

Development of Light-Weight Convolutional Neural Network Model to Diagnose Tuberculosis

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ABSTRACT

Tuberculosis (TB) is a contagious chest infection. World Health Organization has introduced different TB control programs in various countries. For the diagnosis of TB, the doctors mostly recommend chest X-ray (CXR) because it is more cost-effective and less time-consuming than existing sputum tests and Tuberculosis Skin Tests (TST). As per the research, deep learning models are best for TB diagnosis, by using CXR rather than normal eye-sight-based traditional method. Since doctor's eye-sight or his experience is prone to human error; therefore, to solve this problem many Convolutional Neural Network (CNN) based models are introduced. Some of these models have high computational costs, and better accuracy making them heavy model. Whereas, others have less computational costs and lower accuracy making them light-weight models. Such models are further modified by the researchers to be more appropriate for better TB diagnosis, termed as Transfer Learning (TL) technique. However, TL leads to complex CNN structure and high computational cost. The proposed model named as Light TBNET(L-TBNET), attempts to provide less computational costs and higher accuracy simultaneously, as compared to other models such as, ShuffleNet, ResNet-50, MobileNet v2, Inception, and DenseNet. Moreover, the proposed does not include TL technique. This is accomplished by combining standard convolutional layers as well as depth-wise separable convolutional layers resulting in a hybrid model. The accuracy of the proposed model is 96% with lesser computational cost. In this way, the model contributes in providing a light-weight CNN model with higher accuracy.

KEYWORDS

Chest x-ray CXR, Tuberculosis Skin Tests (TST), Transfer learning (TL), Light TBNET(L-TBNET).

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1. INTRODUCTION

Tuberculosis (TB) is a fatal disease which spreads in the lungs space of the human body [1]. It is listed in the top 10 fatal infection diseases worldwide [2]. There are various test methods used to diagnose pulmonary TB, such as blood tests and sputum test analysis. However, these tests are time taking [3]. The most popular tool to diagnose Pulmonary Tuberculosis (TB) is a radiographic image known as Chest X-ray (CXR) [4]. In developing countries, Physicians examine the CXR to diagnose TB instead of using any intelligent system [5]. However, such traditional method has high chance of error as it depends on factors like the doctor's eye sight, formal training, and clinical expertise. Research shows that disease diagnosis through this method is only 75% accurate [6]. According to the World Health Organization survey, there are rare chances to properly diagnose and treat TB by using the traditional method [7]. As a result, computer-assisted system technology came into being to assist doctors in identifying such disease [5]. It leads to Artificial Intelligence (AI) tools, that are recommended to help physicians to diagnose TB [8]. A part from this, deep

learning which is a branch of AI, explicitly well-known for the health care and medical diagnosis process [9]. The deep learning based Convolutional Neural Networks (CNN) are more famous specifically for the diagnosing task [10]. Deep learning models are called deep due to high number of "Layers" in order to learn from the dataset [11] such as ResNet-50 [12], DenseNet [13] and inception [14]. Moreover, the accuracy of deep-learning based models can be increased by making them deeper (i.e. increasing number of parameters) which leads to complicated development [15], [16], [17], [12]. However, making them deeper increase their computational cost as well [18], [19]. To solve this problem, light-weight CNN models were introduced, such as MobileNet v2 [12] and shuffleNet [20], These light-weight CNN models consume less computational resources due to their novel architecture [12]. Although lightweight models have fewer parameters and computational cost, however accuracy is generally weaker [5]. By considering mentioned limitations, many other light-weight models are trained by using TL technique, where TL deals with learning in the domain of new task by using already pre-trained model [21].



