Using Teaching Learning-Based Optimization with Convolutional Neural Network (CNN) to Detect Pneumonia Based On Chest X-Ray Images

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***Abstract*—Chest X-ray imaging plays a vital role in the treatment of respiratory diseases such as pneumonia. Recent technological innovations have significantly improved the efficiency of the image analysis process especially Artificial and convolutional neural networks. However, there is a need to improve the accuracy of the outputs. It is important to develop an automated, early diagnosis system that can deliver quick decisions and significantly lower diagnosis error. Recent advancements in emerging Artificial Intelligence (AI) approaches, particularly Deep Learning (DL) algorithms, have made the chest X-ray pictures a viable option for early Pneumonia screening. Therefore, this study focused on using Teaching Learning Based Optimization (TLBO) with Convolutional Neural Network (CNN) to improve the accuracy of detecting pneumonia in Chest X-ray images. The study was conducted on the chest X-ray images of pneumonia data set and compared with previous works. Results confirm that TLBO with CNN is a good choice for detecting pneumonia at the accuracy with 98.88% and is an improvement over benchmark studies. This study provides insight into TLBO-CNN for pneumonia detection and its potential to enhance the accuracy of chest X-ray analysis.**

***Index Terms*—Pneumonia; Detection; TLBO; CNN; Deep learning (DB)**

I. INTRODUCTION

Pneumonia is a serious and potentially life-threatening disease that can either enter through the respiratory tract or spread from other parts of the body [1]. Without prompt diagnosis and medical treatment, pneumonia can result in serious complications and even death. Notably, pneumonia was rated ninth on a list of major causes of death in the United States in 2020 [2].In addition, Pneumonia-related deaths are more prevalent than pneumonia-unrelated deaths, so it is important to plan and prepare for prevention to reduce the occurrence of pneumonia [3]. It is therefore important to embrace the most effective and accurate diagnosis techniques. Machine learning (ML) is a powerful and advantageous method for detecting pneumonia based on chest X-Ray images. ML allows for the automated detection of patterns in the images that are indicative of pneumonia, as well as the differentiation between normal and abnormal patterns [4]. Through machine learning, a computer system can learn to distinguish between the two states without any prior knowledge or guidance, based solely on the X-Ray images [5]. This form of diagnosis allows for a much more accurate diagnosis of the condition compared to other techniques. Modified CNN models are a powerful and advantageous method for detecting pneumonia based on chest X-Ray images [6]. Unlike other methods such as manual interpretation of X-Ray images or rule-based systems that rely on predefined rules, machine learning algorithms can learn from the data they are presented with and dynamically adapt to changes in the data [7]. The adaptability enables a more accurate and efficient diagnosis that can be completed faster and with improved accuracy [8]. Furthermore, as machine learning algorithms are not constrained by a set of rules, they can detect complex patterns and more accurately diagnose pneumonia based on chest X-Ray images than other techniques. The rapid development of machine learning algorithms has allowed for the generation of highly accurate x-ray imagery [9]. However, the accuracy of these results can be improved further, as demonstrated by Alenezi and Ludwig. [10]. This is evident from the fact that the accuracy of the x-ray imagery results in most studies based on machine learning is still below 90% [9], [10]. These studies imply that there is a need for models' optimization to increase the accuracy of the machine learning predictions for medical imaging, and can be achieved through data augmentation, transfer learning, exploring model architectures, and using ensemble methods. This would lead to more reliable results and reduce the risk of misdiagnoses.

Similarly, by utilizing Teaching Learning Based Optimization, this paper aims to create an unique method for identifying pneumonia using chest X-ray pictures. The effectiveness of detection will be compared with the findings of previous articles as the novel approach is examined utilizing a data set taken from Ayan et al. [11] and research [10]. The outcomes will aid in illustrating the increased accuracy of TLBO over deep learning in detecting pneumonia using chest X-ray pictures.

This paper is organized into five sections following the introduction. The related work is discussed in Section II. In Section III, the methodology is detailed including the background of reinforcement learning, AIGym and CNN as well as the proposed approach. The experiments and results are illustrated in Section IV, where the results are obtained from the TLBO-CNN model and the comparison with previous works [10], [11] are provided. Section V summarizes the paper and presents the paper's findings.

II. Related Work

Alenezi and Ludwig presented a detection model based on Reinforcement Learning (RL) with a convolutional neural network (CNN) to help detect pneumonia based on chest X-ray images [10]. The results of the model indicated improved efficacy in detecting pneumonia whereby the performance was evaluated using precision, recall, F1-score, accuracy, and confusion matrix.

