Indonesian Journal of Electrical Engineering and Computer Science
Vol. 36, No. 3, December 2024, pp. 1778~1786
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v36.i3.pp1778-1786

Pneumonia stage analyzes through image processing

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Article Info

Article history:

Received Apr 4, 2024
Revised Aug 20, 2024
Accepted Aug 31, 2024

Keywords:

Contour detection
Ensemble learning
Lung infection
Morphological opening
Pixel analysis
Thresholding
Transfer learning

ABSTRACT

A physical examination and diagnostic imaging techniques including lung biopsies, ultrasounds, and chest X-rays are typically used to make the diagnosis of pneumonia infection, an infectious disease that has the potential to be life-threatening. The objective of this research is to categorize the stages of pneumonia through image processing methods. Before that, an ensemble model for diagnosing pneumonia infections is created utilizing the transfer learning algorithms ResNet50V2 and DenseNet201. The 5,857 images were taken from the PAUL MOONEY dataset for this research. The proposed ensemble averaging model recognizes lung infection appropriately and accurately. By applying a contour detection approach, the left and right chests are separated and the affected pixels from there to analyze the stage of pneumonia. It is very crucial to identify the stage for treatment purposes.

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1. INTRODUCTION

An infectious illness called pneumonia results in inflammation in both of the lungs [1]. Pneumonia causes about a million hospital admissions in Bangladesh annually. Fortunately, pneumonia is treatable with medications like antivirals and antibiotics. Early stage and treatment identification is critical to prevent complications that could result in pneumonia-related mortality [2].

Numerous studies deal with pneumonia identification. Wu *et al.* [3] developed an anchor-free object detection framework and RSNA dataset for detecting pneumonia. They proposed an anchor-free framework. The chest X-ray samples are first denoised and enlarged using a number of data pre-processing techniques, which increases the training set and enhances the performance. Second, an anchor-free detection framework is used to select the feature layers that incorporate the features. Kanwal *et al.* [4] presented a novel for diagnosing community-acquired pneumonia (CAP) applied single-channel photoplethysmography (PPG) with machine learning. In their experiment, KNN shows good test accuracy. Sharma and Guleria [5] applied VGG16 with neural network (NN) model for detecting and classifying pneumonia and they achieved 92.15% accuracy. Baloch *et al.* [6], provides an overview of the coronavirus disease in 2019. However, several studies use a range of deep learning and artificial intelligence-based pneumonia detection techniques, especially for segmentation and classification. The medical field refers to these automated detection techniques as computer-aided diagnosis (CAD), which makes use of artificial intelligence-based solutions [7], [8]. Sharma and Guleria [9] discuss a variety of deep learning methods, such as ensemble models, pre-trained models, and convolutional neural networks, for detecting pneumonia. The review assesses the efficacy of these models in addressing diverse medical domain difficulties and presents a comprehensive explanation of their design and operational mechanism.

Asnake *et al.* [10] uses CNN and support vector machine to extract features and for classification and they achieve 99% accuracy respectively. Parthasarathy and Saravanan [11] use the Harris Hawks optimizer with deep learning (CAD-HHODL) approach, CAD can detect pneumonia on CXR images. The CXR images are examined by the CAD-HHODL approach in order to identify and categorize pneumonia. Mudasir *et al.* [12], applied six deep learning models—CNN, InceptionResNetV2, Xception, VGG16, ResNet50, and EfficientNetV2L and assessed in this work. The Adam optimizer, which successfully modifies the epoch for each model, is also included in the research. A dataset is used to train the models. For pneumonia detection, EfficientNetV2L has the best accuracy and resilience. Parthasarathy and Saravanan [13], present a novel technique on CXR images called chaotic sea horse optimization with deep learning method for pneumonia detection and classification (CSHODL-PDC). Automated pneumonia detection and categorization on CXR images is the primary goal of the CSHODL-PDC method. To remove the noise, the CSHODL-PDC technique first devises a noise eradication strategy based on Gaussian filtering (GF). Furthermore, the NASNetLarge model is utilized by the CSHODL-PDC approach to generate a set of feature vectors. Furthermore, for the automated diagnosis and categorization of pneumonia, an enhanced fuzzy deep neural network (FDNN) model is utilized. Ultimately, the work's originality is showcased when the CSHO algorithm determines the improved FDNN model's ideal hyperparameter values.