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Although TL technique can solve the training problem of CNNs on small-scale dataset, but it increases CNN's parameters and computational cost and complexity of CNN based architectures [22]. There are several models which used TL technique for TB diagnosis [23], [24], [25]. For instance Jeevith et al [22] used MobileNet v2 as a TL model to diagnose TB having 86% accuracy. In another study a model has been developed by Rajaraman et al. [26] called Tuberculosis Neural Net TBNN with 91% accuracy. Moreover, Kazemzadeh et al [27] also introduced a pre trained TL technique with accuracy of 90%. However, TB diagnosis process demands high accuracy [27].

To address the issue of high computational cost and low accuracy, this study proposes a new light weight architecture to diagnose TB. The model integrates Standard Convolutions with Depth-wise Separable Convolutions in order to improve accuracy and minimize the number of parameters respectively.

Pakistan is the fifth among high burden countries for TB [28]. According to recent record of national TB control program of Pakistan 573,000 new cases were notified in 2020 [29].

A survey conducted in Pakistan shows 80% of TB patients got services from private clinics. Therefore, according to the recommendation of the World Health Organization (WHO), Pakistan adopted a strategy known as Directly Observed Treatment Short-course (DOTS) in order to control TB. According to a another survey conducted by the doctors on TB-DOTS for the rural area of Sindh, 14% suspected person recommended sputum test for the diagnosis, rest 86% suggest for other tests such as CXR [30]. In order to avoid the lengthy procedure of diagnoses such as blood test or sputum test, the CXR is known as best suggested, and deep learning based tools are known as perfect for the mentioned task [8]. A dedicated light-weight CNN model best suits for such purpose in order to avoid additional computing resources for the third world country such as Pakistan [5]. In reflection to the significance of computational resources, this model can be better use due to its accuracy in diagnosis of TB and minimum computational complexity e.g., minimum parameter requirements. The paper is structured as follows: The relevant work that has previously been completed is highlighted in Section 2. Section 3 places emphasis on the variety of materials and approaches employed in this research. Section 4 elaborates metrics of Evaluation section 5 demonstrates the results and contributions of proposed work. Section 6 describes the limitations of the proposed work. Section 7 illustrates the Future work, and section. Section 8 provides a summary of the study's overall results.

2. LITERATURE REVIEW

Deep learning based CNN models using TL technique are best fit for the diagnosis of TB [10]. Conversely, it is revealed from the literature that, in order to enhance the accuracy of a model, traditionally the stack of standard convolutional layers is increased. The increasing of

layers inevitably increased the computational cost of a model. On the other hand small dataset acquired TL technique to improve accuracy in realm of standard metrics [31]. Additionally, there are several TB screening deep learning based CNN models introduced in developing countries [32], [33]. There are many other models were introduced which are known as state-of-the-arts methods such as DenseNet [13], ResNet-50 [34], ShuffleNet [20], Inception [14] and MobileNet v2 [12]. Most of the existing research in the area of computer-aided TB screening employed TL technique with small data sets for evaluation and validation [35], [36], [37], [38], [39], [40], [41]. However, TL technique requires a lot of manual efforts due to compatibility issues of TL technique with unseen datasets, diagnosis accuracy can be compromised. However, TB diagnosis process demands a high accuracy to properly facilitate doctors for pharmaceutical recommendation. Likewise, TB based diagnosis of infection from Chest X-ray images is a challenging task, owing several issues: such as similar spatial characteristics, multi-scale variations in texture shapes and sizes of infected regions are obvious issues in finding the infected area from CXR images. For example, infected disease regions are varying as small and large sizes, this easily leads to the diagnosis of false-negatives during inference time. The above literature reflects a research gape which conclude that, mostly CNN based models which uses standard convolutional layer has high accuracy with high computational cost. On the other hand, if model consists depth-wise separable convolutional layer then the model has low computational cost. However, the accuracy is compromised. In order to compensate this problem TL technique is recommended, which directly increases the accuracy of the CNN model, however increases the complexity of CNN model. Therefore, a model is proposed which is light weight which integrates standard and depth-wise convolutions and have higher accuracy without using any TL techniques.

