Performance Analysis of Different Convolutional Neural Network (CNN) Models with Optimizers in Detecting Tuberculosis (TB) from Various Chest X-ray Images

Salman Fazle Rabby, Anamul Hasan, Md. Janibul Alam Soeb, GourobpPathok Shirsho, and Bijoy Talukdar

Abstract — Tuberculosis (TB) is one of the top 10 infectious-disease-related deaths. This paper uses Convolutional Neural Networks (CNN) to investigate the accuracy and performance of three pre-trained models with different optimizers and loss functions to diagnose tuberculosis based on the patient's chest X-ray scans. The odds of treating and curing tuberculosis (TB) are better if the disease is diagnosed early in a patient. Early detection of tuberculosis could lead to a decreased overall mortality rate. The best and quickest way to identify tuberculosis is to look at the patient's chest X-ray image (CXR). A qualified professional Radiologist is required to make an accurate diagnosis. But do not have qualified doctor or radiologist everywhere. On the other hand, it is quite difficult for a doctor or radiologist to diagnose from any x-ray images with open eyes.

914 normal chest x-ray images and 892 TB infected images were used from different sources to train and evaluate these images to detect the exact x-ray of Tuberculosis infected people. Different famous pre-trained models like VGG16, InceptionV3 and Xception etc. were applied. Approximately 80% of the data was used for training and the remaining 20% was used for validation. From all of these datasets, randomly 190 images from normal and 180 images from TB chest x-ray images have been taken. Those randomized 370 (190 for TB and 180 for normal) images were used to evaluate the data finally.

Performance of different algorithm like VGG16, InceptionV3 and Xception by applying different optimizers (Adam, Adadelta, Adagrad, Adamax, RMSprop, Nadam, SGD), different loss functions (Binary Cross Entropy, Hinge, Squared Hinge), varying input image size and also varying batch size were also been recorded. Note that, huge variations of performance for different combinations of algorithm, optimizer, loss function, input image size, batch size have been observed. Confusion matrix, precision, recall, f1-score value have also been recorded to understand and justify how accurately the model is predicting the disease from different angles.

Keywords — chest x-ray, pre-trained CNN, tuberculosis.

I. INTRODUCTION

A. Small Overview about Tuberculosis

Tuberculosis is an infectious, sometimes lethal disease caused by the microorganisms Mycobacterium tuberculosis (MTB) [1]. Tuberculosis is mostly a lung disease, although it can also affect other regions of the body [1]. When an infection does not cause symptoms, it is referred to as latent tuberculosis. Active tuberculosis is characterized by a chronic cough with blood-containing mucus, fever, night sweats, and weight loss. Because of the weight reduction, it was previously referred to as consumption [2]. Other organ infections can generate a variety of symptoms [3]. When people with active tuberculosis in their lungs cough, spit, talk, or sneeze, tuberculosis spreads via the air [4]. Tuberculosis is not disseminated by those who have latent tuberculosis [1]. Patients with HIV/AIDS and smokers are more likely to be infected [1]. Active tuberculosis is diagnosed by chest X-rays, microscopic examination, and body fluid culture [5]. To identify latent tuberculosis, a tuberculin skin test (TST) or blood tests are employed [5].

B. Symptoms of TB

Cough that won't go away, chest pain, bloody sputum, shortness of breath, urine discoloration, murky and reddish urine, fever with chills, and weariness, to name a few symptoms. [6]

C. Different Types of TB test

1) Mantoux tuberculin skin test (TST)

The tuberculin skin test is one of the few examinations from the nineteenth century that is still rigorously used as an essential test for TB diagnosis. Despite the fact that it is broadly utilized by physicians all around the world, its interpretation is really challenging and contradictory [7].

2) Blood test

TB blood tests are sometimes known as interferon-gamma release assays, or IGRAs. Two TB blood tests approved by the US Food and Drug Administration (FDA) and available in the US are the QuantiFERON-TB Gold Plus (QFT-Plus) and the T-SPOT. T-Spot test for tuberculosis [8].

3) Imaging test

If the skin test is positive, the doctor will almost certainly order a chest X-ray or a CT scan. This could be white spots in the lungs where the immune system has fought TB infection, or it could represent abnormalities in the lungs produced by active tuberculosis [9].

4) Sputum test

If a chest X-ray reveals tuberculosis, a doctor may take sputum samples (the mucus that comes up when you cough).
Tuberculosis bacteria are tested in the samples. Drug-resistant TB can also be detected in sputum samples. This helps the doctor choose the drugs that are most likely to work [9].