Zhong *et al.* [14] compare and analyze three distinct deep-learning approaches for the classification of pneumonia in order to identify cases in patients. A convolutional neural network (CNN), a transfer learning strategy based on the ResNet152V2 architecture, and a fine-tuning strategy also based on ResNet152V2 were among the methodologies examined. A thorough evaluation and comparison of the models was conducted using a number of variables, such as testing accuracy, loss, precision, F1 score, and recall. Abid [15], applied advanced methods such as CNN and HOG are required to obtain and process the pertinent image information in order to automate the pneumonia identification procedure. To achieve high accuracy in distinguishing pneumonia regions from normal lung tissue, the model is combined with the VGGNet classifier model after being trained on a substantial amount of CNN data. Maniruzzaman *et al.* [16] applied five established deep learning models such as VGG-16, VGG-19, ResNet-50, Inception-V3, Xception pre-trained on ImageNet have been applied for predicting pneumonia from chest x-ray. Shah *et al.* in [17] applied CNN model for pneumonia classification. Chowdhury *et al.* [18] have developed an ensemble hybrid deep learning system that uses three distinct classification processes. The features are extracted in the second stage once the weights have been determined. Finally, CXR image classification has been achieved by the use of the computer-aided model. To predict pneumonia using CXR images, Mabrouk *et al.* [19] extended a DL model by merging DenseNet169, MobileNetV2, and Vision Transformer models. To extract the features from the images three models are applied. Based on this earlier research, it can be said that there are several works related to classifying and detecting pneumonia. But, to know the stage of pneumonia for treatment purposes is necessary.

Our major challenge is to find out the stage of pneumonia from chest X-rays with an image processing approach. In this regard, this study makes the following contributions:

- Catagorizing chest X-rays as pneumonia or normal through an ensemble learning approach. ResNet50V2 and DenseNet201 pre-trained transfer learning approaches are applied and their output is ensembled with the averaging method.
- The main objective of this work is to analyze chest X-rays for detecting the pneumonia stage.
- So, after the classification of pneumonia x-ray, the contour detection process is used for separating the chest portion from the x-ray image.
- After separating the chest portion from the x-ray images, white and black pixels in the chest portion are calculated. The bounding-react function is utilized for counting the number of white pixels that are not a portion of the chest and discarding the number from the total number of white pixels. If the percentage of white pixels is greater than 60% then the chest x-ray will be treated as severe otherwise mild.

2. METHOD

2.1. Platform applied

The laptop used in the research contains an Intel(R) Core(TM) i5-8250U CPU running at 1.60GHz and 8 GB of RAM, among other hardware characteristics. Using the Matplotlib data visualization software, graphs that depict the model's performance are plotted. TensorFlow and the Keras library are used for machine learning. This implementation takes advantage of Google Colab, and the GPU process is employed to carry out the task [18].

2.2. Chest X-ray images, the datasets

This study's dataset was sourced from the Kaggle website. The collection is referred to as "PAUL MOONEY." Chest X-rays with and without pneumonia are included in this dataset. Pneumonia and Normal are the two sub-organizers of each organizer (train, test, valid). The 5,840 images total—4,265 of pneumonia and 1,575 of normal—make up the training and testing data, while 16 images—eight of normal and eight of pneumonia—make up the validation data. The dataset is described in Table 1, and Figure 1 displays three samples of both normal and pneumonia chest x-ray images as shown in Figures 1(a) and (b).

Table 1. An explanation of the dataset

Label	Train set	Validation set	Test set	Total
Pneumonia	3,875	8	390	4,273
Normal	1,341	8	234	1,583

(a) (b)

Figure 1. Samples of the dataset's data (a) normal and (b) pneumonia

2.3. Preprocessing state

Lowering the images' high dimensionality without compromising feature details are the principal goal of the applications in image classification. Based on the dataset's criteria, the image resolutions vary from 712×439 pixels to 2,338×2,025 pixels. The images were resized to 224×224. Duplicate image reduction is done in addition to the rigorous iterative training necessary to reduce the chance of overfitting. This calls for a substantial image dataset.