3. MATERIAL & METHODS

The dataset of the research is collected from Tawsifur Rahman et. al. [42]. It included 3700 x-rays of normal persons and 3700 x-rays of infected persons. The mentioned dataset consists of 224×224 image size in PNG format. According to the requirement, resizing method is done, in order to the proposed model for training purpose. Many tools are available for resizing of CXR such as Data squeeze [43] and Fit2D [44]. However, they fall short in speed of image integration, e.g., a few seconds required for a single image having 2048×2048-pixel image, if Fit2D is used. Another main issue with existing software is that detector geometry calibration capabilities are limited. These software are crucial for reliable data analysis [45]. To avoid such problems python code is used for resizing process. This procedure is done without impacting on the quality of images. Moreover, Figure. 1 demonstrates the overall steps that used in this paper.

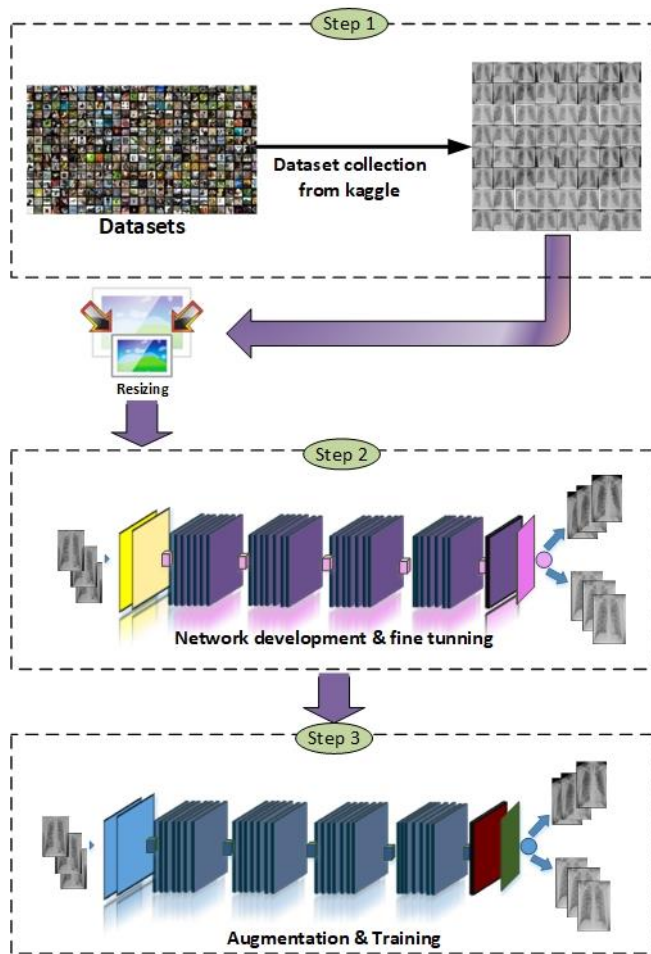


Figure 1. Represents the working flow of the proposed method

3.1 NETWORK DEVELOPMENT AND FINE-TUNING

All parameters affect quality of the network as well as computational cost. Proposed model dynamic parameters are set to find the solution to both problems discussed before (low accuracy and high computational cost without using transfer learning). Initially, standard convolutional layers are implemented in order to construct the model, which increased its computational cost. After that all layers are replaced with depth-wise separable convolutional, which decrease the computational cost. However, model has low accuracy in that state. Therefore, both depth-wise separable convolutional and standard convolutional layers are used, which make it hybrid approach. At every step, fine-tuning procedure is done, as the proposed model has the parameter on the basis of needs, rather than using TL method.