D. TB disease situation in the world

Notifications of tuberculosis cases have dropped dramatically: The most visible effect of the COVID-19 pandemic disruptions on tuberculosis is a massive global drop in the number of people newly diagnosed with tuberculosis and reported in 2020, compared to 2019. (Fig. 1). Following strong expansion from 2017 to 2019, the number of people in the United States fell by 18% between 2019 and 2020, from 7.1 million to 5.8 million [10].

E. Deep Learning in Healthcare

Deep Learning is gaining popularity in the medical industry. It demonstrates predictive tendencies capable of effectively analyzing complicated medical data. With artificial intelligence (AI) becoming integrated into many disciplines of medicine, it is critical for healthcare practitioners to grasp its potential and limits. It’s expanding popularity and presence in healthcare has resulted in considerable media coverage, allowing a greater percentage of our society to become aware of its tremendous potential to assist. In health-care reform, obtaining information and meaningful insights from complex, high-dimensional, and heterogeneous biological data remains a fundamental challenge. Several types of data have evolved in current biomedical research, including electronic health records, imaging, sensor data, and text, all of which are complex, diverse, poorly annotated, and often unstructured. Feature engineering is often required in traditional data mining and statistical learning techniques to build meaningful and durable features from data, followed by the creation of prediction or clustering models on top of them. Both processes provide various challenges when dealing with complex data and a lack of subject expertise [11]. Healthcare’s future has never been more promising. Not only can AI and ML enable the development of solutions that address very particular industrial demands, but deep learning in healthcare has the potential to be extremely powerful in aiding doctors and revolutionizing patient care [12].

F. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a type of deep neural network that is widely used (CNN). Convolution, a mathematical linear process between matrices, is where it all started. A convolutional layer, a non-linearity layer, a pooling layer, and a fully-connected layer are among the layers that make up CNN. Convolutional and fully-connected layers have parameters, whereas pooling and non-linearity layers do not. The CNN works admirably in machine learning problems [13].

II. RELATED WORK

Mostafa Ahsan, Rahul Gomes, and Anee Denton investigated whether CNNs could be a good alternative to decision tree-based medical image categorization systems. They used CNNs on a dataset of chest X-rays (CXRs) to see if the patient had tuberculosis (TB). They employ the traditional decision tree method. Because CNNs have multiple hidden layers with filters, their model can attain a high level of accuracy of 80% without augmentation and 81.25 percent with augmentation. They employed a total of 1324 CXR images from the Shenzen datasets and 276 images from the Montgomery datasets [14]. Rahul Hooda, Sanjeev Sofat, Simranpreet Kaur, Ajay Mittal, and Fabrice Meriaudeau used a CNN architecture with seven convolutional layers and three fully linked layers to investigate the problem. Three distinct optimizers’ performance has been compared. Adam optimizer fared the best among them, with an overall accuracy of 94.73 percent and validation accuracy of 82.09 percent. The Montgomery and Shenzhen datasets were used to get all the results.