2.4. Data augmentation

To train this model, images are eventually obtained by the application of the image augmentation technique. The quantity of images is boosted by the use of data augmentation. The data augmentation parameters are shown in Table 2.

Table 2. Augmentation configuration [18]

Rotation	Zoom
Probability 0.7	Probability 0.3
Max_left_rotation 10	Min_factor 1.1
Max_right_rotation 10	Max_factor 1.6

2.5. Proposed model

This paper proposes deep learning model to classify chest X-rays into two categories: normal and pneumonia. For classifying pneumonia initially from chest X-rays ensemble deep learning approach is used. Algorithm 1 explains the methodology used in the suggested method.

Algorithm 1. An algorithm for detecting diseases from a chest image

1. Gather information from the databases. Transfer the datasets onto Google Drive. Remove duplicate images from the dataset. The datasets are separated into train, test, and validation.
2. Increase the number of training and validation samples by using augmentation.
3. An ensemble model for identifying images as pneumonia and normal is developed using the Resnet50 and Densenet201 models.
4. The average approach is employed after ensembling the two models' outputs to get the final result.

ResNet50V2 and Densenet201 pre-trained models are applied to chest X-ray images to produce precise and accurate classifications. Globalaveragepooling is used for downsampling in every model. Overfitting decreases by using dropout 0.4. Following the combination of these models' outputs, the average outcome is calculated. A set of pre-trained of chest X-rays images are input into many deep-learning models, including ResNet50V2 and Densenet201. This suggested model's layers were changed to improve accuracy. These models (X,Y) are applied to all of the chest X-ray images in the dataset, where X is the set of N images, each with a size of 224 x 224, and Y has labels that are equivalent. The proposed model uses layering during testing to aggregate each model's output and generate an overall output for class label prediction of the unseen sample. The ensemble averaging strategy combines the advantages of multiple models to improve performance. To minimize loss, the models combine with the optimizer Adam. The SparseCategoricalCrossentropy loss function is used. By doing this, our model finishes its initial phase and is able to differentiate between chest X-rays that are normal and pneumonia. The sigmoid function is adopted to the output values by the loss function. Figure 2 provides a detailed representation of the proposed paradigm. The recommended model's design details and several parameters are shown in Table 3.

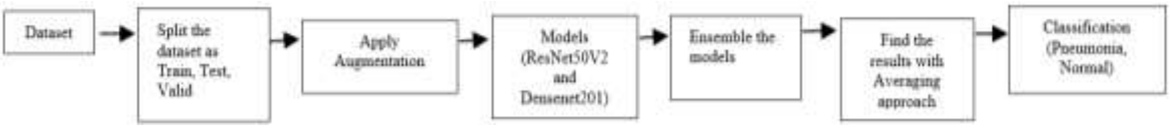


Figure 2. Flow diagram for the suggested model

Table 3. Parameters of the model [18]

Parameters	Values
Epoch	5
Validation Step	1
dropout	0.4
Optimizer	Adam
Loss Function	SparseCategoricalCrossentropy
From_logits	False
Batch size	32
Hidden layers	512
Output Layer	Sigmoid

2.6. Assessing the illness's severity

If the condition is identified as pneumonia, the chest x-ray image is utilized to assess the severity of the illness. Before applying the morphological opening procedure, the image is transformed into a grayscale version. The opening procedure keeps the general structure and shape of larger things in the front (bright areas) of an image while removing little objects or noise from them. In the opening procedure kernel sizes (3*3), (5*5), and (7*7) are used. Kernel size (3*3) is used to extract the filters with more accuracy. For getting small details, smaller kernels are helpful. To capture the boundary characteristics, kernel sizes (5*5) and (7*7) are simultaneously utilized. Performance, resilience, and flexibility can all be improved by combining kernels of various sizes simultaneously. Before performing the contour operation on the opening image, the threshold operation is applied to extract the fine contour from the image. Here, 127 is used as the threshold value and THRESH_BINARY method is applied for performing thresholding. To extract the contours from the image, RETR_TREE and CHAIN_APPROX_SIMPLE are used. Figure 3, describes the process of contour detection.

