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Comparative Analysis of Pneumonia Detection using Deep Neural Networks on Chest X-ray Images

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ABSTRACT: Pneumonia is a lung infection that causes inflammation in the alveoli and remains a major health concern not only in India but also across the world due to its high mortality rate. Novel therapeutic strategies are required to address pneumonia, a complicated pulmonary disease. A number of medical diagnostic applications have recently seen a surge in the use of deep learning (DL) techniques. Examining how well DL models identify and categorize pneumonia from chest X-ray (CXR) pictures was the primary goal of this study. This study focuses on improving the performance of automatic pneumonia detection from chest X-ray images by optimizing model parameters in deep learning architectures. In this research, pre-trained convolution neural network (CNN) models, Resnet-50, VGG-19, EfficientNetB0, and a proposed DEEP neural network (DNN) models have been developed. The experimental results show that two models, one pre-trained (EfficientNetB0) and proposed DNN achieve strong classification performance, with accuracy 89.2% and 90% respectively. Proposed DNN model consistently delivers the highest accuracy and very good statistical parameter performance with KAPPA 82%, F1-score 94.0% and AUC 96.5%. These findings indicate that proposed DNN model is moderately an effective balance between accuracy and other parameters.

INTRODUCTION

The use of medical imaging has become fundamental in modern healthcare. Consequently, the diagnosis procedure is accelerated since doctors can more precisely localize the condition. Radiographs, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and a host of others are examples of common imaging methods [1]. All of these imaging techniques are widely used in medical practice for the common goal of finding tumors, fractured bones, and other health concerns. Because of its low cost and widespread availability, X-ray imaging has become the diagnostic imaging standard. Although advanced imaging methods such as computed tomography (CT) and magnetic resonance imaging (MRI) may produce extremely detailed and high-quality images of the body, they are also quite costly and may not be available at smaller or more distant institutions. This is why primary care physicians often recommend X-rays to patients seeking a diagnosis [2].

The lung parenchyma can become infected with pneumonia due to a number of factors, including pathogenic microbes, physical and chemical agents, immunologic injury, or certain drugs [3]. Several common ways pneumonia is categorized are as follows: (1) infectious pneumonia is classified as involving bacteria, viruses, mycoplasmas, chlamydial pneumonia, and other similar organisms; (2) non-infectious pneumonia is classified as involving immune-associated factors, aspiration pneumonia caused by physical and chemical factors, and radiation pneumonia; and (3) infectious pneumonia is classified using various pathogeneses. (2) Pneumonia can be caused by a variety of illnesses; subtypes include ventilator-associated pneumonia (VAP), community-acquired pneumonia (CAP), and hospital-acquired pneumonia (HAP) [4]. Among pneumonias, CAP is by far the most frequent [5]. The wide range of HAP-causing microorganisms increases the likelihood that they may develop resistance to treatment [6].

Recent years have seen a dramatic shift due to the use of deep learning to medical image analysis [7]. Due to their superior performance in image segmentation, classification, and feature extraction, deep convolutional neural networks (CNNs) have been essential in the advancement of automated medical imaging systems [8]. Deep convolutional neural networks (CNNs) have shown encouraging results in the diagnosis of pneumonia [9], leading some to believe that lung infections may be autonomously and rapidly recognized, which would have far-reaching consequences for patient management. However, current algorithms still struggle to deal with the intricate issues of pneumonia picture classification, despite these enhancements. Pneumonia symptoms are multifaceted and easily confused with those of other lung illnesses; furthermore, issues such as data imbalance and inconsistent imaging standards persist [10]. The inability of many existing models to differentiate between subtle but significant illness patterns has unfortunate consequences, including the possibility of inaccurate diagnosis [11]. The opaque nature of many deep learning models raises further questions about their interpretability and reliability in therapeutic settings [12]. Plus, it takes a lot of time and computing resources to train most models to get decent results [13]. The majority of CNN models rely on a single model to extract and analyze features, which may not be sufficient to grasp the intricate details of the data. Furthermore, scalability and generalizability are two features that are crucial for models to have in order to be used in the real world, yet they are absent from many models. Not to mention that a lot of strategies use attention processes without thinking about how those mechanisms could interact with one another.