In another case, Ayan and Unver compared two CNN networks' performance on the diagnosis of pneumonia disease from chest X-ray images, with Vgg16 outperforming Xception by accuracy, specificity, precision, recall, and f1 score [11]. They employed transfer learning and fine-tuning in their training stage. The test results showed that the Vgg16 network exceeded the Xception network at an accuracy of 87%, and 82% respectively [11]. However, the Xception network achieved a more successful result in detecting pneumonia cases. As a result, they realized that every method has its special capabilities on the same data set.

Ghoneim et al. [12]. applied the TLBO to improve the accuracy of diagnosing transformer faults. Ideally, concentrated gas ratios are used for dissolved gas analysis (DGA) to assess the fault types. Thus, the authors develop an optimization model for concurrently optimizing gas concentration ratios and percentages to maximize diagnostic accuracy [12].

Ang et al. [13]. proposed that metaheuristic-search-based techniques can be used to develop highly efficient and accurate CNN network architectures. Metaheuristic search algorithms (MSAs) are population-based algorithms that mimic natural phenomena and can be combined with CNN for image classification. The TLBO algorithm is employed to determine an optimal CNN network architecture design on a specific data set with symmetrically distributed data samples in every class. A variable-length encoding scheme should be provided to depict each learner as a possible CNN architecture with dissimilar layer parameters. Adapted processes of deriving the differences between two learners with different lengths and updating the respective positions are needed in the teacher and learner stages to acquire new learners. This approach can obtain symmetrical performance and accuracy in classifying data sets and achieve CNN models with minimal complexity [13].

Mohant and Tripathy [14] applied the TLBO to determine the optimal location and size of distributed generation (DG) units in distribution networks, using the voltage stability index as the objective function. It performs significantly better than alternative optimization techniques.

Yu et al. [15] proposed a self-adaptive TLBO for identifying parameters in photovoltaic (PV) models. The learners in the algorithm are used to self-adaptively choose different learning stages based on their knowledge. In this case, learners at different phases fixate on varying searching capacities to improve the searching algorithm efficiently. This scenario is based on the tendency of better learners to select the learner stage to increase population diversity and the poor learners to pick the teacher phase to improve the algorithm performance. The authors also introduce an elite learning method in the teacher phase and a diversity learning strategy in the learner stage to optimize the searching ability at different levels. Assessments of this TLBO approach illustrate better reliability and accuracy than substitute parameter extraction techniques.

Similarly, Allam and Nandhini [16] demonstrate the efficacy of the TLBO for optimal feature selection. The TLBO is selected for its lack of control parameters, which provides a significant advantage over conventional optimization algorithms. The TLBO is implemented in six sequential steps. Firstly, the number of instances and features and the termination conditions are initialized. Secondly, each feature's mean is computed for all learners. Thirdly, the fitness of the respective individuals is determined. Fourthly, a teacher is used to update the learners. Fifthly, learner interactions are used to update each learner. Finally, the process ends once the termination condition is achieved. Like all previous implementations, this TLBO instance achieves optimal accuracy. Overall, the presented literature illustrates that TLBO implementations are similar across the algorithm's diverse uses, especially regarding the teacher and learner phase translations.

As seen on the findings of previous works, the various models were used different techniques and their performances were different. Hence this is the reason for this study to developing a model to detect pneumonia using TLBO technique with CNN on chest X-ray images, the paper intends to examine the performance of this model compared to previous works in [10], [11].

III. METHODOLOGY

This section provides the background on Teaching Learning Based Optimization(TLBO), Convolutional Neural Network (CNN), and the proposed approach used.

A. Background of Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning neural network used for image and video recognition tasks. Thus, they are became so effective become increasingly important tools for analyzing medical imaging data, including X-ray images. X-ray images are important in medical diagnosis and are commonly used to diagnose various conditions such as fractures, tumors, and cardiovascular diseases [17], [18]. CNNs have been used to detect and classify various types of objects from X-ray images as well as image segmentation, which is the process of dividing the image into different regions [17], [19].This can be used for the automatic detection of anatomical structures and for measuring disease progression. In addition to object detection and segmentation, CNNs can be used for the automatic classification of X-ray images, which can be used to quickly identify which condition is present in the X-ray image, reducing the need for manual review by medical professionals [20].

A CNN works by taking an input image, applying a series of convolutional and pooling operations to extract features and reducing the dimensionality of the image, and then using these features to make a final prediction [21], [22]. The convolutional operation involves taking a small matrix and sliding it over the image, performing an element-wise multiplication, and summing up the results to get a new matrix [21], [22]. This operation is repeated multiple times with different filters to learn multiple features of the image [21], [22]. The pooling operation is used to down-sample the feature map, reducing its dimensionality and preventing overfitting. This is typically done by taking the maximum or average value of a small region of the feature map. Finally, the extracted features are fed into a fully connected layer, where the final prediction is made [21], [22].

Overall, the architecture of a CNN is designed to automatically and adaptively learn features from input images that are useful for making a prediction and used weight sharing and filters to produce one neuron per pixel [22], [23].

