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Pneumonia Detection Using Image Enhancing Techniques and Deep Learning

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Abstract
Pneumonia is a lung inflammation that mostly affects the tiny air sacs known as alveoli. The disorder can range in severity. The most prevalent causes of pneumonia are infections with viruses or bacteria, other microbes, or certain drugs. Cystic fibrosis, chronic obstructive pulmonary disease (COPD), asthma, diabetes, heart failure, a history of smoking, having a defective cough reflex, such as after a stroke, and having a weakened immune system are risk factors. The physical exam and symptoms are frequently used to make a diagnosis. One of the most common illnesses that are challenging to diagnose because of a shortage of professionals is pneumonia. Early and accurate diagnosis is crucial for effective treatment and better patient outcomes. Pneumonia, along with Covid-19, became one of the more serious medical conditions. The most popular procedure for diagnosis is a chest X-ray. In recent years, deep learning-based approaches have shown great promise in automated pneumonia detection using chest X-ray images. However, examining a chest X-ray is a difficult task. It follows that automated diagnostic systems are necessary. Hence one such system is the proposed CNN model described in this paper with an accuracy of 97.02%. It comprises of image enhancing techniques specially designed for X-ray images and the proposed CNN model.
***Keywords*— Chest X-ray images, CLAHE, CNN, Deep Learning, HFE, Image enhancing techniques, Pneumonia, Unsharp Masking**

1. Introduction
Pneumonia is an infection that causes the air sacs in one or both lungs to become inflamed. People with this disease have lungs that fill up with discharge fluids, which causes chills, fever, coughing up mucus, and breathing difficulties. Children under the age of five and elderly patients with weakened immune systems are particularly susceptible to these infections. It is the most serious illness in children under the age of 5 with 4 million deaths each year. If this disease is not detected or diagnosed earlier it could be life-threatening. The study, which was released on World Pneumonia Day, estimated that by 2030, the deadly disease will likely claim the lives of up to 11 million children under the age of five. Doctors diagnose pneumonia in hospital patients using a variety of procedures, including physical examination, medical history, clinical investigations like sputum or blood tests, chest X-rays, and some other imaging techniques. Due to technological advancements in bio-medical equipment, chest X-rays are now becoming less expensive.

In this research, we developed a prediction model based on chest X-rays. The dataset was obtained from Kaggle which contains 5856 chest X-ray images, including normal and pneumonia cases. The proposed project's objective is to determine whether or not the child has pneumonia by using deep learning algorithms.

2. Literature Survey
Puneet Gupta et al [2] analyzed various models of deep learning and transfer learning in this work for the image classification application. The author says, unlike traditional approaches the

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deep learning algorithms give the best feature extraction which greatly reflects on the accuracy and specificity. The author used deep learning algorithms to extract features and x-ray images and used convolutional neural network architecture to train images for further classification. The performance of three models—VGG16, VGG19, and CNN that the authors created themselves were evaluated by them. The validation accuracy for VGG16 was 92%, the training accuracy was around 97%, and the training accuracy for VGG19 was around 95%. And for the CNN model that the authors created, they obtained a training accuracy of roughly 99% and a validation accuracy of 93%.

Ashitosh Tilve et al [1] focused on surveying and comparing the detection of lung diseases using different machine learning techniques like CNN, DENSENET, RESNET, ANN, and KNN. They used different computer-aided techniques to find a more accurate model to detect pneumonia. They also used image pre-processing techniques to convert raw X-ray images to standard formats for better detection and analysis. The authors concluded that VGG16 gives the best accuracy compared to other models and the accuracy and speed can be improved with better pre-processing of images with different techniques.

Devansh Srivastav et al [3] to address the issue of class imbalance, concentrated on populating the dataset using the DCGAN technique and then augmenting the datasets. According to the author, augmenting the images using the model improves the deep learning neural network model's accuracy and performance. These enhanced images put into CNN models can offer excellent accuracy, but he paired the model with transfer learning to further increase accuracy. The model was trained over 25 epochs, and on the validation set, it was able to achieve 94.5% accuracy with a loss of 16.2%.