Chang Liu, Yu Cao, Marlon Alcantara, Benyuan Liu, Maria Brunette, Jesus Peinado, and Walter Curios investigated and proposed a new strategy for dealing with unbalanced, less-category X-ray images that uses CNN. Which has a high level of accuracy in diagnosing multiple TB symptoms. In a huge TB picture collection, they attained an accuracy of 85.68 percent [16]. Mustapha Oloko-Oba and Serestina Viriri used a Computer Aided Detection model based on Deep Convolutional Neural Networks to detect tuberculosis from Montgomery County (MC) radiographs. Their proposed model has a maximum validation accuracy of 87.1 percent [17]. Three separate proposals for the use of pre-trained CNNs in tuberculosis detection were provided by U.K. Lopes and J.F. Valiati. Three distinct CNN architectures are employed in the first proposal to extract features from a scaled radiography image. A SVM classifier is then trained using the retrieved features. The same three CNN architectures are utilized in the second proposal to extract features from CR sub-regions. After that, the retrieved features are merged to form a single global descriptor that is used to train an SVM. The best SVMs trained on Proposals 1 and 2 are utilized to generate ensembles of classifiers in the final proposal. Their models have an accuracy of 84.7 percent [18]. Michael Norval, Zenghui Wang, and Yanxia Sun investigated the accuracy of two techniques for detecting pulmonary tuberculosis using Convolutional Neural Networks based on patient chest X-ray images. Various picture preparation methods are compared to see which combination produces the best results. A hybrid strategy was also studied, combining the original statistical computer-aided detection method with Neural Networks. A total of 406 normal and 394 aberrant photos were used in the simulations.
Even greater results are obtained when the photos are further enhanced using the hybrid method. The hybrid technique yielded the maximum accuracy of 92.54 percent [19]. Pike Msonda, Sait Ali Uymaz, and Seda Sogukpinar Karaagac discussed the effects of Spatial Pyramid Pooling on automatic tuberculosis diagnosis using CXR. With and without SPP, three distinct CNN models (AlexNet, ResNet50, and GoogLeNet) were trained from scratch. SPP offers the capacity to obtain a more robust combination of characteristics, which increases accuracy, thanks to multi-level pooling. This study employed three separate datasets to create these CNN models. Two of them (Montgomery and Shenzhen) are publicly available datasets that were utilized to compare the success of the suggested SPP models to other approaches. The Konya Education Research Hospital provided the third dataset (KERH) (Turkey). In comparison to the outcomes of models on their two other public datasets, the training results of all the models on KERH’s dataset performed better. AlexNet scores 0.94 without SPP and 0.95 with SPP, which is rather impressive. ResNet50 has a score of 0.93 without SPP and 0.94 with SPP, which is comparable to AlexNet. Untrained GoogLeNet and GoogLeNet-SPP yield the best results, with 0.97 and 0.98 validation accuracy, respectively [20]. Xudong Liu, Haoxiang Lei, and Sicun Han developed a method that allows a computer to extract features and recognize images of human lungs, as well as automatically determine the lungs' health status using a database. To train the datasets, they used a CNN model. Following the training, the system was able to perform some basic analysis. They also employed a fixed coordinate to reduce noise and paired the canny algorithm with the Mask algorithm to increase the system's accuracy even more. Finally, they achieved a maximum accuracy of 87.0 percent [21]. A model for identifying tuberculosis was proposed by Payal Gidwani, Urmi Gori, Aayush Dedhia, and Nasim Banu Shah. The overall accuracy with Adam Optimizer was 87 percent, with a validation loss of about 0.32 [22]. Thi Kieu Khanh Ho, Jeonghwan Gwak, Om Prakash, Jong-In Song, and Chang Min Park use the public ChestXray14 as a training database. To train the datasets, they used a CNN model. DeTraC allows for more separable learning at the subclass level, with the potential for faster convergence. They used three separate cohorts of chest X-ray images, histological images of human colorectal cancer, and digital mammograms to validate their suggested method. They compared DeTraC to current CNN models to show that it outperforms them in terms of accuracy, sensitivity, and specificity [24].

III. DATA INFORMATION

The dataset was taken from a famous online platform called Kaggle. The original owners are Tawsifur et al. [25]. The dataset contained 3500 Normal or Non-TB images and 700 TB patient images. Due to high mismatch between two classes, we have taken 914 normal images. Then 202 TB images have been augmented and added with 700 TB images to make it 902. This total of 1816 images with resolution 512 x 512 pixels have been divided into training and validation sets according to the Table I.

IV. RESEARCH METHODOLOGY

Fig. 2 shows a flow chart of our methodology. After collecting the image datasets, the images were resized to 224x224 pixels for faster training. Due to lack of TB X-rays, augmentation was done. Before starting training, batch size was taken as 10. Loss calculation was done using Binary Cross Entropy as this is a binary (Normal or TB) Classification.

The X-ray pictures are then classified as having pulmonary TB symptoms or as healthy using three distinct pre-trained DCNNs, namely ResNet152, Inception-ResNet, and DenseNet121 models. They find that proper data augmentation approaches can further improve DCNN accuracies, resulting in the best classifier with an average accuracy of 95 percent for DenseNet121, 91 percent for Inception-ResNet, and 77 percent for ResNet121, respectively [23]. Decompose, Transfer, and Compose (DeTraC) is an unique CNN architecture based on class decomposition presented by Asmaa Abbas, Mohammed M. Abdelsamea, and Mohamed Medhat Gaber to improve the performance of medical image classification utilizing transfer learning and class decomposition technique. DeTraC allows to enhance using the hybrid method.

DOI: http://dx.doi.org/10.24018/ejeng.2022.7.4.2861

Vol 7 | Issue 4 | August 2022 23
V. AUGMENTATION AND PRECAUTIONS

202 TB images have been created using augmentation. During this maximum rotation range was allowed to 10º. Parameters like width shift, height shift, shear and zoom ranges were given only 5% of the original image only. Fig. 3 shows some augmented images.