There was some consideration for the different classes' training intensities in the proposed loss. To solve the problems of over-fitting and spatial sparseness caused by ordinary convolution operation, Liang et al. [14] used a residual connection network and dilated convolution in a backbone network model. This improved the model's generalizability. The final recall rate and F1 score for their model were 96.7% and 92.7%, respectively. Combining the CNN method described by Jain et al. [15] with transfer learning, which effectively used picture features learned from a large dataset, sped up the model's training and prevented it from falling into local minimum points. In addition, two models were proposed for the training set. Furthermore, the dataset used by Jain et al. originated from the popular firm and competition website Kaggle, which hosts several tournaments and attracts eager players aiming for higher ranks. The dataset is partitioned into three parts: the training part, which is utilized for model training; the validation part, for parameter modification; and the test part, for model generalizability confirmation.

Verma et al. [16] employed a variety of data pre-processing and data augmentation approaches, including randomly translating and rotating horizontally and vertically, to increase the CNN model's representation capacity and broaden the dataset. Their model ended up with an impressively high level of accuracy. Ayan et al. [17] used transfer learning and fine-tuning to train two standard CNN models, Xception-Net and VGG16-Net, to classify pictures that include pneumonia. A CNN architecture, an LSTM network, and two pre-trained models, ResNet152V2 and MobileNetV2, were suggested by the authors [18] as four effective CNN models. Another thing they did was compare and contrast the parameters that the two models had trained. All four of their models outperformed the 91% threshold in terms of accuracy, recall, F1-score, precision, and area under the curve (AUC).

METHODOLOGY

Figure 1 shows a prediction model that uses deep learning approaches to enhance the diagnosis of pneumonia using chest X-ray photographs. First, the whole dataset is loaded and resized according to the suggested method. After that, dataset was separated into three parts: training, testing, and validation. Data augmentation techniques has been employed to produce more training examples by randomly rotating, shifting, flipping, and zooming the original photos. This helped make the model more robust and prevented over-fitting. Our suggested DNN Model, together with Resnet-50, Efficient-NetB0, and VGG-19, are utilized in a DL method to extract deep features. In order to identify pneumonia, a network's design usually incorporates a series of layers for X-ray picture processing. The main objective of the architecture is to teach itself to differentiate between those who have pneumonia and those who do not using the visual data. In addition, the DL models' performance and analysis are laid out in depth.