Pranav Rajpurkar et al [4] developed an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Their algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14. Their proposed algorithm exceeds average radiologist performance on the F1 metric. They have extended CheXNet to detect all 14 diseases in ChestX-ray14. ChexNet inputs a chest X-ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia. The authors conclude that the difference in F1 scores is 0.051 (95%CI0.005,0.084) and does not contain 0, and therefore conclude that the performance of CheXNet is statistically significantly higher than radiologist performance.

Karim Hammoudi et al [5] have tailored models based on CNNs that have been designed to take three sets of image categories (e.g.; normal case, viral pneumonia case, and bacterial case) as input and output the predicted probability for each of the categories. The trained models exploit the CNN backbones ResNet34, ResNet50, and DenseNet169 through the fastai library. Besides, a trained model exploits the CNN reference backbone VGG-19. A dual-use model (Inception ResNetV2 - RNN) is prepared for i) characterizing categories of input split images by getting a hidden layer output of a fin-tuned Inception ResNetV2 architecture, ii) predicting final categories of split images using a bidirectional Long Short-Term Memory (RNN-LSTM) architecture. For these last ones, a Keras and TensorFlow workflow is used. The InceptionResNetV2 model has detected the minimum of false negatives for pneumonia on the COVID-19 blind test set (0.7%). They have shown from their experiment that the transfer of knowledge from pediatric chest X-ray training to infection screening of adults can be efficient.

Zhang et al [6] address that they conducted an analysis and discovered that using a CT scan to detect pneumonia is more accurate and effective in terms of resource use. The three algorithms that the author proposed—DC-Net-S, DC-Net-E, and DC-Net-R—all use AlexNet as their foundation. The author notes that they trained both Net-0 and Net-1 of the aforementioned models in order to integrate batch normalization into AlexNet. This boosts the model's general stability and pace of convergence. The RVFL method and batch normalization are combined in the DC-Net-R structure.

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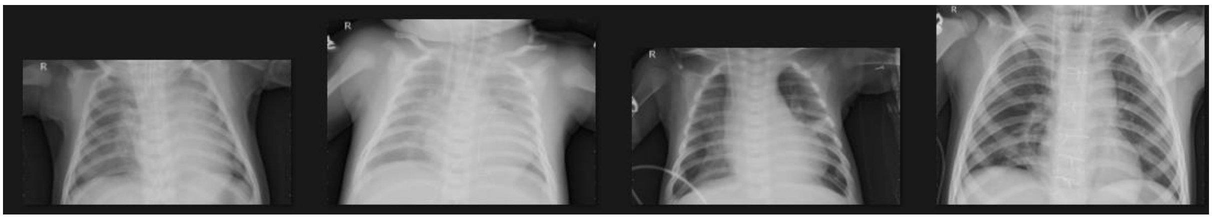
The final DC-Net-R is revealed as a realistic and potential option for neural networks in this classification task by the comparative analysis among DC-Net-S, DC-Net-E, and DC-Net-R.
WASIF KHAN et al [7] proposed a methodology to help practitioners to select the most effective and efficient methods from a real-time perspective. This study discusses the quality, usability, and size of the available chest X-ray datasets and techniques for coping with unbalanced datasets. A detailed comparison of the available studies reveals that the majority of the applied datasets are highly unbalanced and limited, providing unreliable results and rendering methods that are unsuitable for large-scale use. The authors conclude that by generating high-quality synthesized images using GANs along with data augmentation techniques instead of traditional oversampling techniques such as SMOTE, which generates samples based on the line between instances of the minority class.
HAO REN et al [8] first build a large dataset of community-acquired pneumonia consisting of 35389 cases (distinguished from nosocomial pneumonia) based on actual medical records. They train a prediction model with the chest X-ray images in the dataset, capable of precisely detecting pneumonia. Later they proposed an intuitive approach to combine neural networks with an explainable model such as the Bayesian Network. The experiment result shows that their proposal further improves the performance by using multi-source data and provides intuitive explanations for the diagnosis results. Their results show that their model is better than just using only images or only reports. The model works best when compared to a variety of baselines. They are also working on classifying pneumonia deeper, such as to determine whether it is bacteria, viruses, or fungi.