3.2 NETWORK OVERVIEW

The proposed model has distinctive architecture, which is not following any baseline based pre-trained weights. In order to build the mentioned model, all parameters are chosen based on requirements accordingly, like low computational cost and higher accuracy than other baseline models. The model accepts an input image having the size of 60, 124, 128 width and height in PNG format; the proposed model consists of six blocks after each block ReLU activation function is used. The first block consists standard convolutional layer with a 3×3 kernel and 64 channels with batch normalization. The other four blocks consist of depth-wise separable convolutional layers, which consist of 7 layers in each, and different output channels. The second block has 64 output channels. The third block has 32 output channels. The fourth has 16 channels, and the fifth has 8 output channels. The sixth block is attention, which has two output channels. The model is further described in Figure 2.

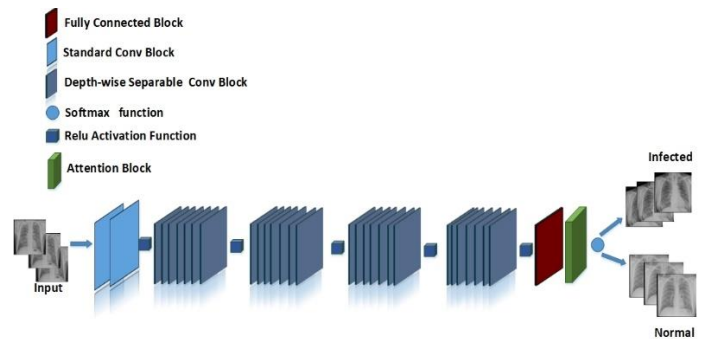


Figure 2. Network Architecture

3.3 DATA AUGMENTATION

This procedure is done to increase the amount of data during model training to avoid overfitting. The data augmentation method applies some techniques such as changing the position of the image, zooming of images, vertical and horizontal flipping of images, the data of a dataset can be increased by this procedure. The procedure of augmentation makes sure that this expansion of data will not change any image's original structure and that it won't be affected by flipping or any other transformation techniques.

3.4 TRAINING DETAILS

The division spotted in the training samples of the TB dataset can be represented as 90% training (3330) and 10% validation (370). The datasets for TB are individually trained at 300 epochs. GPU is used only on initial stage for all experiments with batch sizes of 8, 16, 32, and 64. The images of infected by TB, and normal images were included in the network's training input. The network training utilized the binary cross-entropy loss as a loss function, as shown in Figure 3.

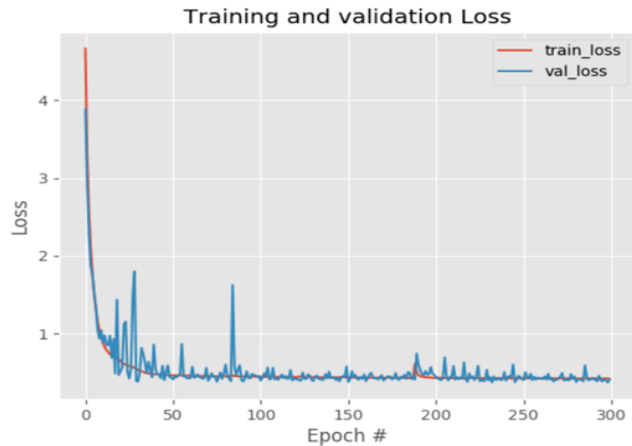


Figure 3. Training and validation loss graph

Table 1. Architectural settings of network

Methods	h_{α}	h_{β}	h_{γ_1}	h_{γ_2}
S _{n1}	4	5	0.001	0.001
S _{n2}	6	6	0.002	0.002
S _{n3}	6	6	0.01	0.01
S _{n4}	3	4	0.01	0.01

Table 2. Reflecting results of proposed model in different settings of network from ablation studies.