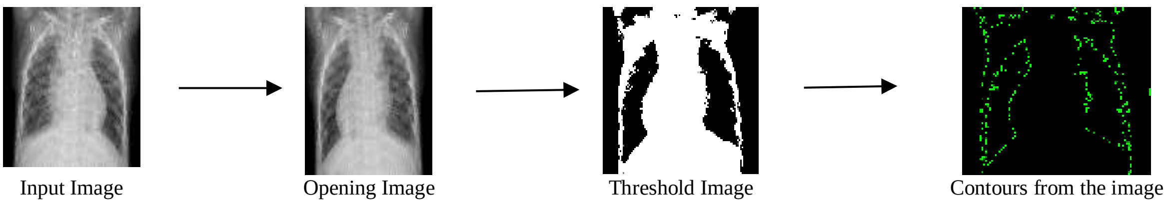


Figure 3. Contour detection process from the input image

Our primary goal is to assess the pneumonia's severity based on the chest x-ray. The set of contours must first be sorted in reverse order in order to extract the lung component from the chest x-ray. The left and right lungs will be obtained in the second and third iterations. The black and white pixels are obtained in the lung portion. There are more black pixels than white pixels in a normal chest x-ray. However, white pixels can be seen in a normal chest X-ray because of bone and heart shadows. Moreover, compared to a normal chest x-ray, there will be more white shadows when a lung is impacted. This BoundingRect function sets a boundary which are not portion of the lung. Here, the number of white pixels and black pixels that are not belong with the lung portion is counted using two boundingRect functions. This function returns four values: x, y, w, and h. The coordinates of the rectangle's upper-left corner are (x, y). W is the rectangle's width. The rectangle's height is denoted by h. To get the percentage, we count the number of white pixels from outside the boundary regions. Table 4 describes the configuration of the boundingRect function and Figure 4 describes the process of getting white and black pixels.

In the final analysis, the chest x-ray image classification model is the first in the model architecture. This classification model uses an averaging strategy to combine the Resnet150v2 and Densenet201 models. The model uses the chest X-rays to classify pneumonia in this manner. Following pneumonia classification, the model will assess the disease's severity. Therefore, to reduce noise and improve the subject's details, a morphological opening operation on that pneumonia case is applied. Next, the system will process the image by applying a threshold operation and then doing contour detection. The system can obtain the left and right lung portions from the chest X-ray by sorting the contours in reverse order. The system divided the lung area in this way. The white and black pixels from the lungs will then be calculated using the boundingReactfunction. Because of heart or bone shadow, a typical x-ray has a lot of white pixels. Thus, these pixels will be subtracted by the system. The general architectural design of the proposed architecture is given in Figure 5.

Table 4. Configuration of left and right lung for boundingRect function

Left lung	Right lung
Region 1	
start_x, start_y=round(h-h/4),0	start_x, start_y=round(h/4),0
end_x, end_y=round(h), round(w-w/5)	end_x, end_y=round(h-h/6), round(w/2)
Region 2	
start_x,start_y= 0, round(w-w/5)	start_x, start_y=round(h-h/6),0
end_x,end_y=round(h), round(w)	end_x, end_y=h,w