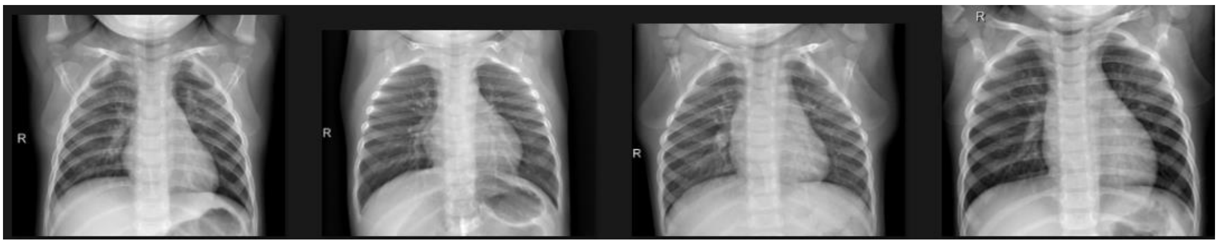
3. Methodology

3.1 Data Preparation

The data preparation step involve splitting the gathered images into training, validation, and testing sets with a ratio of 70:15:15. Sample dataset images are shown in Fig1. The images are pre-processed to remove unwanted noises and cropped to the region of interest (lung area), resized to a uniform size, and normalized to values between 0 and 1. Data augmentation such as flipping, rotation, ZCA whitening, and zooming are also done. The workflow of the proposed methodology is shown in Fig 2.
The data preparation step also involves processing the augmented images with three different image-enhancing techniques as listed below.



(a)



(b)

Fig1: Sample dataset images (a) Pneumonia (b) Normal

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3.2 Image Enhancing Techniques

A. Contrast Limited Adaptive Histogram Equalization (CLAHE)

We have used the Contrast Limited Adaptive Histogram Equalization technique in image pre-processing which is an effective method for boosting the contrast of chest X-ray images of pneumonia, and it can considerably increase the accuracy of pneumonia identification in these images. By increasing the contrast of the pictures, this approach helps clinicians more easily spot significant features such as opacities, consolidations, and pleural effusions. The histogram of the image, which is a graphic representation of the frequency distribution of pixel intensity values in the image as shown in Fig 4, serves as the foundation for histogram equalization. Histogram equalization aims to re-distribute the intensity values over the range of potential values in a more uniform manner. As a result, the image has increased contrast because the lighter regions of the image appear darker and the darker areas of the image appear lighter as shown in Fig 3.

B. Unsharp Masking (UM)

Unsharp masking is a common method in image processing that improves an image's sharpness by boosting the contrast of its edges. By removing a blurred copy of the image from the original, the approach highlights the image's edges. Images of pneumonia can be blurred using the Unsharp masking technique by applying a Gaussian filter and the approach. In image processing, the Gaussian filter is a popular filter that blurs the image while keeping the edges sharp. In photos of pneumonia, the Unsharp masking method with a Gaussian filter can be especially helpful since it can help to highlight the margins of the lungs and any lesions or infiltrates that may be visible in the images. The processed image is shown in Fig 3. This can help with the recognition and treatment of pneumonia, as well as the monitoring of its development.