Methods	Acc(%)	Sn(%)	Sp(%)	Acc(%)
S _{n1}	93.5	90.9	94.3	92.0
S _{n2}	93.8	93.5	91.2	93.1
S _{n3}	95.7	94.2	90.1	94.5
S _{n4}	96.0	95.4	96.1	96.3

3.5 ABLATION STUDY

The proposed model analysis the capability of the proposed model, which is by experimental product of our ablation study, performed on dynamic aspects on various settings of proposed light-weight CNN model. In this study different hyperparameters of proposed model are analyzed e.g. setting of these Hyperparameters are inspired from [46], like S_{n1}=L-TBNET+Max, S_{n2}=L-TBNET+Aaverage, S_{n3} = L-TBNET+Aaverage, S_{n4} = LW-TBNET+attention are demonstrated with respect to, Accuracy (AC), Sensitivity (SN), Specificity (SP), Area under the Curve (AUC). Table 1,2 represent architectural settings of network.

Initially the model was configured with standard convolutional layers, which increases accuracy, but at the expense of high computational cost as discussed in section

3.1. In order to solve this problem, standard convolutional layers are replaced with depth-wise separable inside the whole model completely. This construction decreased the computational cost; however, also decreases the diagnosing accuracy.

After these experiments and all analysis, a new hybrid configuration was tried by combining both layers (standard convolutional layers and depth-wise separable convolutional

layers) using a block wise scheme. This resulted in the solving of both complications including low accuracy and high parameters complexities. The ReLU is used as an activation function for the purpose of non-linearity.

Another experiment was addition of max-pooling layer to evaluate the increase in evaluation metrics like AC, SN, and SP of the model. Nevertheless, no any increase of metrics based accuracy are observed. Therefore, pooling layers are completely removed in order to reduce the network architectural complexity and gain image features without any reduction. Moreover, attention block is attached at the end of the proposed model in order to increase the accuracy of the network to gain more attention to classify Normal and infected images as Tuberculosis. The achievement of higher accuracy marks the contribution of this model by setting the

Hyperparameters as these specifications can further observed in Table 1, 2.

4. STANDARDIZED METRICS OF EVALUATION

Accuracy (AC), sensitivity (SN) and specificity (SP) are fundamental evaluation factors used by this study to calculate the effectiveness of proposed model. Determine the factors of infected and healthy images by using True Positives (TPs), False Negatives (FNs), False Positives (FPs), and True Negatives (TNs). Additionally, the areas effectively identified as infected by the model are characterized as the factors, whereas those categorized as normal fall under FN. In accordance, TN designates the appropriately diagnosed normal disease images; if not, they fall within the FP category. Sensitivity ($TP/(TP+FN)$) is the capacity of proposed Model to precisely identify an infected image. Similar to this, a model's specificity ($TN/(FP+TN)$) refers to its capacity to locate healthy images. Similarly, accuracy is obtain by dividing the sum of the TP and TN into the sum of the TP, TN, FP, and FN. Conversely, the parameters based calculation on each layers of model is done by using expression as $(\text{shape width of the filter} \times \text{shape height of the filter} \times \text{number of filters in previous layers} + 1) \times \text{number of filters}$. The term "filter" in this context indicates the number of filters in the current layer. Finally, the model parameters are evaluate by the sum of all parameters in each layer, except pooling layers.

5. RESULTS AND DISCUSSION

The proposed research model is a unique hybrid architecture which is composed of depth-wise separable convolution layers and standard convolution layers. At the end of the proposed model, Network Attention Block is attached in order to guide the model to better classify TB and uninfected images. The proposed model effectively detects the TB infection and normal CXR, as shown in Figure 4,5. The AC, SN and SP of the proposed model are compared with other baseline models like ResNet-50 [47], ShuffleNet [20], MobileNet v2 [12], DensNet [13] and inception [14]. Which

are shown in Table 3. The hybrid model not only increases the AC, but also comes out to be a light-weight model. Before this combination, the accuracy of the proposed model was 93% as per conducted experiments of ablation study. However, the combination of layers in order to make it hybrid model increased the accuracy up to 3% hence rising it up to 96%. Further modification of other settings such as pooling layers are removed with 1×1 convolution layers in order to decrease the complexity of the model.