![Augmented Images](image)

Fig. 3. First figure (A) shows the actual TB CXR image. And from B to F all are augmented images with applying different parameter.

Fig. 4 shows how horizontal flipping, high value of rotation and zooming can distort the X-ray images which might be anatomically incorrect. Thus, precautions should be taken during augmentation, otherwise the model may be trained with wrong kind of medical images which may be classified as Tuberculosis.

![Distorted Images](image)

Fig. 4. Example of A) Actual TB Image, B) Abnormal Heart Position due to flipping, C) Over Rotation, D) Over Zoom.

VI. TRANSFER LEARNING WITH PRE-TRAINED CNN MODEL

After augmentation, total 1446 images were taken for training in 3 pre trained models named InceptionV3, VGG16 and Xception. Normal chest X-ray were 724 in number and TB class had 722 images. 7 different types of optimizers were used. VGG16, which have 13 convolutional layers, 3×3 sized filters and 2×2 max pooling [26] performed the best among the three ImageNet networks. Other models fluctuated in their validation sets. This happens due scarcity of data in training set.

VII. EXPERIMENTAL RESULT

In first session three pre trained CNN models named InceptionV3, VGG16 and Xception were used along with a combination of 7 optimizers named Adam, Adagrad, Adadelta, Adamax, Nadam, RMSprop and SGD. So, a total of 21 models were trained and checked on 370 test images. By changing other parameter like loss function, batch size have also been trained & checked.

Finally, accuracy was measured from confusion matrices and accuracy, precision, recall and F1 scores were observed.

A. Loss and Accuracy Curves

The loss curves of validation set of VGG16 with Adagrad and Adamax optimizers and loss function as Binary Cross Entropy has maintained a good similarity with that of training set which can be seen in Fig. 5 and 6 which means the models are not over fitting. After 20 epochs (in X axis) the training and validation losses for Adagrad were 0.1119 and 0.1011, respectively and for Adamax were 0.0234 and 0.0258, respectively.

![Loss Curves](image)

Fig. 5. Loss curves of VGG16 model with Adagrad optimizer.

![Loss Curves](image)

Fig. 6. Loss curves of VGG16 model with Adamax.

The accuracy curves for both optimizers with loss function are also given in Fig. 7 and 8. These models have shown excellent result is detecting from validation sets which we will be discussing sooner. After 20 epochs (in X axis) the training and validation accuracy for Adagrad were 0.9682 and 0.9865, respectively and for Adamax were 0.9945 and 0.9865, respectively.
Others model as InceptionV3 and Xception showed fluctuation in validation. The cause should be inadequate data in training. Augmentation did not help that much in their cases. Some loss curves for 20 epochs (in X axis) are given in Fig. 9, 10, 11.

B. Confusion Matrix

As expected VGG16 did very good classification, in RMSprop and Nadam with loss function Binary Cross Entropy and Squared Hinge it had only 1 misclassified TB images. Confusion matrix of those two are given in Fig. 14 and 15.
Fig. 14. Confusion matrices of VGG16 with RMSprop and Loss function as Binary Cross Entropy.

Fig. 15. Confusion matrices of VGG16 with Nadam and Loss function as Squared Hinge.

The confusion matrix for Adam and Nadam optimizer with Loss function as Binary Cross Entropy is also perform well. Those are given in Fig. 16 and 17 respectively.

But Adadelta optimizer did not perform well like the others in case of detecting TB images. Confusion matrix using Adadelta optimizer using all three CNN networks are given in Fig. 18-20.

Fig. 16. Confusion matrices of VGG16 with Adam and Loss function as Binary Cross Entropy.

Fig. 17. Confusion matrices of VGG16 with Nadam and Loss function as Binary Cross Entropy.

Fig. 18. Confusion matrix of InceptionV3 with Adadelta Optimizer and loss function as Binary Cross Entropy.

Fig. 19. Confusion matrix of VGG16 with Adadelta Optimizer and loss function as Binary Cross Entropy.
Full performance summary of all parameter combination is presented in Table II. Top 3 best and worst case for validation loss, validation accuracy, precision, recall, f-1 score also been tabulated in Table III.

VIII. DISCUSSION

VGG16 models are executing well in this dataset. That’s why its classification report is showing higher results, showing maximum recall rates for normal 100% and for recall rates for TB is 99%. Showing maximum precision for Normal is 99% and for TB it shows 100%. F-1 scores are also much higher (maximum 100% for normal as well as TB) than any other model like InceptionV3 and Xception. The performance of this paper with Abbas et al. [24] is shown in Table IV.