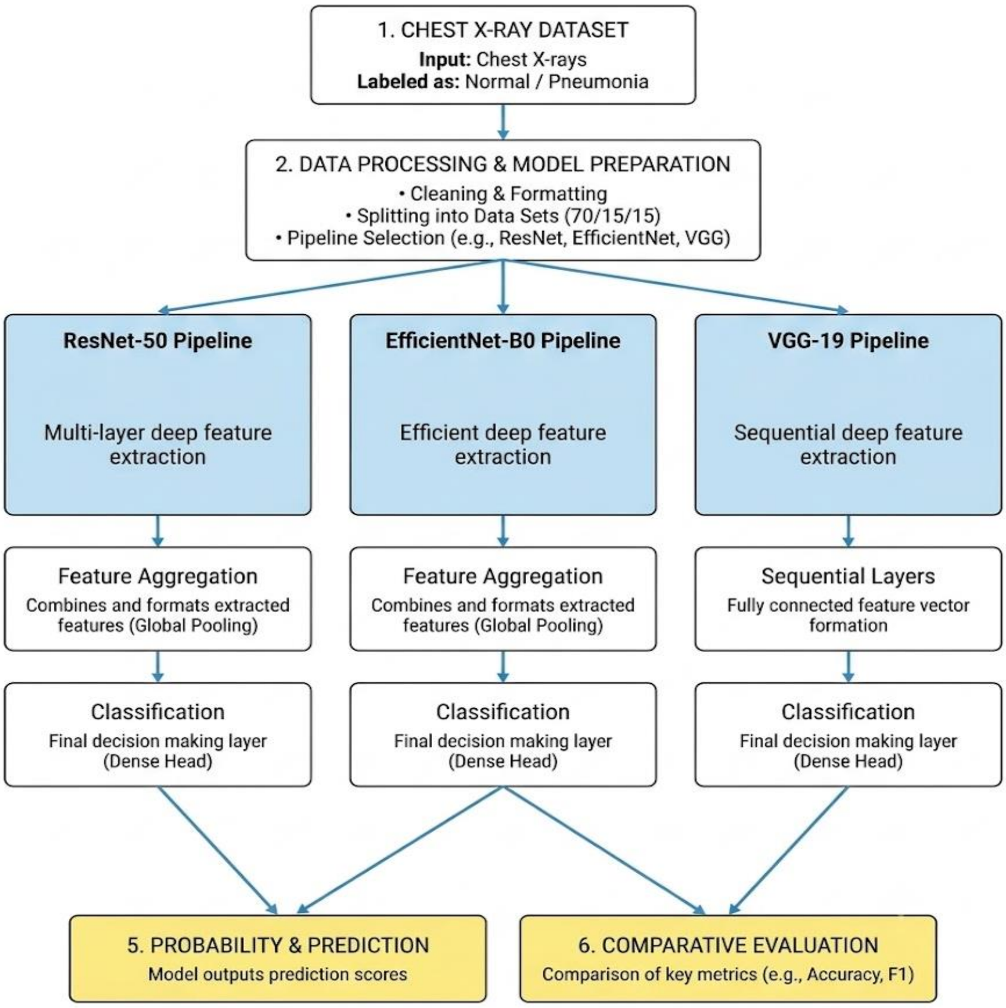

Figure 1: Deep learning Model for Pneumonia Detection and Analysis

DATA SET

Kaggle is the source of many deep learning competition datasets, including the one utilized in this work. The X-ray pictures of the chest used in this investigation came from an open-source database. Figure 2 shows a sample of both healthy and diseased pictures from the normal and pneumonia classes. In the collection of 5840 tagged photos, 3875 were positive for pneumonia and 1965 were negative. An augmentation is employed to produce additional pictures for the minority class, which were utilized solely during training, in response to the imbalance in the dataset. Using augmentation methods like horizontal flipping, picture rotation, brightness adjustment, and mild scaling can help reduce over fitting and boost data variety. Adding random horizontal flips (Random Flip (horizontal)) and random rotations (using Random Rotation (0.75)) between −0.75 and +0.75 radians, or around −25° to +25°, to the training set of data made the model more robust. In order to test the method, no produced picture was utilized. The scans ranged in pixel size and were all single-channel intensity pictures. In order to conform to the input requirements of the majority of CNN network designs, all photos were converted to 224x224x3 format.

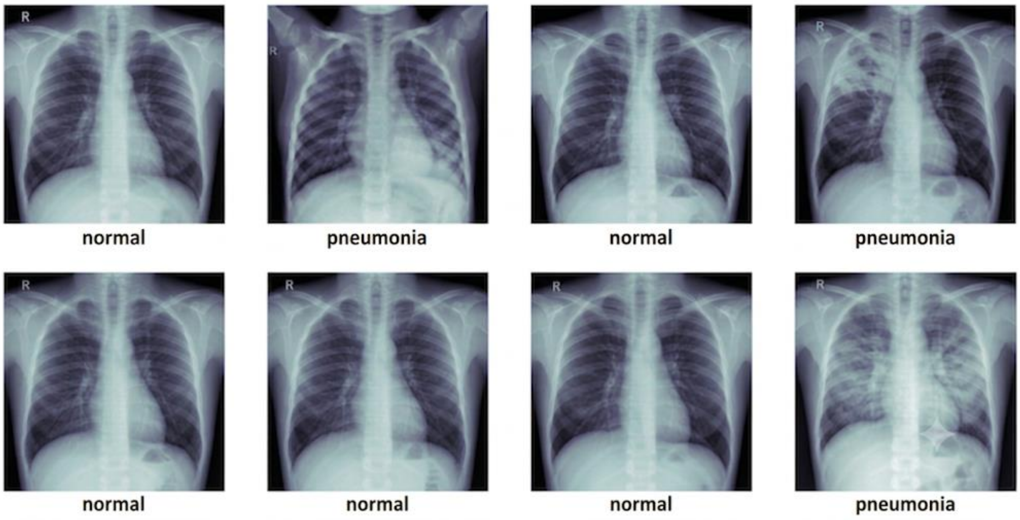

Figure 2: Sample images of Normal and Pneumonia

RESNET

One variant of the ResNet architecture, the ResNet-50 (residual neural network) uses 50 deep layers and was trained using at least one million photos from the ImageNet database. The "shortcut connections" shown in Figure 3 link the input of one layer to the output of another layer; this is how ResNet utilizes residual blocks. The output of the stacked layers F(x) is enhanced by the identity function x, which is added to it via the shortcut connections. This function returns its input as output. The ability to skip layers is a benefit of these residual blocks as it reduces the degradation problem that occurs with a large model [19].