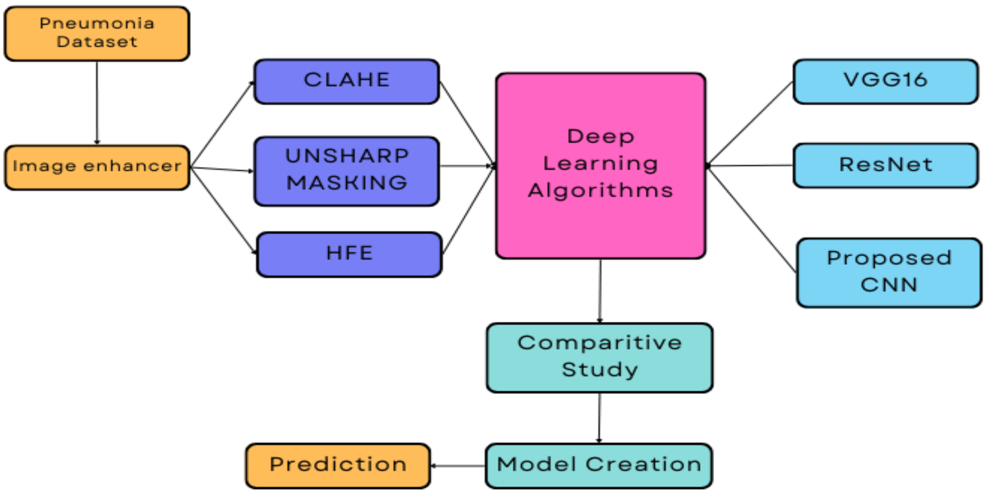

Fig 2: Workflow of the proposed methodology

C. High-frequency Emphasis Filtering (HFE)

High-frequency Emphasis Filtering (HFE) stresses the high-frequency components linked to edges and features, improving the sharpness and contrast of a picture. HFE filtering can be helpful in the context of pneumonia imaging to enhance the quality and accuracy of the images for diagnosis and treatment. Furthermore, HFE filtering can be used to enhance the quality of pictures collected from several imaging modalities, including X-rays, CT scans, and ultrasounds, which can help with the overall management of pneumonia patients. A high-pass filter is applied to the image as part of the HFE filtering technique, attenuating the low-frequency components and enhancing the high-frequency components. Many techniques, including Laplacian filtering, wavelet transformations, and Gaussian high-pass filtering, can be used to generate the high-pass filter. The processed image is shown in Fig 3.

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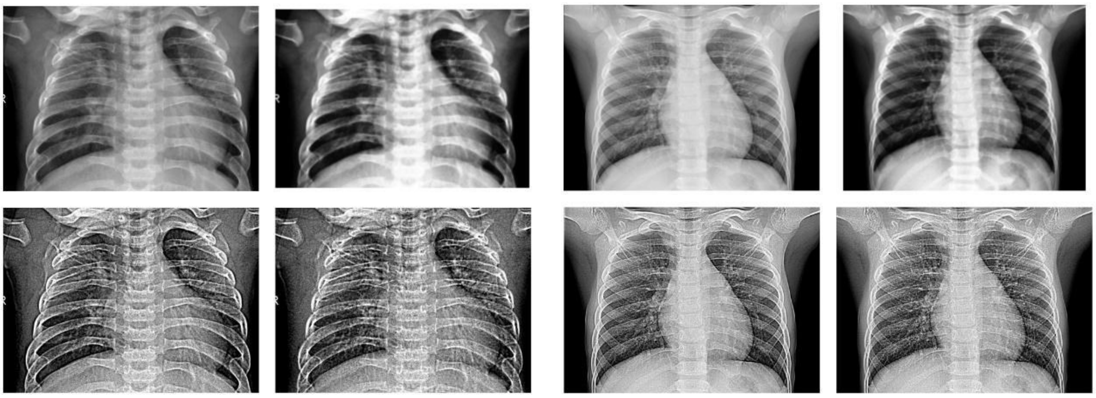

(a) (b)

Fig 3: Processed images using different image processing techniques of (a) Pneumonia (b) Normal
Where,
Upper-left corner: Original Image, upper-right corner: CLAHE, lower-left corner: UM, lower-right corner: HFE processed image

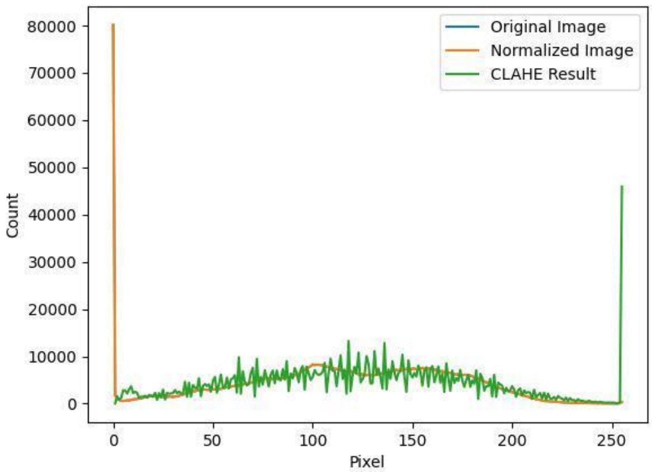

Fig 4: Histogram equalization chart of pneumonia image

The enhanced images are passed as input to three different deep-learning models such as CNN, VGG16, ResNet, and their accuracies are compared for the best model.