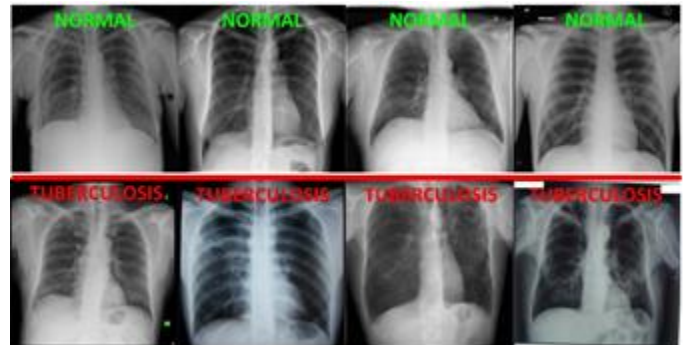


Figure 4. Results with original dataset [42]

For the generalization we got 300 images of infected people from National Library of Medicine [21] and 300 images of normal persons, the results shown in Figure 5, the model has 96% accuracy, Table.3.

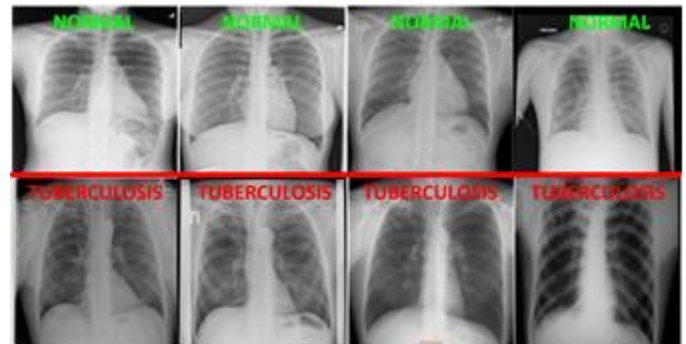


Figure 5. Results of Model Generalization on unseen dataset [21]

Table 3. Comparisons of proposed model with other models using evaluation metrics like AC, SN and SP. Bold text indicates the best results

Model	AC	SN	SP	AUC
MobileNet v2	95	94.33	93.91	95.0
ShuffleNet	90	90.0	88.3	90.3
ResNet 50	94	93.11	93.16	94.9
Inception	94	95.73	95.92	94.6
DenseNet	92	95.07	95.12	92.8
Proposed Model	96.0	95.4	96.1	96.3

5.1 RECEIVER OPERATING CHARACTERISTICS (ROC) CURVE

The performance of a model is examined graphically using receiver operating characteristic (ROC) analysis. Likewise, the effectiveness of the proposed diagnostic model is assessed using two statistics: true positive rate and false positive rate. False positive rate is drawn on the x-axis and true positive rate is plotted on the y-axis in a two-dimensional graph of the statistics. The generated plot is used to assess whether the model outperforms random guessing and to compare the relative performance with comparative baseline models such as MobileNet v2, ShuffleNet v2, ResNet 50, Inception, DenseNet.

The Capacity of model, which discriminates the accuracy by Receiver Operating Characteristics (ROC). A huge area above the random area shows higher AUC, which is 96%. Moreover, the comparison of proposed model with other baselines shows higher accuracy as demonstrated in Figure 6.

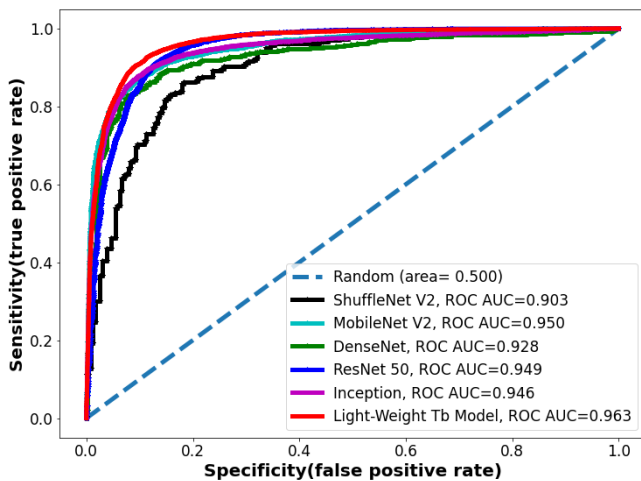


Figure 6. ROC curve shows the comparison with proposed model which identifies the higher accuracy than others