B. Background of Teaching Learning Based Optimization(TLBO)

The application of Teaching-learning-based optimization (TLBO) in medical x-ray imaging is rapidly gaining traction due to its many advantages. TLBO is based on the teaching-learning process, which provides rapid convergence, requires no algorithm-specific parameters, and is easy to implement [24], [25]. As a result, it has been successfully applied to a variety of real-world problems in diverse fields. TBLO can be applied in models for X-ray image analysis, becoming an important approach in medical diagnosis. TLBO is based on the concept of a teacher and a learner. The teacher is responsible for generating solutions, while the learner is responsible for improving those solutions [26]. The teacher and learner work together to generate better solutions to the optimization problem [27]. The teacher uses a heuristic or evolutionary algorithm to generate solutions, while the learner uses a knowledge-based methodology to improve on those solutions [27], [28]. As the name suggests, TLBO has two main phases; teaching and learning.

1) Teaching phase: The Teaching Phase of TLBO (Teaching-Learning-Based Optimization) is a method of finding global optima in a search space. This phase is used to preserve diversity in the population of solutions, and to help the population move towards the global optimum [29]. In the teaching phase, one student, the one with the minimum fitness value, is chosen as the teacher, and all other students in the class are considered as the students. To generate a new solution, the teaching phase uses the Xmean, which is the mean of all the students in the class [30]. Thus, there is an n number of learners and an m number of subjects at every iteration i. Equation (1) is used to compute the difference between each subject's mean result (X_mean) and the teacher's corresponding result (X_teacher).

$$Difference\_Mean_i = r\_i(X_{teacher,i} - T_F X_{mean,i}) \quad (1)$$

TF is the teaching factor determining the mean value to be altered, X_teacher,i is the best student's result, and r_i represents a random number in the range from 0 to 1. Notably, TF can either be 2 or 1, determined randomly based on Equation (2).

$$T_F = round[1 + rand(0,1)\{2-1\}] \quad (2)$$

T_F is not a TLBO parameter, and its value is only randomly chosen. Research on the algorithm suggests that it performs best when the T_F value is either 1 or 2 [30]. With the teaching factor determined, the existing solution is updated in the teacher stage depending on the Difference_Mean_,i.

The new solution generation equation (3) is:

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \quad (3)$$

In Equation (3), T_F is the teaching factor and is either 1 or 2 (chosen randomly). If $X_{new}$is better than $X_{old,i}$, then $X_{old,i}$ is replaced with X_{new} [30].

The teaching phase of TLBO helps the population move closer to the global optimum, which can be very useful in solving complex optimization problems. It is also useful in preserving diversity in the population, as solutions can be generated from the mean of the population and from the teacher. This helps ensure the population does not get stuck in local optima.

2) Learning Phase: The learner phase involves students improving their knowledge through random peer-to-peer interactions. New knowledge is only obtained when a learner connects with a more knowledgeable peer [30]. Various premises are used to derive the learning results, considering an n population size. The learning phase consists of two steps:

The first step is to select 2 learners, from the population of solutions [31] where randomly 2 learners (P and Q) are chosen at the end of the teacher's phase. This choice must respect the relationship $X_{newP,i} \neq X_{newQ,i}$,where $X_{newP,i}$ represents the updated $X_{oldP,i}$ function value of P, and $X_{newQ,i}$ represents the updated $X_{oldQ,i}$ function value of Q.

The second step is to generate a new solution of $(X_{new,i})$ which is computed by adding the difference between $X_{newP,i}$ and $X_{newQ,i}$, multiplied by a learning rate (r) as shown on Equations (4)and(5):

if $X_{newP,i} > X_{newQ,i}$

$$X_{new,i} = X_{old,i} + r_i(X_{newP,i} - X_{newQ,i}) \quad (4)$$

Or if $X_{newQ,i} > X_{newP,i}$

$$X_{new,i} = X_{old,i} + r_i(X_{newQ,i} - X_{newP,i}) \quad (5)$$

If the new solution $(X_{new,i})$ is better than the current solution $(X_{old,i})$, then it replaces $X_{old,i}$ as the current solution [30], [31]. The process is repeated until convergence, at which point the algorithm is complete.