3.3 Deep Learning Models

A. Convolutional Neural Network (CNN):

CNN is a type of deep learning model that is widely used for image classification tasks, including pneumonia detection in chest X-ray images. The proposed CNN takes in images of two categories (i.e. normal and pneumonia) as input and the output is the predicted probability for each of the categories. The trained model exploits the CNN reference backbone VGG-16. For these Keras and Tensorflow are being used. When the images are passed to the trained model, a sequence of images is generated by placing a grid on the original image. This not only increases the dataset size but also limits the image details loss, that is the loss that occurs when the images are resized to fit the grid. This additional process is done to focus on the region of interest (i.e. lungs) and also to make it easier for the model to identify the parts of the lung area to further improve the accuracy of the model.

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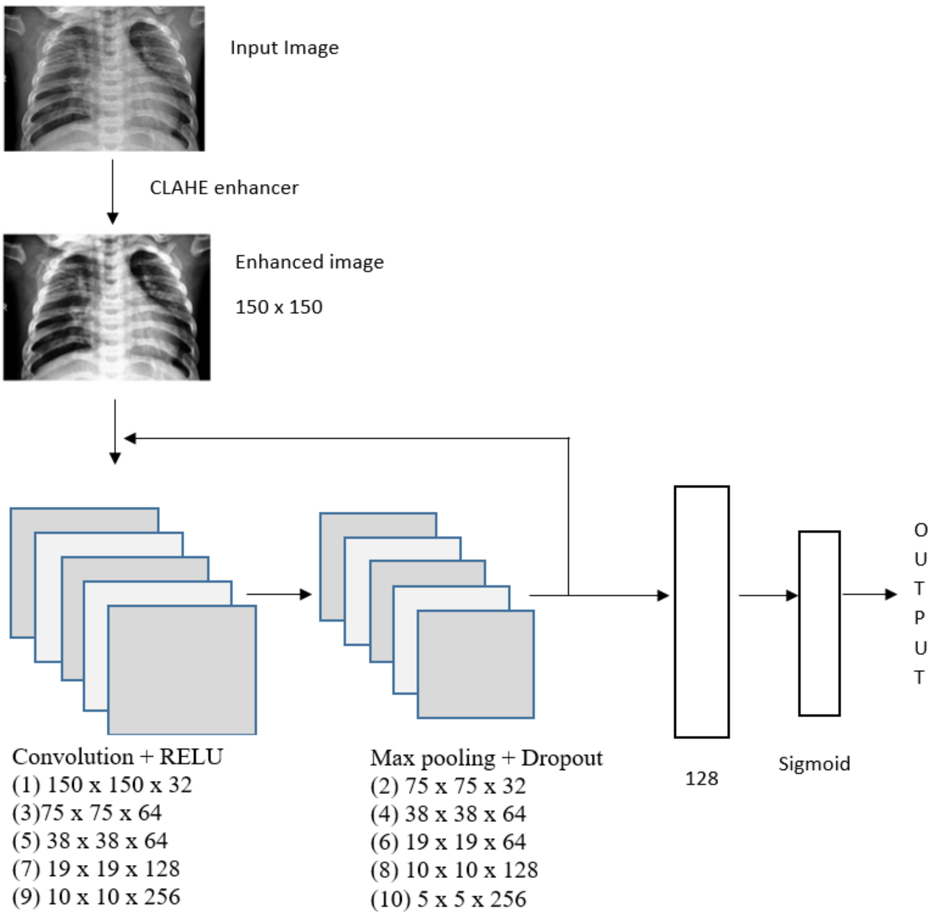

Fig 5: Architecture of the proposed CNN model

The architecture for pneumonia detection may involve multiple convolutional and pooling layers, followed by fully connected layers and an output layer and is shown in Fig 5. The hyperparameters of the model, such as the number of layers, number of filters, and kernel sizes are optimized using techniques such as grid search. CNNs are trained to automatically extract features from images through convolutional layers and pooling operations, and they have achieved high accuracy in detecting pneumonia and differentiating it from normal chest X-rays.