Data used comparison with Abbas et al. [24] details is shown in Table V.

IX. CONCLUSION & FUTURE WORK

This paper is a preliminary guideline for new biomedical researchers interested in Machine Learning or Deep Learning. It will give an idea about how pre trained networks can be used to classify medical images, how to observe loss and accuracy curves and create classification reports. We propose a hyper tuned networks for those which could not perform well in this dataset as future works. Also, the image segmentation can be done only for lung field for better outcome using networks like U-net.

![Confusion Matrix with labels](image)

Fig. 20. Confusion matrix of Xception with Adadelta Optimizer and loss function as Binary Cross Entropy.

| Parameter | Position | CNN | Optimizer | Loss | Batch size | CXX | Test | Total | Resolution (Pixels) |
|-----------|----------|-----|-----------|------|------------|-----|------|-------|---------------------|
| Lowest loss on validation set | 1 | VGG16 | RMSprop | BCE | 32 | Highest loss | 1 | Xception | Adam | BCE | 10 |
| Highest precision (Normal) | 1 | InceptionV3 | Nadam | BCE | 10 | Precision | 1 | VGG16 | Adam | BCE | 10 |
| Highest f-1 score (TB) | 1 | VGG16 | RMSprop | BCE | 32 | Lowest f-1 | 1 | InceptionV3 | Adam | BCE | 10 |
| Highest Recall (Normal) | 1 | VGG16 | Adagrad | BCE | 10 | Lowest Recall (TB) | 1 | VGG16 | Adam | BCE | 10 |
| Highest f-1 score (TB) | 1 | VGG16 | AdaMax | BCE | 10 | Lowest f-1 score (TB) | 1 | VGG16 | Adam | BCE | 10 |
| Highest precision on validation set | 1 | VGG16 | Nadam | BCE | 10 | Highest on validation set | 1 | VGG16 | Adam | BCE | 10 |

**TABLE III: TOP 3 BEST AND WORST CASE AMONG ALL COMBINATIONS**

| Network | Optimizer | Loss function | Batch Size | Accuracy | Recall (TB) | Network | Accuracy | Recall |
|---------|-----------|----------------|------------|----------|-------------|---------|----------|--------|
| VGG16   | RMSprop   | Binary Cross Entropy | 32 | 99.73% | 100% | AlexNet | 99.2% | 98% |
| VGG16   | Nadam     | Squared Hinge | 32 | 99.73% | 100% | VGG16 | 97.6% | 98% |
| VGG16   | RMSprop   | Binary Cross Entropy | 10 | 99.46% | 100% | GoogLeNet | 98.2% | 97% |
| VGG16   | Adam      | Binary Cross Entropy | 32 | 99.46% | 100% | ResNet | 99.8% | 98% |
| VGG16   | Nadam     | Binary Cross Entropy | 32 | 99.46% | 99% | VGG16 | 99.73% | 98% |
| InceptionV3 | Adagrad | Binary Cross Entropy | 32 | 97.30% | 96% | InceptionV3 | 97.30% | 98% |
| Xception | Nadam     | Binary Cross Entropy | 10 | 97.03% | 98% | Xception | 97.03% | 98% |

**TABLE IV: PERFORMANCE COMPARISON TABLE**

**TABLE V: DATASET DISTRIBUTION COMPARISON OF OUR PAPER AND REFERENCE PAPER**

| Type of CXR | Train | Test | Total | Resolution (Pixels) |
|-------------|-------|------|-------|---------------------|
| Normal      | 724   | 190  | 914   | 512×512             |
| TB          | 722   | 180  | 902   | 512×512             |
| Normal      | 1446  | 370  | 1816  | 512×512             |