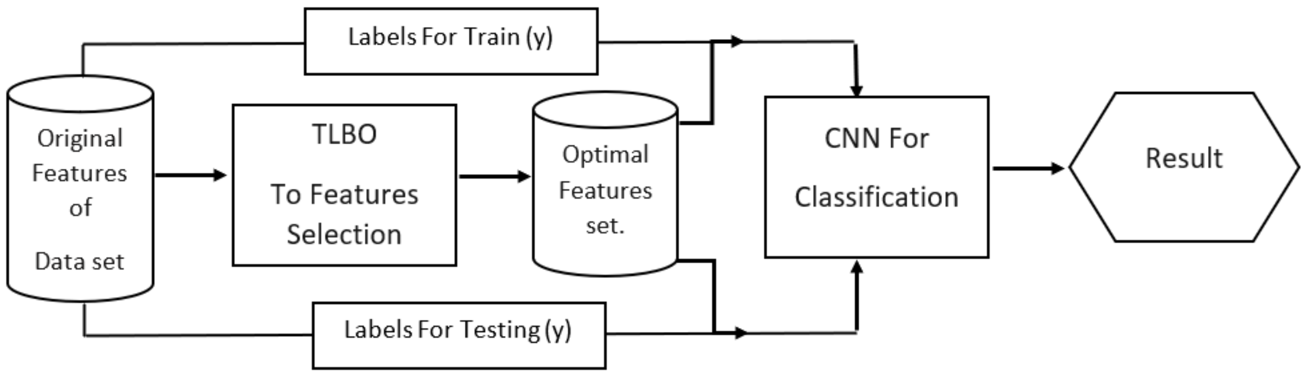


Figure 1. TLBO-CNN Model Structure

3) Fitness Function: The fitness function is designed to measure the similarity between two images using pixel-wise distance and feature matching. By minimizing this distance, the fitness function encourages the generation of images that closely match a target image or desired style [32]. This approach can be applied to tasks like image segmentation, where the fitness value can be computed by measuring the overlap between the predicted segmentation and the actual segmentation using the following Equation(6):

$$f(x) = \frac{1}{1+x}, where \quad x \in [0,1] \tag{6}$$

4) Sphere Function: The sphere function is a well-known benchmark function used to test and compare optimization algorithms. It is a simple, smooth, and convex function that has a global minimum at the origin $(0, 0, ..., 0)$ with a value of zero. The function is defined as:

$$f(\mathbf{x}) = \sum_{i=1}^{n} x_i^2 \tag{7}$$

where $\mathbf{x}$ is a vector of n input variables, and x_i is the ith component of $\mathbf{x}$. The sphere function is a useful tool for evaluating and comparing the performance of optimization algorithms.

C. Proposed Approach

In this paper, a novel approach is proposed for finding the best subset of features in a given solution space. The approach combines the Teaching-Learning-Based Optimization (TLBO) algorithm with Convolutional Neural Networks (CNN). The structure of the TLBO with CNN model is illustrated in Fig (1). The TLBO section connected to the CNN includes the creation of a TBLO class and a "MTLBO" function.

Algorithm 1 TLBO class

Require: $learner$: learner object, $learner\_index$: index of the learner
Ensure: Tuple of best learner and its fitness

function $teacher\_phase$($learner$, $learner_index$)
    $teacher \leftarrow get\_teacher$=min(fitness)
    $T_F \leftarrow rand.randint$(1, 2) as Eq (2)
    $c \leftarrow$ len($teacher$.subjects)
    for $i \leftarrow 0$ to len(learner.$subjects$) **do**
        $s\_mean \leftarrow s$.subjects[i]
        $r \leftarrow$ random number in the range from 0 to 1
        $diff_{mean} \leftarrow teacher$.subjects[$i$] - ($T_F \times s\_mean$) as Eq (1)
        $c[i] \leftarrow$ subject + ($r \times diff_{mean}$) as Eq (4)
    end for
    $rounded\_c \leftarrow np.around$(c, decimals=4)
    $best, best\_fitness \leftarrow$ select_best(learner.subjects, $rounded\_c$)
    return ($best$, $best\_fitness$)
end function
function $learner\_phase$($learner$, $learner\_index$)
    $k\_index \leftarrow$ random_learner[$learner\_index$]
    $k\_learner \leftarrow [k\_index]$
    $k\_subjects \leftarrow k\_learner$.subjects
    $c \leftarrow len(learner.subjects)$
    for $i \leftarrow 0$ to $len(learner.subjects)$ **do**
        if learner.fitness < k_learner.fitness **then**
            $diff \leftarrow subject - k\_subjects[i]$
        else
            $diff \leftarrow k_s ubjects[i] - subject$ as Eq (1)
        end if
        $r \leftarrow rand.random()$
        $c[i] \leftarrow$ subject + ($r \times diff$) as Eq (4)
    end for
    $rounded\_c \leftarrow np.around$(c, $decimals$=4)
    $best, best\_fitness \leftarrow$ select_best($learner.subjects$, $rounded\_c$)
    return ($best$, $best\_fitness$)
end function