B. VGG16:

VGG16 contains 16 layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers have small 3x3 filters and are followed by max pooling layers to reduce the spatial dimensions of the feature maps. The model is trained using the cross-entropy loss function and stochastic gradient descent with momentum. The VGG 16 model achieved state-of-the-art performance on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), demonstrating the effectiveness of deeper neural networks for computer vision tasks.

The model is trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. We use binary cross-entropy as the loss function and monitor the validation accuracy to prevent overfitting. The model is trained for 50 epochs with early stopping if the validation accuracy does not improve after 10 epochs.

Studies suggest that VGG16 can be an effective deep-learning model for pneumonia detection using chest X-ray images, especially when combined with transfer learning techniques.

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C. ResNet:

ResNet is a deep-learning architecture that has been used for pneumonia detection with good results. It's a deep neural network architecture that uses residual connections to allow for the training of much deeper networks, capturing complex features in the data and showing success in pneumonia detection. ResNet's residual connections enable the network to skip over layers that do not contribute to the final output, reducing the risk of vanishing gradients and allowing for the training of much deeper networks. ResNet has been used in different variations, such as ResNet-50 and ResNet-101, for pneumonia detection.

4. Results and Discussion

We employ a deep convolutional neural network (CNN) architecture for pneumonia detection. The proposed CNN model is compared with VGG16 and ResNet. The use of image enhancers has proved to be playing an important role in the outcome of the model. The models were affected both positively and negatively. Specifically, the proposed CNN with the use of Contrast Limited Adaptive Histogram Equalization (CLAHE) in our datasets has provided us with more promising results than using Unsharp Masking and High-frequency Emphasis Filtering image enhancers. The accuracy of the proposed CNN model has been increased after enhancing the images with a training accuracy of 97.02% and a test accuracy of 93.19%. Though the VGG16 model is known for its high accuracy in image classification tasks in several studies on pneumonia detection, our proposed CNN model has proven to be even more accurate with the use of CLAHE. The comparison of different models with different image-enhancing techniques is shown in Table 1.

Model	Enhancer (Image Preprocessing)	Train Accuracy	Test Accuracy
Proposed CNN	**CLAHE**	**97.02**	**93.19**
	UM	86.12	83.98
	HFE	85.76	82.13
	None	96.06	91.27
VGG 16	CLAHE	95.31	91.31
	UM	85.14	77.12
	HFE	82.78	72.95
	None	94.55	91.02
ResNet	CLAHE	73.65	67.43
	UM	63.34	57.76
	HFE	63.76	56.65
	None	67.34	59.21

Table 1: Comparison of different deep learning models with image-enhancing techniques

We found that the CLAHE-enhanced images gave higher accuracy on all the deep learning models tried. A comparative study of the train and test accuracies of the three different models using CLAHE is shown in Fig 6. A confusion matrix for the proposed CNN using CLAHE is visualized for better understanding as shown in Fig 7. A graph for training accuracy and training loss is also visualized and shown in Fig 8.

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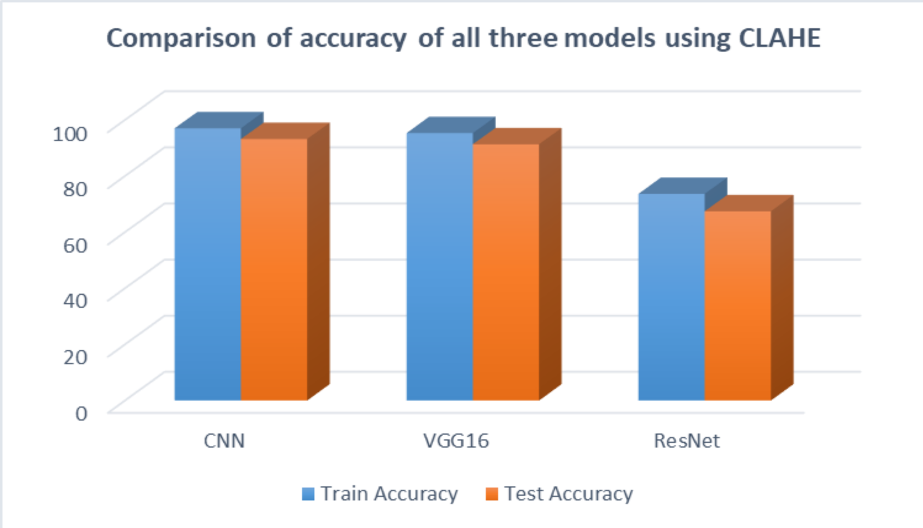