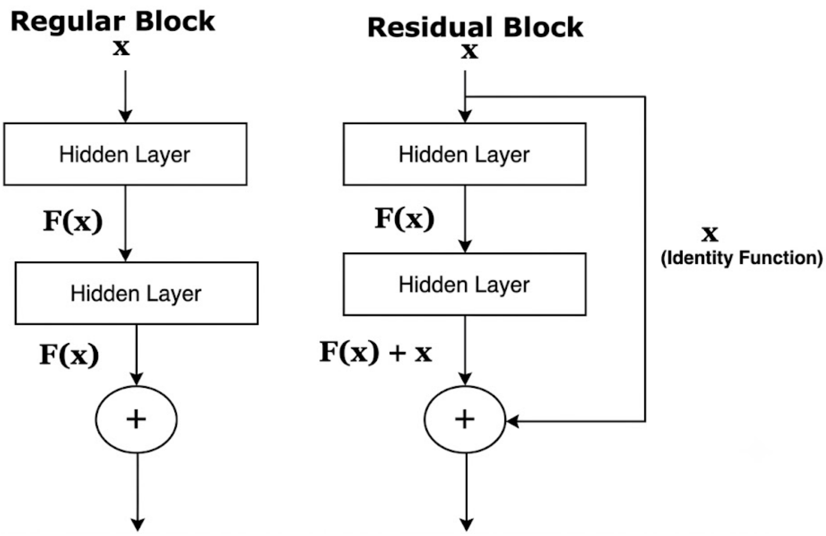

Figure 3: Regular stacked network and Residual block in RESNET architecture

Figure 4 shows the results of a ResNet50 model that uses deep learning and chest X-ray images to predict pneumonia. Their design allows them to understand nuanced details and complicated patterns since it incorporates residual connections. After being trained on a large dataset, ResNet50 models can accurately detect visual signs of pneumonia.

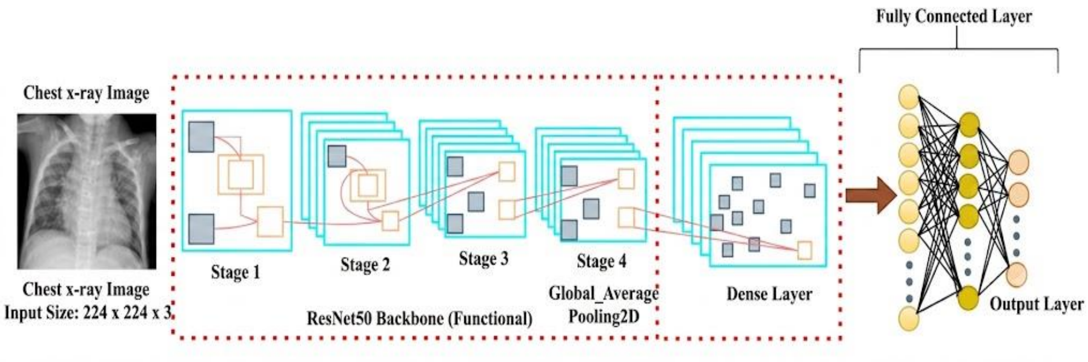

Figure 4: Res-Net 50 Model for pneumonia detection

EFFICIENTNET-B0

Figure 5 shows that EfficientNet-B0 is able to diagnose pneumonia with a high degree of precision by utilizing 16 MB-Convolution bottleneck blocks and compound scaling to pick up on even the most minute pulmonary opacities in chest X-rays. A Global Average Pooling head handles 224 × 224 x 3 scaled pictures in its lightweight design, directly mapping 1,280 feature mappings to a probability score for binary classification [20].

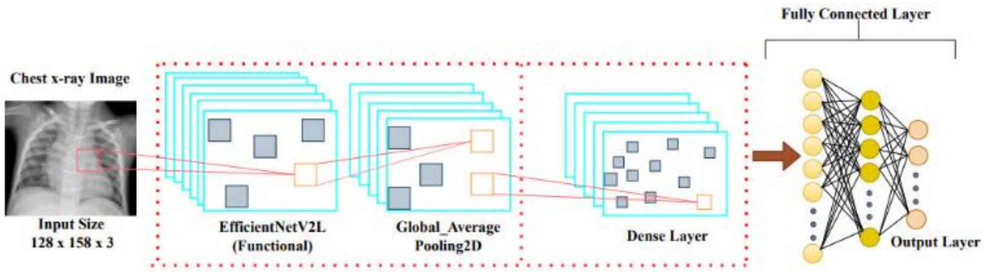

Figure 5: Efficient-Net Model for pneumonia detection

VGG-19

Figure 6 shows the traditional 19-layer deep convolutional neural network VGG-19, which extracts rich visual patterns from chest X-rays for pneumonia diagnosis using a simple sequential stack of 3x3 filters. Although architecturally simple, it is computationally costly due to its reliance on two hefty 4,096-unit fully linked layers before to its final output stage, in contrast to recent bottleneck architectures [21].

