used a different dataset and has different parameters. In terms of comparing accuracy, our model has achieved the highest. However other parameters can be used to evaluate the model.

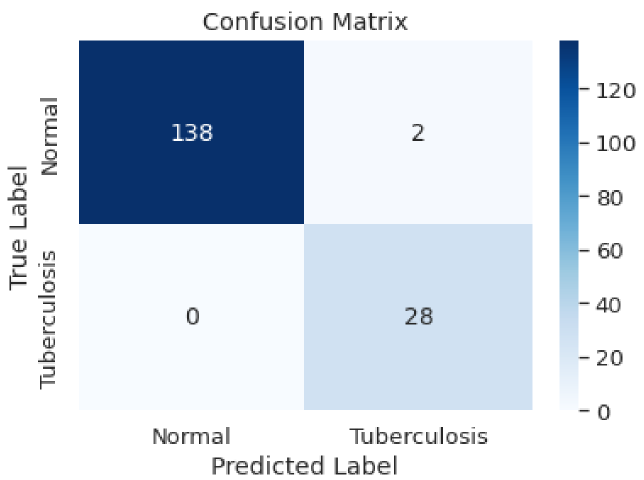
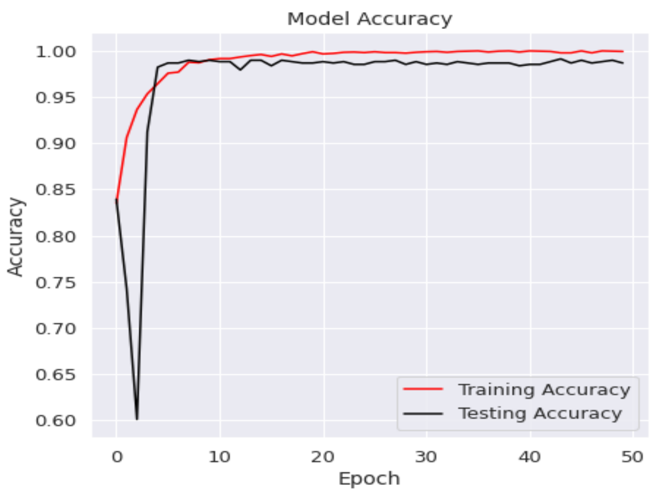


Figure 4: Confusion Matrix

Table 4: Comparison with existing techniques

Reference	Techniques	Dataset (No. of images)	Accuracy
[1]	CNN	Shenzhen dataset Normal=326 TB=336	99.01%
[2]	CNN	Pneumonia=20,000 Lung Opacity=6012 Covid-19=3615 Normal=10,992 TB=1400	93.75%
[10]	ResNet-50, GLCM, DWT and LBP features with dataset 1	Shenzhen dataset Normal=326 TB=336	99.2%
[14]	ResNet-50, GLCM, DWT and LBP features with dataset 2	Shenzhen dataset Normal=326 TB=336	99.78%
[15]	Ensemble Method	Shenzhen dataset Normal=326 TB=336	99.01%
[16]	CNN	TB = 4248 Normal =453	85.68%
[17]	VGG-19	TB CXR images=3500 normal CXR images=3500	98.61%
[19]	Deep Fused Linear Triangulation (FLT)	TB CXR images=3500 normal CXR images=3500	99.2%
[20]	E-TBNet	The Shenzhen, China dataset (CHN)=663 The Montgomery dataset (MC)=138	85.0%
[21]	CNN	AbiyeV Dataset (Turkey) =120.120	92.40
[22]	CAD4TB(V6)	Nepal and Cameroon Dataset=1,196	92%
[22]	Lunit	Nepal and Cameroon Dataset=1,196	94%
[22]	qXR	Nepal and Cameroon Dataset=1,196	94%
[16]	Ensemble: Inceptionv3, InceptionResnetv2	Shenzhen dataset = 662 TB Chest Radiograph = 4200	93.7%
[16]	VGG16, VGG19, MobileNet ResNet50, Xception	Shenzhen dataset = 662 TB Chest Radiograph = 4200	97.59%
[14]	ResNet		94.89%
[17]	3D-ResNet	nontuberculous mycobacterium lung disease (NTM-LD) = 399 Mycobacterium tuberculosis lung disease (MTB-LD) = 952	83%
Our proposed model	**Novel CNN architecture**	**Normal = 700 TB = 3500**	**99.41%**