The TBLO class has main methods for performing the phases of the TBLO algorithm that are the teacher phase and the learner phase. In the teacher phase, the algorithm selects the best solution from the previous iteration and uses it to guide the search for the new solution [30], [31]. The learner phase aims to explore the solution space using the information obtained from the teacher phase [30], [31]. The two phases are repeated until a stopping criterion is met,such as reaching a maximum number of iterations or achieving a desired level of fitness using the fitness function as in Equation (6) provided to the TBLO class. In each iteration, the best solution found by the algorithm is considered as the best learner and is used to guide the search in the next iteration. This process continues for a certain number of samples, allowing the algorithm to converge towards the optimal set of features. The step by step process of the TLBO is as shown in Algorithm 1

Algorithm 2 MTLBO Function

Require: folder, savefolder
Ensure: images, $imgs\_tlbo$

images ← []
$imgs\_tlbo$ ← []
count ← 0
for each file in folder **do**
    img ← read image from file
    add img to images
    pieces ← split img into 2x2 pieces
    tlbo ← [] empty list
    for each piece in pieces **do**
        $piece\_flat$ ← flatten piece into 1D array
        $tblo\_sphere$ ← TBLO(list_2d, 4, 100, sphere, fn_lb=[0, 0], fn_ub=[255, 255])
        min ← optimize $tblo\_sphere$
        add min to tlbo
    end for
    newimg_1d ← convert tlbo to 1D array
    newimg_2d ← newimg_1d
    add newimg_2d to imgs_tlbo
    save newimg_2d to file in savefolder
end for
return (images, imgs_tlbo)

A function called ”MTLBO” has been created with two parameters, namely ”folder” and ”savefolder”. The objective of this function is to import a group of grayscale images from the directory specified by ”folder”, split each image into patches of 2x2 pixels, optimize each patch using the TBLO class as in Algorithm 2 and the Sphere Function as in Equation (7). The TBLO class performs optimization using a variant of Teaching-Learning-Based Optimization (TLBO) algorithm, which is a metaheuristic algorithm inspired by the teaching and learning process in a classroom. In this case, the algorithm is being applied to minimize a given function sphere, which presumably calculates the sphere function on the input array. Then merging the optimized patches to create new images. These new images are saved in new then passed on to a CNN model for classification. The step by step process of MTLB function is as shown in Algorithm 2 By combining TLBO with CNN, the proposed approach can effectively search for the best subset of features for a given classification problem, which can significantly improve the performance of the classification model.

IV. Experiments and Results

In this section, we will first introduce and elaborate on the pneumonia data set derived from chest X-ray images, followed by a presentation of the results obtained from the TLBO-CNN model. We will also compare these results with those of previous studies, and analyze the accuracy and other relevant metrics of the model.

A. Data Set Description

The chest X-ray image data set utilized in this study is the same as the one used by Alenezi and Ludwig [10] and Ayan et al. [11], which comprises a total of 5,856 images. Out of these, 1,583 images are normal cases while 4,273 are pneumonia cases. During the training phase, 1,349 normal images and 3,883 pneumonia images were used, whereas during the testing phase, 234 normal images and 390 pneumonia images were used. During both the training and testing phases, the data is labeled with 1 representing pneumonia cases and 0 representing normal cases.

B. Results Obtained

We present the results obtained from the TLBO with CNN model and evaluate its performance using metrics such as precision, recall, F1-score, accuracy, and confusion matrices. Additionally, we compare the results of our model with a Reinforcement Learning Model that uses CNN as an agent, as developed in study [10], and a deep learning model proposed that used Vgg16 and Xception in study [11]. We assessed our model using the test set, which consists of 624 chest X-ray images. The test set includes 234 normal cases and 390 pneumonia cases.

*1) **Precision Results**:* Our experiments measure precision as the proportion of pneumonia instances among the retrieved image instances that were utilized. The precision metric formula is:

- $Precision = TP/(TP + FP)$

Table I provides an overview of the outcomes from the experiment featuring the TLBO-CNN model. The results indicate that the performance of the TLBO-CNN model was highly satisfactory and outperformed earlier studies. Specifically, our model achieved a 99% accuracy rate for identifying pneumonia cases and a 99% accuracy rate for detecting normal cases, which surpassed the values reported in previous works for both types of cases.

*2) **Recall Results**:* The recall metric measures the proportion of pneumonia instances that were correctly identified out of the total number of image instances used. The recall formula is:

- $Recall = TP/(TP + FN)$

Table I
PRECISION RESULTS

Class	Our-TLBO-CNN	RL-model [10]	Vgg16 [11]	Xception [11]
Pneumonia	**99%**	**98%**	91%	82%
Normal	**99%**	**97%**	83%	86%

Table II presents a summary of the recall outcomes from the experiment involving the TLBO-CNN model. The table highlights that the TLBO-CNN model outperformed earlier studies, with our model achieving a 98% recall rate for both pneumonia and normal cases, while previous researches reported lower values for both types of cases except in the case of the RL model, which achieved the same recall rate for pneumonia.