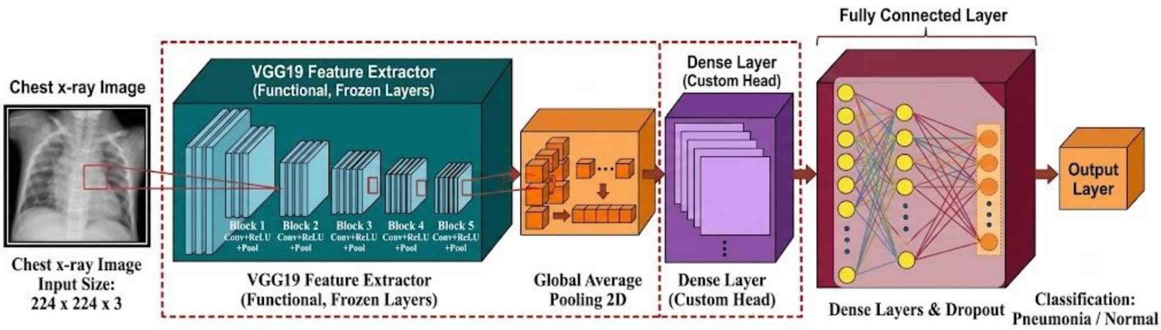

Figure 6: VGG-19 Model for pneumonia detection

Table 1: Summary of Deep Learning Model with layers

Architecture	Depth / Layers	Key Structural Advantage	Classifier Head Strategy
ResNet-50	50 Layers	Residual identity skip connections solve vanishing gradients in deep networks.	Global Average Pooling (2048 maps) → Dense(512) → Dropout(0.5) → Sigmoid
EfficientNet-B0	16 MB Conv Blocks	Compound scaling uniformly balances network depth, width, and image resolution.	Global Average Pooling (1280 maps) → Dense(512) → Dropout(0.5) → Sigmoid
VGG-19	19 Layers (16 Conv + 3 FC)	Simple sequential architecture using small 3×3 convolution filters throughout.	FC-4096 → FC-4096 sequential vectors → Final Dense Output Layer

DEEP NEURAL NETWORK (DNN)

To enable the network to learn more abstract and high-level characteristics from the data, the number of filters and complexity often grow as the design develops. Fully linked (dense) convolutional layers that aggregate the learnt data and decide if a chest X-ray shows pneumonia may be part of the design. In order to mimic intricate radiological patterns, Deep Neural Networks (DNNs) employ several hidden convolutional layers to handle 224x224 x3 chest X-ray data. From labeled training photos, the network extracts important visual traits including lung abnormalities and pulmonary opacities to diagnose pneumonia. As shown in Table 2, the global average pooling, dense layer, and dropout classifier head receive the extracted features and use them to translate visual patterns to a final diagnosis. An effective automated diagnostic tool, the system can reliably anticipate unseen chest X-rays after training.

Table 2: Parameters used in the proposed DNN Model

DNN	Parameters
Image dimension	$224 \times 224 \times 3$
Dense Layer 1	8 neurons+ Relu
Dense Layer 2	16 neurons + Relu
Dense Layer 3	32 neurons + Relu
Dense Layer 4	48 neurons + Relu
Dense Layer 5	64 neurons + Relu
Dropout Layer	Drop out 0.5
Output Layer	2 neurons + Softmax