DOI: http://dx.doi.org/10.24018/ejeng.2022.7.4.2861

Vol 7 | Issue 4 | August 2022
| Network name | Optimizer | Batch size | Loss function | Train Loss | Train Acc. | Validation Loss | Validation Acc. | Precision (Normal) | Recall (Normal) | F1 Score (Normal) | F1 Score (TB) |
|--------------|-----------|------------|---------------|------------|------------|----------------|-----------------|------------------|----------------|----------------|----------------|
| InceptionV3  | Adam      | 10         | BCE           | 0.2131     | 0.988     | 0.778          | 0.954           | 0.92             | 0.99           | 0.91           | 0.96           |
| InceptionV3  | Adam      | 10         | BCE           | 0.2193     | 0.9232    | 0.3991         | 0.8135          | 0.76             | 0.93           | 0.69           | 0.84           |
| InceptionV3  | Adagrad   | 10         | BCE           | 0.0412     | 0.9882    | 0.1216         | 0.9703          | 0.96             | 0.98           | 0.96           | 0.97           |
| InceptionV3  | Adamax    | 10         | BCE           | 0.0479     | 0.9848    | 0.1385         | 0.9676          | 0.95             | 0.98           | 0.95           | 0.97           |
| InceptionV3  | Nadam     | 10         | BCE           | 0.0838     | 0.9924    | 0.8861         | 0.9432          | 0.9               | 1              | 1              | 0.88           |
| InceptionV3  | RMSprop   | 10         | BCE           | 0.2019     | 0.9862    | 0.5056         | 0.9622          | 0.94             | 0.98           | 0.94           | 0.96           |
| VGG16        | Adam      | 10         | BCE           | 0.0088     | 0.9986    | 0.0296         | 0.9892          | 0.98             | 1              | 1              | 0.98           |
| VGG16        | Adagrad   | 10         | BCE           | 0.486      | 0.8949    | 0.5228         | 0.8595          | 0.8              | 0.96           | 0.97           | 0.88           |
| VGG16        | Adamax    | 10         | BCE           | 0.1119     | 0.9682    | 0.1011         | 0.9865          | 0.99             | 0.98           | 0.99           | 0.99           |
| VGG16        | Nadam     | 10         | BCE           | 0.0234     | 0.9945    | 0.0258         | 0.9865          | 0.99             | 0.98           | 0.99           | 0.99           |
| VGG16        | RMSprop   | 10         | BCE           | 0.0079     | 0.9993    | 0.0199         | 0.9919          | 0.98             | 1              | 1              | 0.98           |
| VGG16        | SGD       | 10         | BCE           | 0.015      | 0.9945    | 0.0176         | 0.9946          | 0.99             | 1              | 1              | 0.99           |
| Xception     | Adam      | 10         | BCE           | 0.0466     | 0.9813    | 0.0378         | 0.9838          | 0.99             | 0.98           | 0.99           | 0.98           |
| Xception     | Adagrad   | 10         | BCE           | 0.0477     | 0.9959    | 1.4219         | 0.8865          | 0.82             | 1              | 1              | 0.77           |
| Xception     | Adagrad   | 10         | BCE           | 0.1956     | 0.9405    | 0.3957         | 0.7919          | 0.72             | 0.96           | 0.98           | 0.95           |
| Xception     | Adamax    | 10         | BCE           | 0.0418     | 0.9855    | 0.1458         | 0.9432          | 0.91             | 0.99           | 0.99           | 0.95           |
| Xception     | Nadam     | 10         | BCE           | 0.0155     | 0.9945    | 0.2213         | 0.9324          | 0.88             | 1              | 1              | 0.86           |
| Xception     | RMSprop   | 10         | BCE           | 0.0575     | 0.9952    | 0.317          | 0.9703          | 0.98             | 0.96           | 0.96           | 0.97           |
| Xception     | SGD       | 10         | BCE           | 0.1346     | 0.9882    | 0.7402         | 0.9595          | 0.93             | 0.99           | 0.99           | 0.96           |
| InceptionV3  | Adam      | 32         | BCE           | 0.0657     | 0.9799    | 0.1297         | 0.973           | 0.96             | 0.99           | 0.96           | 0.97           |
| VGG16        | Adam      | 32         | BCE           | 0.0114     | 0.9979    | 0.0205         | 0.9946          | 0.99             | 1              | 1              | 0.99           |
| VGG16        | Adagrad   | 32         | BCE           | 0.1517     | 0.9578    | 0.1459         | 0.9838          | 0.98             | 0.98           | 0.98           | 0.98           |
| VGG16        | Adamax    | 32         | BCE           | 0.0465     | 0.9889    | 0.0599         | 0.9892          | 0.98             | 1              | 1              | 0.98           |
| VGG16        | Nadam     | 32         | BCE           | 0.0137     | 0.9986    | 0.0224         | 0.9946          | 0.99             | 0.99           | 0.99           | 0.99           |
| VGG16        | RMSprop   | 32         | BCE           | 0.0219     | 0.991     | 0.0107         | 0.9973          | 0.99             | 1              | 1              | 0.99           |
| VGG16        | SGD       | 32         | BCE           | 0.0882     | 0.9703    | 0.1248         | 0.9514          | 0.99             | 0.91           | 0.91           | 0.95           |
| Xception     | Nadam     | 32         | BCE           | 0.0756     | 0.9848    | 0.3769         | 0.9505          | 0.9               | 0.99           | 0.99           | 0.94           |
| VGG16        | Adam      | 32         | H.            | 0.758      | 0.6957    | 0.7501         | 0.5865          | 0.55             | 1              | 1              | 0.15           |
| VGG16        | Nadam     | 32         | H.            | 0.5124     | 0.9938    | 0.5118         | 0.9919          | 0.99             | 0.99           | 0.99           | 0.99           |
| VGG16        | RMSprop   | 32         | H.            | 0.5124     | 0.9903    | 0.5084         | 0.9919          | 0.99             | 0.99           | 0.99           | 0.99           |
| VGG16        | Adam      | 32         | Sq. H.        | 1          | 0.816     | 1              | 0.8378          | 0.99             | 0.75           | 0.69           | 0.99           |
| VGG16        | Nadam     | 32         | Sq. H.        | 0.5197     | 0.9917    | 0.5101         | 0.9973          | 0.99             | 1              | 1              | 0.99           |
| VGG16        | RMSprop   | 32         | Sq. H.        | 0.5095     | 0.9965    | 0.5113         | 0.9946          | 0.99             | 1              | 1              | 0.99           |
APPENDIX