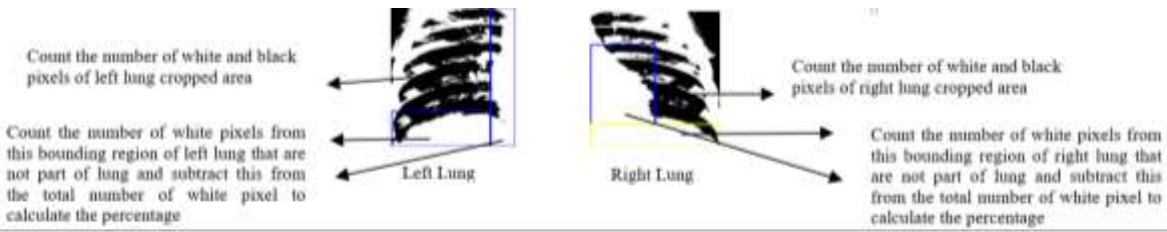


Figure 4. Process of getting the percentage of white and black pixels

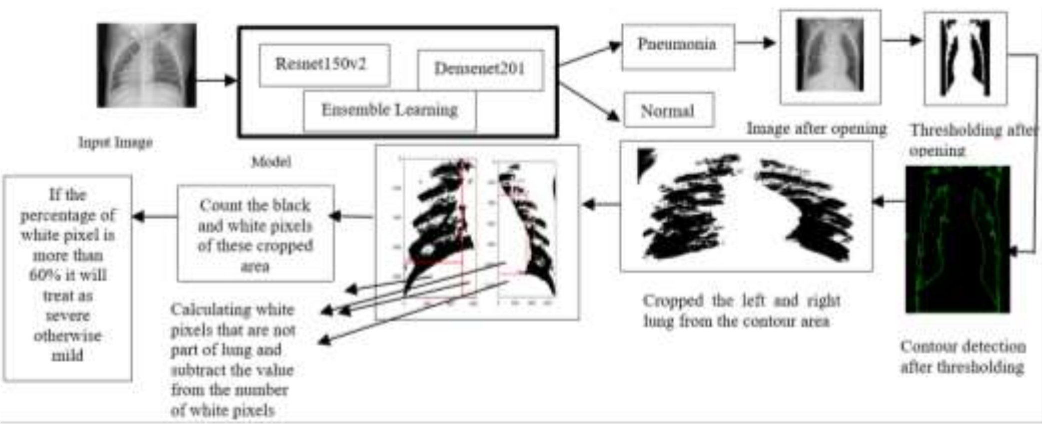


Figure 5. The suggested model's architecture

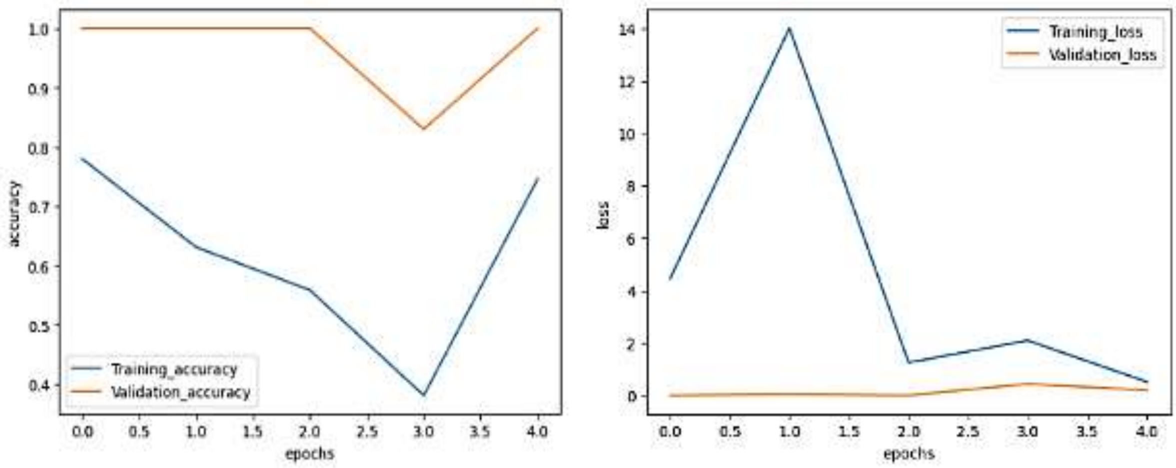
3. RESULTS AND DISCUSSION

The experiments for the suggested approach were conducted using Python programming, the TensorFlow framework, and the Keras open source libraries. The primary findings of the proposed model were as follows:

– Diagnosing illnesses using chest x-ray images.
– Once the image has been classified as pneumonia, determine the severity of the condition.