PERFORMANCE EVALUATION

A DNN model that has been both developed and trained before is used in the proposed system to identify cases of pneumonia. There are a number of standard performance indicators (SPIs) that may be used to evaluate a system's accuracy, sensitivity, and overall reliability; these SPIs are based on commonly used statistical models [22].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1 Score} = \frac{2 * \text{Recall} * \text{Precision}}{\text{Precision+Recall}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{5}$$

$$\kappa appa = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

- Observed Agreement (p_o) :

$$p_o = \frac{TP + TN}{N} \tag{7}$$

- Expected Agreement (p_e) :

$$p_e = \frac{(TP+FP)(TP+FN) + (TN+FP)(TN+FN)}{N^2} \tag{8}$$

Where, $N = TP + TN + FP + FN$

RESULT AND DISCUSSIONS

For the computation processes, intel core i5-7gen CPU, with 16 Gb system memory for implementing the DNN models for the detection of pneumonia. Data set from the kaggle , which is publically available for the researchers has been used in this work. At the time of feature extraction this image of both the class are resized to 224 x 224 x 3. Here, 5840 images have been used to conduct the experiment. Out of the available image 70%, 15% and 15% are used for train, test and validation purpose. The statistical parameters like Accuracy, precision, recall have been computed and tabulated. Detecting pneumonia using functional chest X-ray images involves training a model to accurately classify images as depicting individuals with pneumonia or Normal. During the training process, data is split into training and validation sets, with the model learning from the training data and fine-tuning itself based on validation performance. Training and validation accuracy, along with loss metrics and the number of epochs, provide insights into the model's learning progress and generalization capability. Training accuracy measures how well the model performs on the training data, while validation accuracy gauges its performance on previously unseen validation data.

PRE-TRAINED MODELS

The ROC curve in Figure 7 was used to check how well the model separated Normal from pneumonia. It compares the true positive rate and false positive rate at different threshold values. A better classifier gives a curve closer to the top-left side of the graph. The area under the curve is called AUC. In this work, the AUC value was more than 0.5 and curves are above the diagonal line, which shows that the models separated both classes clearly under the tested conditions. Figure 7 shows the ROC curve of the pre-trained models. The result supports the models because it indicates strong classification performance on the tested data with higher AUC values. Among the pre-trained models efficientnetB0 achieved highest AUC value (0.913) and the lowest AUC value (0.825) for VGG-19 model. High accuracy has been observed for efficientnetB0 among the pre-trained DL models.

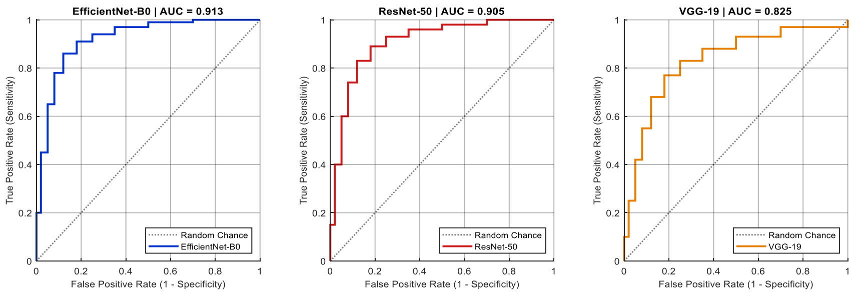

Figure 7: ROC plot for pneumonia detection using pre-trained models

The confusion matrix was used to check the actual and predicted class labels. It gives a simple view of correct and wrong classifications. Figure 8 shows the confusion matrix for all the pre-trained models used in the research. The diagonal values show the correct classifications. Since the off-diagonal values are small, there were minimal wrong classifications in this test. As per the observation for normal class minimum wrong classification (20) was observed for efficientnetB0 and highest wrong classification (45) is for VGG-19 model. Hence high accuracy has been observed for efficientnetB0 among the pre-trained DL models.