Table II
RECALL RESULTS

Class	Our-TLBO-CNN	RL-model [10]	Vgg16 [11]	Xception [11]
Pneumonia	**98%**	**98%**	89%	94%
Normal	**98%**	**96%**	86%	65%

*3) **F1-Score Results**:* The F1-Score is a performance metric that is commonly used in binary classification tasks. It is a measure of a model's accuracy that takes into account both precision and recall. The F1-Score is calculated as the harmonic mean of precision and recall, and it ranges from 0 to 1, with higher values indicating better model performance. The formula for the F1-Score metric is as follows:

- $F1score = 2 \times (precision \times recall)/(precision + recall)$

A summary of the F1-score outcomes obtained from the TLBO-CNN model experiment is displayed in Table III. The results demonstrate that our model performed remarkably well, achieving a 98% F1-score rate for both pneumonia and normal cases. In comparison, previous research reported lower F1-score rates for both case types, except for the RL model, which attained an equivalent F1-score rate for pneumonia.

Table III
F1-SCORE RESULTS

Class	Our-TLBO-CNN	RL-model [10]	Vgg16 [11]	Xception [11]
Pneumonia	**98%**	**98%**	90%	87%
Normal	**98%**	**97%**	84%	74%

*4) **Accuracy, Sensitivity and Specificity Results**:* To assess the performance of our model, accuracy, sensitivity, and specificity are commonly used metrics. The accuracy metric calculates the proportion of correct predictions out of the total number of predictions. Sensitivity, also known as recall or true positive rate, measures the proportion of positive samples that are correctly identified. Specificity calculates the proportion of negative samples that are correctly identified.They are commonly used formulas to evaluate the performance of classification models. The formulas are as follows:

- $Accuracy = (TP + TN)/(TP + FN + TN + FP)$
- $Sensitivity = TP/(TP + FN)$
- $Specificity = TN/(TN + FP)$

Where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

Table IV provides a summary of the accuracy, sensitivity, and specificity results. The TLBO-CNN model outperformed previous works and obtained the highest scores.

Table IV
ACCURACY, SENSITIVITY, AND SPECIFICITY RESULTS

Class	Our-TLBO-CNN	RL-model [10]	Vgg16 [11]	Xception [11]
Accuracy	**98.88%**	**97%**	87%	82%
Sensitivity	**99%**	**96%**	82%	85%
Specificity	**99%**	**98%**	91%	76%

*5) **Confusion Matrix Results**:* Figure 2 depicts the confusion matrices, which offer insight into the performance of the TLBO-CNN model on the chest X-ray image data set, particularly for the Pneumonia and Normal categories. These matrices can be used to evaluate the model's ability to accurately identify and classify images in the data set in relation to previous works.

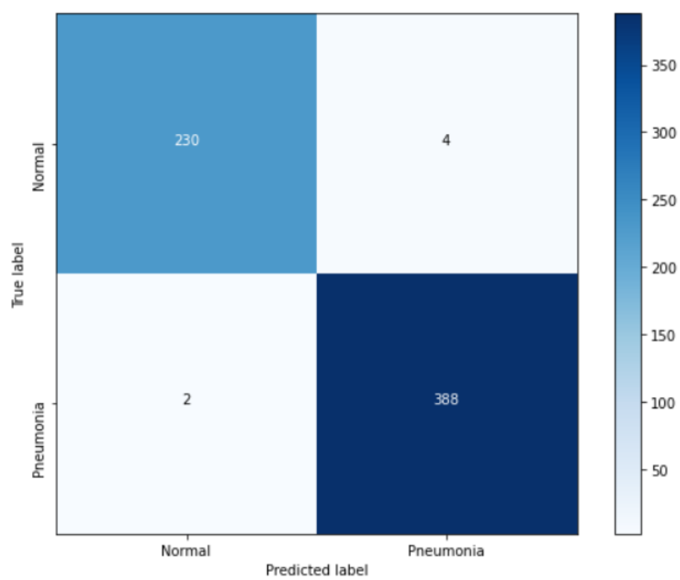


Figure 2. Confusion Matrix

As demonstrated in Table V, our model accurately categorized 618 image samples for both Pneumonia and Normal classes within the test set of chest X-ray images, achieving superior outcomes in comparison to prior methods proposed by [10] and [11].