3.1. The suggested model's performance using the dataset

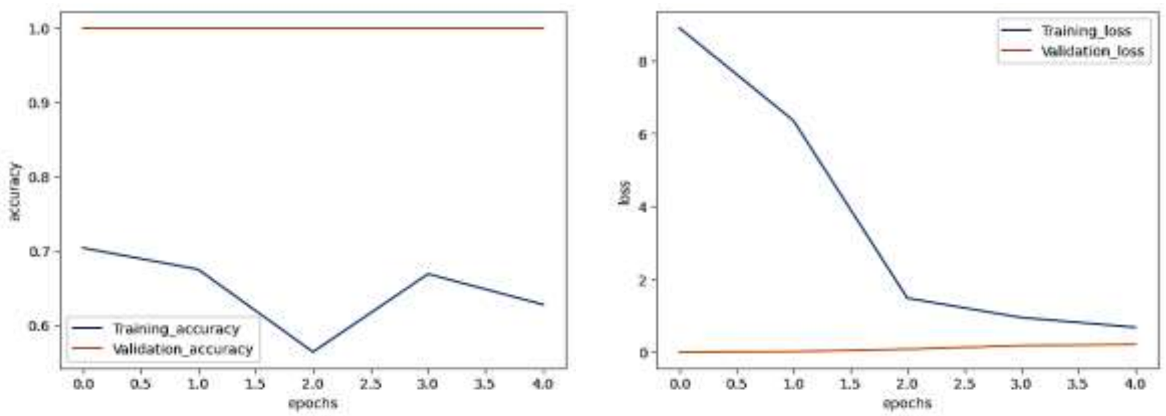
The ResNet50V2 and Densenet201 models were used in this work, and those models were then ensembled to increase accuracy. The Densenet201 model's performance analysis is shown in Figure 5. In this work, the data augmentation technique is used to enhance accuracy. As shown in Figure 5(a), we used five epochs and were able to acquire a good val_accuracy from this model. Furthermore, validation loss displays a low value in Figure 5(b). This graph suggests that overfitting occurs on the second iteration and from this iteration accuracy goes down, and the learning rate reduction method solved this accuracy.



(a) (b)

Figure 5. Densenet201 model performance analysis (a) accuracy graph and (b) loss graph

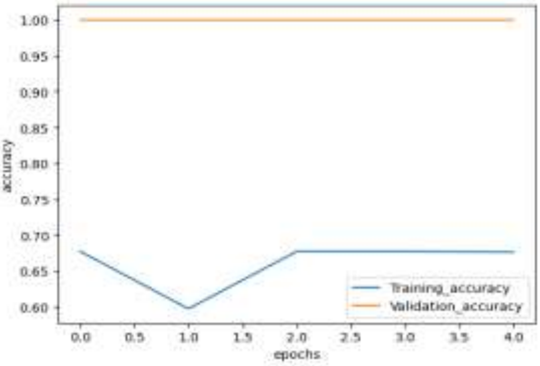
The ResNet50 model's performance is shown in Figure 6. Figure 6(a) clearly shows that there hasn't been any overfitting because the val_accuracy is almost in a good position, and the val_loss is also at a minimal amount. Figure 6(b) shows the validation and training loss.



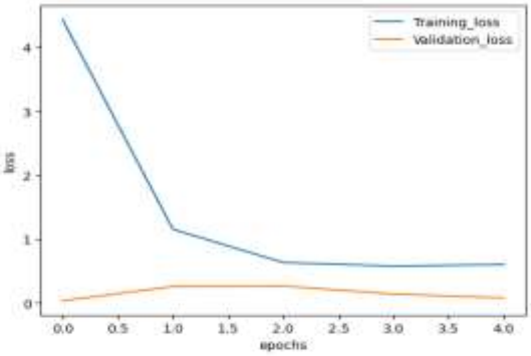
(a) (b)

Figure 6. Analysis of the ResNet50V2 model's performance (a) accuracy graph and (b) loss graph

The ensemble model's performance is shown in Figure 7. The val_accuracy is in a good position, and the value of val_accuracy for each of the epochs are all clearly seen in Figure 7(a). It is also evident from Figure 7(b) that the val_loss is declining consistently. The recommended method outperformed the others in detecting pneumonia from the chest x-rays, according to a thorough examination of all the data.