Fig 6: Comparison of train and test accuracies of three models using CLAHE enhancer

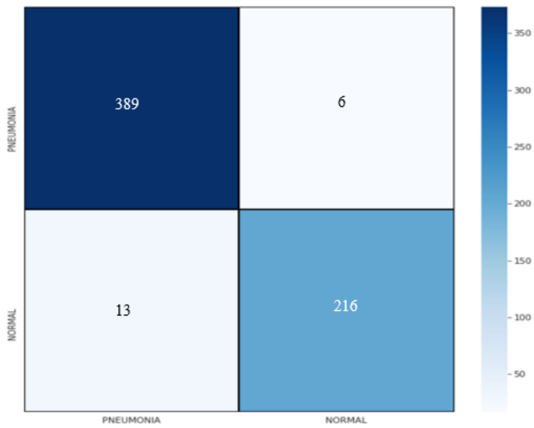

Fig 7: Confusion Matrix for the proposed CNN using CLAHE (Actual Vs Predicted)

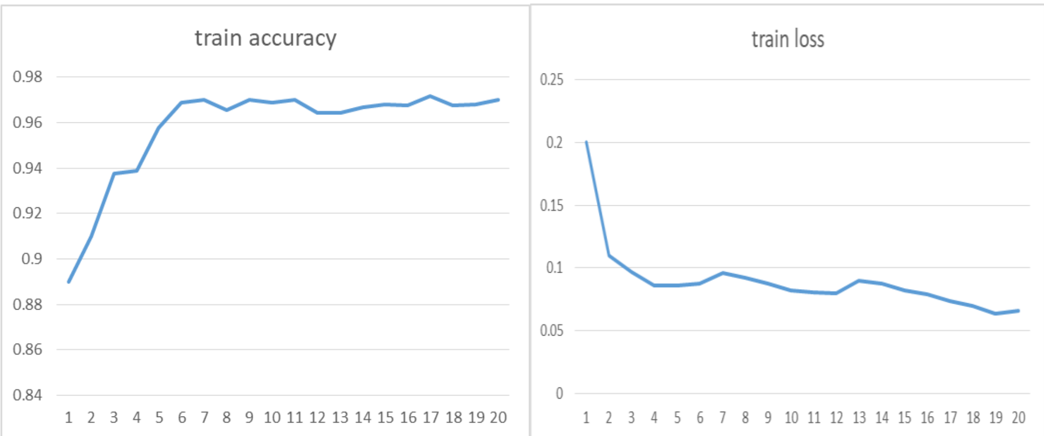

Fig 8: Training Accuracy and Training Loss of Training images

5. Conclusion and Future Work

Deep learning methods have showed considerable potential in the detection and diagnosis of pneumonia. Many research have shown that deep learning algorithms are effective at correctly diagnosing pneumonia from medical imaging data. Convolutional neural networks (CNNs) have

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demonstrated great sensitivity and specificity in the detection of pneumonia, sometimes even beating human radiologists. Deep learning-based pneumonia diagnosis has the potential to drastically enhance patient outcomes while lowering healthcare expenses.

There is still potential for improvement, even if deep learning algorithms have showed great promise in the detection and diagnosis of pneumonia. The creation of more effective and precise deep learning models that can identify pneumonia in a wider range of patient populations, including those with comorbidities or underlying lung problems, may be one area of focus for future study. Further enhancing the precision and timeliness of pneumonia diagnosis is the utilization of multi-modal data, such as fusing clinical and medical imaging data. In order to assure the moral and secure application of deep learning models in healthcare settings, it will be essential in the future to build interpretable AI models and interpretability approaches.

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