Short Form used in this paper:
BCE = Binary Cross Entropy loss.
H. = Hinge loss.
Sq. H. = Squared Hinge loss.

ACKNOWLEDGMENT

First and foremost, praise and appreciation to Almighty Allah for showering his blessings on us throughout our research work, allowing us to successfully conclude the research. Special thanks go to Google for helping us free of cost by creating a virtual environment like Google Colab for running, executing, testing, and validating our code smoothly and very fast throughout our whole thesis work. It really saved a lot of time which we can't express. We are extending our thanks to the persons who make datasets of x-ray and normal images from different hospitals and diagnostic centers by working hard and making our work very easy. Finally, we want to express our gratitude to everyone who has helped us accomplish the research work, whether directly or indirectly.

FUNDING

The research effort is not financially supported or sponsored by the authors.

CONFLICT OF INTEREST

There are no conflicts of interest declared by the authors.

REFERENCES

[1] World Health Organization. *Tuberculosis (TB)* [Internet]. 14 October 2021. [Accessed 14 December 2021]. Available from: https://www.who.int/news-room/fact-sheets/detail/tuberculosis.

[2] The Allied Chambers, *The Chambers Dictionary*, New Delhi: The Allied Chambers India Limited, 1998, p. 352.

[3] Mandell GL, Mandell, Douglas, and Bennett’s Principles and Practice of Infectious Diseases. 7th ed. Philadelphia, PA: Churchill Livingstone; 2010, p. 250.

[4] CDC. *Basic TB facts, Centers for Disease Control and Prevention,* [Internet]. 13 March 2012. [Accessed 14 March 2021]. Available from: https://www.cdc.gov/tb/topic/basics/default.htm.

[5] Konstantinos A. Testing for tuberculosis. *Australian Prescriber.* 2010;33(1):12-18.

[6] Gibbon PG, Abramson M, Wood-Baker R, Volmink J, Hensley M, Costabel U. Evidence-Based Respiratory Medicine. BMJ Books, 2005.

[7] Nayak-Sarajt BA. Mantoux test and its interpretation. *Indian Dermatology Online Journal.* 2012;3(1):2-6.

[8] CDC. *Tuberculosis (TB), Centers for Disease Control and Prevention,* [Internet]. 8 March 2021. [Accessed 15 December 2021]. Available from: https://www.cdc.gov/tb/topic/testing/tbtesttypes.htm.

[9] Mayo Clinic Org. *Tuberculosis: 3 April 2021.* [Internet]. [Accessed 15 December 2021] Available: https://www.mayoclinic.org/diseases-conditions/tuberculosis/diagnosis-treatment/drc-20351256.

[10] World Health Organization. *Global tuberculosis report 2021: executive summary.* Geneva, Switzerland, 2021.

[11] Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. *Briefings in Bioinformatics.* 2018;19(6):1236-1246.

[12] Long M. Deep learning in healthcare – How it’s changing the game, *Aidoc,* 2020. [Internet]. [Accessed 15 December 2021] Available: https://www.aidoc.com/blog/deep-learning-in-healthcare/.