(a)



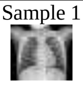
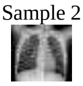
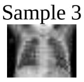
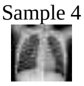
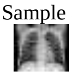
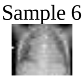
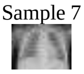
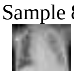
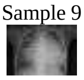
(b)

Figure 7. Analysis of the ensemble model's performance (a) accuracy graph and (b) loss graph

3.2. Evaluation of the effectiveness of the disease severity process

In this work, we examined a few normal and impacted chest x-rays in order to assess the disease's severity. After examining those X-rays, we discovered that the percentage of white shadow in a chest X-ray is less than 50%; this percentage represents both bone and heart shadows. Our goal is to identify the pneumonia shadow, and if a lung is affected, we want to see a sudden increase in white shadow. Thus, we find more than 60% white shadow in the chest X-ray that is affected. Here, we consider lung damage under 60% to be mild, and severe damage above 60%. Table 6 presents the analysis's findings.

Table 6. Analysis of the disease severity from a chest X-ray

Samples	Left lung	Right lung	Left lung percentage	Right lung percentage	Result
Sample 1 	W=712,719 B=926,715	W=1,616,265 B=1,323,243	W=43% B=57%	W=46% B=54%	Left and Right Lungs are normal
Sample 2 	W=1,454,164 B=2,724,209	W=1,399,001 B=1,965,112	W=35% B=66%	W=41% B=59%	Left and Right Lungs are normal
Sample 3 	W= 752,094 B=1,267,410	W=1,072,671 B=1,388,304	W=37% B=63%	W=44% B=56%	Left and Right Lungs are normal
Sample 4 	W=1,454,164 B=2,724,209	W=1,399,001 B=1,965,112	W=34% B=67%	W=42% B=58%	Left and Right Lung is normal
Sample 5 	W=1,873,398 B=2,983,509	W=1,966,127 B=2,700,547	W=38% B=62%	W=42% B=58%	Left and Right Lungs are normal
Sample 6 	W=893,903 B=396,568	W=397,931 B=378,589	W=70% B=30%	W=51% B=48%	Left Lung is severe and Right Lung is mild affected
Sample 7 	W=62,202 B=36,096	W=74,863 B=47,240	W=63% B=37%	W=61% B=39%	Left Lung and Right Lung are severe affected
Sample 8 	W=333,635 B=266,017	W=20657 B=6,115	W=55% B=45%	W=77% B=23%	Left Lung is mild and Right Lung is severe affected
Sample 9 	W=16,208 B=12,700	W=7,093 B=5,264	W=56% B=44%	W=57% B=43%	Left Lung and Right Lung are mild affected
Sample 10 	W=221,812 B=282,743	W=35,329 B=32,855	W=44% B=56%	W=52% B=48%	Left Lung is normal and Right Lung is mild affected

3.3. Evaluating the proposed method in light of current research

To demonstrate the generality of the proposed approach, the performance of the suggested strategy is compared with the current approaches, as indicated in Table 7. When compared to the most modern method, the noval method performs well for analyzing the stage of pneumonia. Table 7 illustrates the methodology and precision of their work.

Table 7. A comparison between the recommended architecture and related works

Related works	Method	Accuracy
[19]	CNN (Pneumonia Classification)	93.91%
[20]	Principle component analysis (PCA), histogram of orientated gradients (HOG) (Pneumonia Classification)	97%
[21]	VGG19+CNN (Pneumonia Classification)	99%
[22]	Resnet-50+ DCNN (Pneumonia Classification)	99.9%
[23]	CNN+LSTM (Pneumonia Classification)	72%
[24]	CNN+RNN (Pneumonia Classification)	97.8%
[25]	CNN (Pneumonia Classification)	99%
Proposed model	Categorize pneumonia cases and assess pneumonia severity	Accurate and precise

4. CONCLUSION

In this study, we presented a model that uses an image processing technique to determine the stage of pneumonia. Prior to that, in this work, a deep learning model is used to classify chest X-ray images into two groups: normal and pneumonia. In this case, 5,840 images are used. The deep learning-based classification model performs well, and we also present some of our experimental findings from the pneumonia stage study here. The outcome of the experiment confirms our desired outcome. Our educated network should prove helpful in the future for pneumonia detection and medical diagnostics, especially in underdeveloped countries. In the future, we anticipate that more datasets containing mild and severe pneumonia patient data will become accessible, which will enable us to enhance the precision of our proposed model.

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