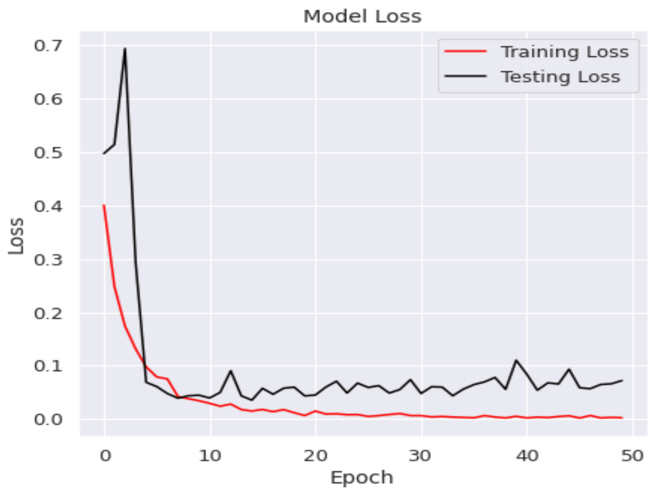


Figure 5: Accuracy curve and Loss curve

5. Discussion

In the present research, A Novel CNN based model has been proposed for detecting TB from Lung X-ray. The proposed model can differentiate TB-infected Lungs from healthy lungs just by seeing the X-ray image of lungs. The proposed model has shown superior performance and can act as a base for further research to detect other pulmonary diseases. The main findings obtained from the experiment indicate that the Convolutional Neural network can accurately distinguish TB and normal Chest X-rays with high precision value and high sensitivity value. Results obtained from the study show that deep learning has a wider scope for creating computer-aided diagnostic systems. The experiment has shown that integrating neural networks in a clinical setting could serve as a valuable tool and can be used widely in areas that have limited access to Radiologists. A similar model can be used for preliminary diagnosis. However, the evaluation metrics used to evaluate the model is not enough. The model should be verified on real-life testing to make it more reliable. Besides achieving good accuracy, it has a few limitations that are discussed below.

Distinguishing Tuberculosis from other pulmonary diseases that share similar symptoms is a big challenge. There are some diseases like lung cancer, Covid-19, Pneumonia, Normal Chest infection, and tuberculosis, these diseases mimic characteristics of each other. So, differentiating tuberculosis from other diseases still needs a lot of research and effort from different domain experts. The dataset used in the present study is homogeneous, primarily consisting of the X-ray images of the patients from specific locations. This could hamper the generalizability of the model for populations other than this specific location. The model may not perform well on data from different demographic and geographic regions. Also, the dataset used in this study was static in nature, one image of each infected person is captured so, the model might not be able to detect the dynamic behavior of the disease. ML being the black box, the present model might lack transparency which cannot be compromised in case of medical diagnosis. The factors on which decision-making is dependent should be highlighted in the model.

Thus, the present study provides a strong base for making diagnostic systems but further research is needed the improve the accuracy of diagnostic systems and address the limitations.

6. Conclusion and Future Work

The present work presents a deep learning approach that has used a convolutional neural network for the detection of tuberculosis-infected Chest X-rays. The performance of the model has been evaluated on different parameters, and it has given promising results when compared with the existing state-of-the-art model. Our model has achieved an accuracy of 99.11% in classifying TB infected Chest X-rays and Normal Chest X-rays. The model has achieved a precision score of 100 for identification of TB lung X-ray whereas for Normal Chest X-ray, it has achieved 93% precession. Precession tells us about the quality of the model to predict positive instances whereas Recall is mostly a Quantitative indicator and mostly indicates how often the ML model is correct in identifying the positive cases. The results obtained from the confusion matrix obtained after the experiment have shown that the model has a recall of 99% for identifying TB X-ray whereas the recall rate is 100% for identifying the normal X-ray. Specificity is another important parameter that tells how many times the model has wrongly classified the Negative label as true which is a Normal chest X-ray in our case. So, the Specificity of the present model tells how many times the model has predicted the Normal Chest X-ray as TB infected X-ray. Specificity calculated from our experiment is 100 for both classifications i.e. The model has never miss mis-classified the Normal Chest X-ray as an infected chest X-ray. It can serve as state-of-the-art for computer-aided diagnosis using Radiological images.

Since the model is trained only to differentiate Tuberculosis and Normal Chest X-ray but it can be the case where the model conflates infections like Pneumonia and other pulmonary diseases with Tuberculosis So in the future model can be enhanced to classify multiple classes of pulmonary diseases. It can also be incorporated with data collected from demographically different regions to enhance the generalizability of the model. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) could be integrated into the present model for visual explanations so that transparency can be maximized and it would build more clinical trust.

To sum up, our newly proposed CNN based approach holds great prospects to ameliorate the diagnosis of TB using lung X-ray images and could revolutionize diagnostic procedures in resource-constrained environments. We can improve patient treatment through the further refinement and validation of this technology by addressing the constraints that have been found and exploring future research area

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Author-1 (Sourabh Shastri): Conceptualization, Methodology, Formal Analysis, Validation, Investigation.
Author-2 (Shiwalika Sambyal): Data Curation, Writing-Original Draft Preparation, Result Analysis.
Author-3 (Sachin Kumar): Visualization, Implementation, Writing-Review & Editing.
Author-4 (Vibhakar Mansotra): Validation, Formal Analysis, Supervision.

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