[13] Albawi S, Mohammed TA, Al-Zawi S. Understanding of a convolutional neural network, in IEEE, Antalya, Turkey, 2017.

[14] Ahsan M, Gomes R, Denton A. Application of a Convolutional Neural Network using transfer learning for tuberculosis detection. *IEEE International Conference on Electro Information Technology (EIT)*, 2019.

[15] Hooda R, Sofat S, Kaur S, Mittal A, Meriaudeau F. Deep-learning: A potential method for tuberculosis detection using chest radiography. *IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, 2017; Malaysia.

[16] Liu C, Cao Y, Alcantara M, Liu B, Brunette M, Peinado J, Curioso W. TX-CNN: Detecting tuberculosis in chest X-ray images using convolutional neural network. *IEEE international conference on image processing (ICIP)*, 2017; Beijing, China.

[17] Oloko-Oha SVM. Diagnosing Tuberculosis Using Deep Convolutional Neural Network. *International Conference on Image and Signal Processing, Cham* 2020.

[18] Lopes JVUK. Pre-trained convolutional neural networks as feature extractors for tuberculosis detection. *Computers in Biology and Medicine,* 2017;89:135-143.

[19] Norval MWZSY. Palmonary tuberculosis detection using deep learning convolutional neural networks. *Proceedings of the 3rd International Conference on Video and Image Processing; 2019; Shanghai, China.

[20] Pike Msonda SAUSSK. Spatial Pyramid Pooling in Deep Convolutional Networks for Automatic Tuberculosis Diagnosis. *Traitement du Signal,* 2020; 37(6):1075-1084.

[21] Xudong Liu HLSH. Tuberculosis Detection from Computed Tomography with Convolutional Neural Networks. *Advances in Computed Tomography,* 2019;(84): 47-56.

[22] Gidwani UGADNBS, Tuberculosis Detection Using Convolutional Neural Network, SSRN, 2021.

[23] Ho TKK, Gwak J, Prakash O, Song JI, Park CM. Utilizing pretrained deep learning models for automated pulmonary tuberculosis detection using chest radiography. *11th Asian Conference on Intelligent Information and Database Systems, ACIDIS; 2019;Yogyakarta, Indonesia.

[24] Abbas A, Abdelsamea MM, Gaber MM. Detrac: Transfer learning of class decomposed medical images in convolutional neural networks. *IEEE Access,* 2020;8:74901-74913.

[25] Rahman T, Khandakar A, Kadir MA, Islam KR, Islam KF, Mazhar R, Hamid T, et al. Chowdhury. Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization. *IEEE Access,* 2020;8:191586-191601.

[26] Simonyan AZK. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

Salman Fazle Rabby, currently working as a Lecturer at the Department of Electrical & Electronic Engineering, Sylhet Engineering College, Bangladesh. He received his B. Sc in Electrical & Electronic Engineering from Chittagong University of Engineering & Technology, Bangladesh. He is pursuing his M. Sc. in Biomedical Engineering from Bangladesh University of Engineering & Technology, Bangladesh. His research interests are Machine learning in Healthcare, Biomedical Signal and Image processing, Biophotonics etc.

Anamul Hasam completed his B.Sc. (Engineering) in Electrical & Electronic Engineering from Sylhet Engineering College, Sylhet-3100, Bangladesh. He loves to work with programming like Android Application Development, VHDL, Analog Circuit Design and simulation. His research interests are Artificial Intelligence, Machine learning and Renewable Energy.
Md. Janibul Alam Soeb, currently working as an assistant professor at the Department of Farm Power and Machinery, Faculty of Agricultural Engineering and Technology, Sylhet Agricultural University, Bangladesh. He received his M. Sc. in Optics and Photonics from Karlsruhe Institute of Technology, Germany and Aix Marseille University, France. He did his B. Sc. in Electrical and Electronic Engineering from University of Dhaka, Bangladesh. He loves to work with renewable energy, non-linear optics, attosecond science and laser technology.

Gouroob Pathok Shirsho completed his B.Sc. (Engineering) in Electrical & Electronic Engineering from Sylhet Engineering College, Sylhet-3100, Bangladesh. Generally he works with PLC, Digital Circuit. His research interest is Microcontroller based PLC and PCB design.

Bijoy Talukdar completed his B.Sc. (Engineering) in Electrical & Electronic Engineering from Sylhet Engineering College, Sylhet-3100, Bangladesh. He loves to research in math based projects. He is an accomplished coder and competitive programmer.