*6) **Accuracy And Loss Graphic of TLBO-CNN**:* Fig. 4 and Fig. 5 illustrate the accuracy and loss results of TLBO-CNN after 50 training episodes. Fig. 4 demonstrates that TLBO-CNN achieved high accuracy in both training and testing phases. Meanwhile, Fig. 5 displays a decreasing trend in the

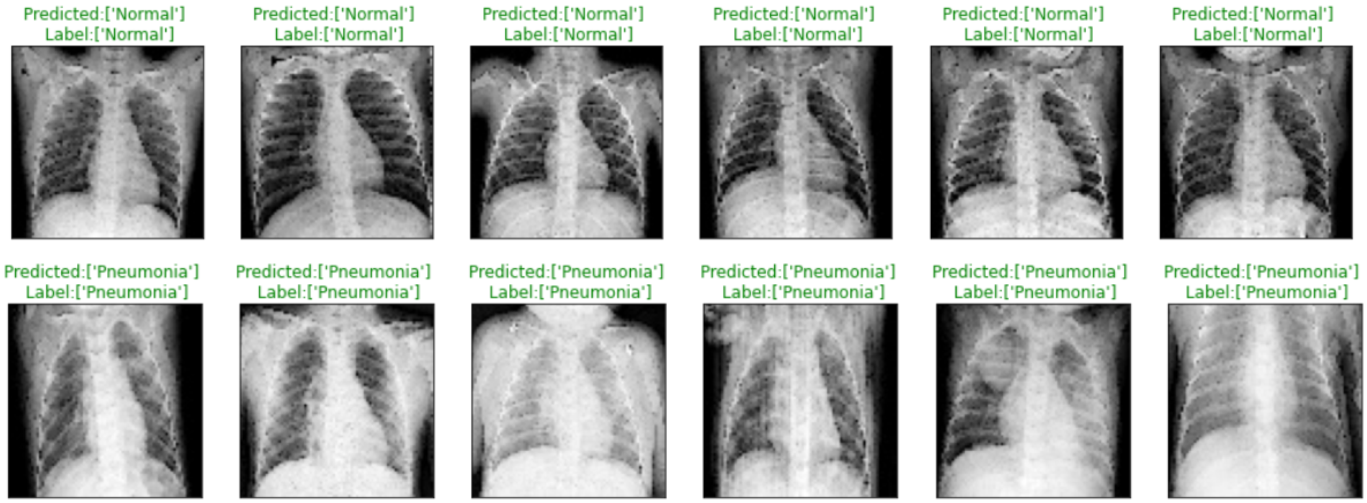


Figure 3. Predicted Pneumonia and Normal Images

Table V
CONFUSION MATRIX FOR CLASSES CORRECTLY CLASSIFIED

Class	Our-TLBO-CNN	RL-model [10]	Vgg16 [11]	Xception [11]
Pneumonia	**388**	383	348	365
Normal	**230**	225	201	152
Total	**618**	608	549	517

loss function, indicating that our model efficiently classified the images.

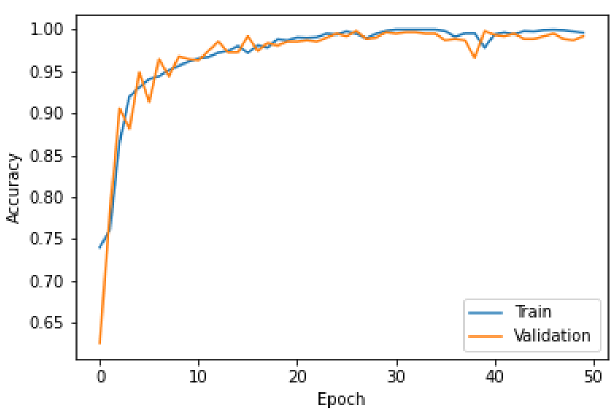


Figure 4. Accuracy Graphic of TLBO-CNN

7) ***Predictions of TLBO-CNN Model:*** Fig.3 displays the outcome of the TLBO-CNN model's prediction on a randomly selected test set consisting of 12 images. The results indicate that the TLBO-CNN model achieved an accurate prediction for all 12 images. In other words, the model correctly classified each of the 12 images from the test set.

8) ***Histogram Analysis:*** A histogram is a graphical representation used to display the distribution of pixel values in