5.2 COMPUTATIONAL COST COMPARISON WITH BASELINE MODELS

This section provides the proposed method's comparative study in the domain of computational cost such as parameters and predicted image inferencing (testing) time with MobileNet v2, ShuffleNet and SqueezeNet, ResNet50, Inception and DenseNet networks. Further, it also reveals from Table.4 that the proposed method has minimum parameters as compared to other baseline models while using image size of 224x224. The proposed method image-testing speed (Inference time) is also compared with aforementioned models. The proposed model takes minimum time to generate results when compared to MobileNet v2, and InceptionNet. However, image-testing speed of the model is less than ShuffleNet, ResNet50 and DenseNet.

Table 4. Comparison with Baseline Models

Model	Layers	Image Size	Parameters (M)	Inference time(s)
MobileNet v2	28	224x224	3.4	3.23
ShuffleNet v2	44	224x224	1.5	0.0378
ResNet 50	50	224x224	25.6	0.026
Inception	48	224x224	24	2
DenseNet	5 blocks where growth rate of 'K' is	224x224	20	0.60
Proposed Model	31	224x224	0.38	1.5

6. LIMITATIONS

As every model based on CNN has some limitations. Similarly, the proposed model also has some limitations. Such as, sometimes, the proposed model is confused between the TB and normal CXR due to visual region similarity. The second reason for this problem is lack of training data; if the model is trained with a huge dataset, the accuracy can be increased. This problem can be solved by an image segmentation technique, which can directly identify the infected regions, instead of classifying the CXR of normal or infected person. However, the performance of the proposed model is also compromised due to color degradation of the mentioned problem. Conversely, the aforementioned issues could be solved by a method known as post-processing.

7. FUTURE WORK

The model performance would be increased by maximizing the dataset; furthermore, the segmentation model could be used to enhance the accuracy of the model by segmenting disease regions. The proposed model is working on binary classification; a new feature can be added to the model, which can be used for multi-class disease detection, which can classify two or more types of pulmonary diseases by using CXR, such as the model can diagnose that the patient has COVID-19, pneumonia or TB by using CXR images. Furthermore, the testing speed of the proposed model will be improved in the future by utilizing a robust preprocessing method.

8. CONCLUSION

This research work contributes to the diagnosis of contagious TB disease with the help of a hybrid model. The hybrid model is developed with the combination of standard convolutional layers and depth-wise separable convolutional layers with a simple attention model. The combination has achieved the goal of producing a light-weight and more accurate model as compared to the available baseline models. The baseline models used for comparison with the proposed model are ResNet-50, ShuffleNet, MobileNet v2, DenseNet and Inception. Consequently, the proposed method comes up with its own unique architecture. Since the

proposed method is more computational cost-effective and more accurate in diagnosis of TB, therefore, it can be best used for the third world countries such as Pakistan. Not only in the third world countries but this model can be best fit anywhere, because of its easy implementation facility as there is no requirement of additional hardware configuration.

CREDIT AUTHOR STATEMENT

Noor Ahmed: Conceptualization, Methodology, Software **Abdul Raziq:** Data curation, Writing- Original draft preparation. **MahGul Bizanjo:** Visualization, Investigation. **Noor Ahmed, Sohrab Khan:** Supervision, **Nooruddin:** Software, Validation, **Rozina:** Writing-Reviewing and Editing

COMPLIANCE WITH ETHICAL STANDARDS

It is declare that all authors don't have any conflict of interest. Furthermore, informed consent was obtained from all individual participants included in the study.

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