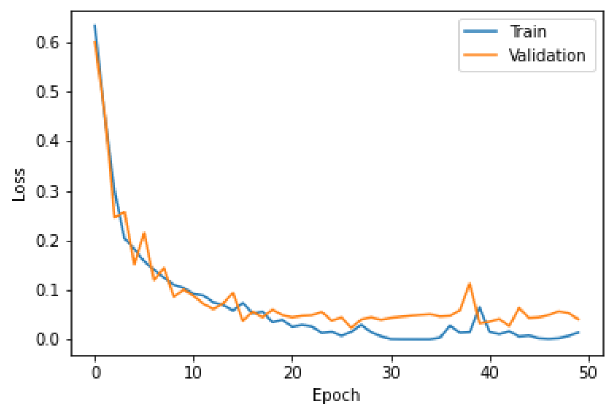


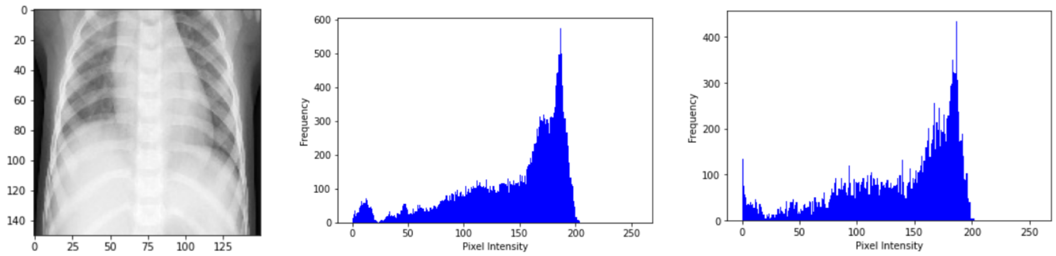
Figure 5. Loss Graphic of TLBO-CNN

an image. For grayscale images, the histogram will indicate the frequency of pixel intensities ranging from 0 (black) to 255 (white). The X-axis of a histogram shows color density and the Y-axis displays the corresponding number of pixels. High contrast images have distinct frequency values in the histogram and reveal more image details, while low contrast images have almost equal frequency values, making analysis more challenging and revealing fewer image details. [33].

The histograms depicted in Fig.6 and Fig.7 displays the image before and after TLBO. The optimized image exhibits a greater distribution of values across various intensity levels, suggesting that it contains more image details. Conversely, the initial histogram indicates that the values in each bin are nearly identical, making it challenging to analyze image details.

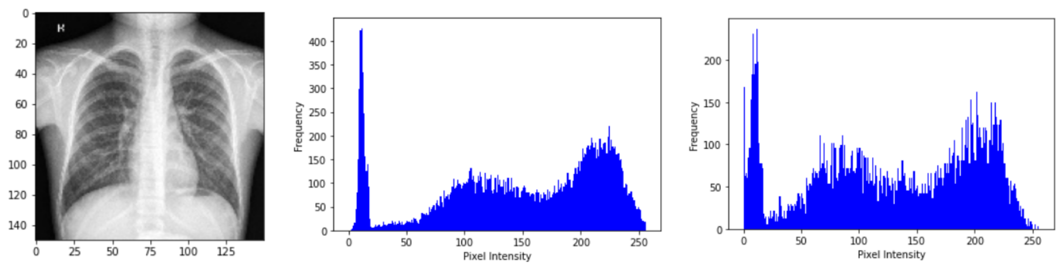
V. Conclusion

The study examined a medical data set of Pneumonia obtained from Chest X-ray images that had been previously



(a) (b) (c)

Figure 6. (a) Pneumonia Image, (b) Histogram before TLBO , (c) Histogram after TLBO



(a) (b) (c)

Figure 7. (a) Normal Image, (b) Histogram before TLBO , (c) Histogram after TLBO

used in two works [10], [11]. The data set contained two classes, and the study utilized Teaching Learning Based Optimization (TLBO) along with convolutional neural networks to minimize and select the best features of the images for the purpose of diagnosing and classifying normal and pneumonia X-ray images. The evaluation metrics comprised accuracy, classification tables, confusion matrices, accuracy and loss graphs for model testing, and a histogram analysis to compare the images before and after TLBO applied .

The TLBO-CNN model demonstrated superior performance in accurately classifying chest X-ray images of pneumonia, achieving the highest values for accuracy, sensitivity, specificity, and F1-measure. Specifically, the TLBO-CNN model attained an accuracy of 98.88%, a sensitivity of 99%, and a specificity of 99%. The confusion matrix results showed that the TLBO-CNN model correctly classified 618 X-ray image samples, which was a greater number than previous studies [10], [11]. The experimental results indicate that the TLBO-CNN model's accuracy was the highest, and its loss was the lowest. These significant findings highlight the TLBO-CNN model's efficiency in image classification.

Common limitations in classifying pneumonia from chest X-ray images include ambiguity and variability in image interpretation, overlap with other lung diseases, limited data, unequal representation, difficulty in detecting subtle abnormalities, and limited interpretability of machine learning algorithms. These challenges must be addressed to improve accuracy and generalization of machine learning algorithms used for pneumonia classification.

Finally, for future research we suggest to focus on expanding the data set to include more diverse cases and incorporating additional imaging modalities, such as computed tomography (CT) scans, to improve accuracy and reduce overlap with other lung diseases. Addressing the limitations of limited data and unequal representation can be achieved by collaborating with a larger number of medical institutions to gather more comprehensive data. Furthermore, developing explainable machine learning algorithms can enhance interpretability and build trust in the results. Finally, integrating TLBO with other machine learning models or algorithms can also be explored to improve the efficiency of pneumonia classification from chest X-ray images.

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