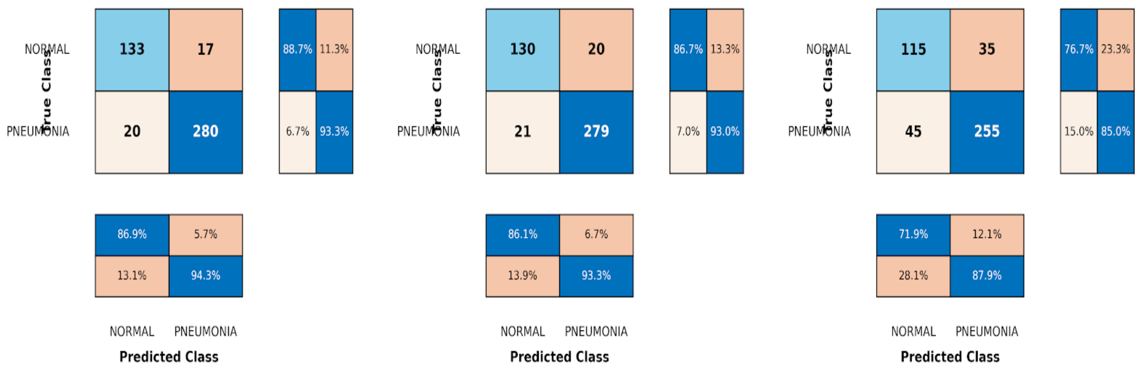

Figure 8: Confusion matrix for pneumonia detection using pre-trained models

PROPOSED DNN MODEL

Typically, as training progresses, both training and validation accuracy increase, but validation accuracy may plateau or even decrease if the model starts over-fitting. Validation loss indicates how well the model's predictions match the true labels in the validation set. AmAP curve with high and consistent values above 90 as in figure 9, indicates that the proposed DNN model excels in both precision and recall across various thresholds. This implies that the model is accurately identifying and retrieving relevant instances while minimizing false positives, resulting in a highly efficient classification process. Moreover, when the loss is near zero, it demonstrates that the model is effectively learning from the training data. Loss quantifies the disparity between the model's predictions and the actual labels; a lower loss value indicates that the predictions closely match the ground truth, underscoring the model's capability to capture intricate patterns in the data. This combination of high efficiency and minimal loss underscores the model's competence in classification tasks and underscores its potential for reliable and accurate predictions. As the mAP curve is plotted, it visually showcases the model's precision-recall trade-off. An ideal mAP curve would rapidly increase and smoothly approach high precision as recall rises. This indicates the model's ability to maintain high accuracy while identifying a larger proportion of relevant instances.

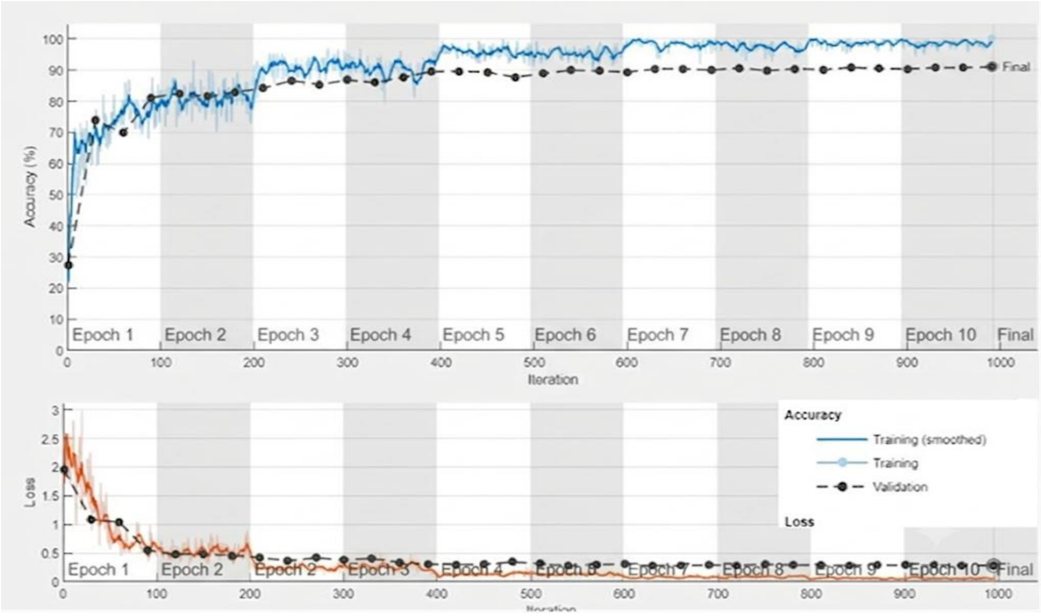

Figure 9: mAP curve for pneumonia detection using proposed DNN model

For the current work, classes pneumonia and Normal have been selected. The metrics are calculated and tabulated for each class in Table 3. The Pneumonia class has the best accuracy (98.9%) compare to Normal class which has an accuracy of 97.7%. Figure 10 indicates the Confusion Matrix's ROC for the proposed DNN model. Diagonal points, which are colored in blue, show the correctly categorised samples, whereas the non-diagonal points show the incorrectly identified face samples. The result supports the DNN model because it indicates strong classification performance on the tested data with higher AUC value (0.9647).

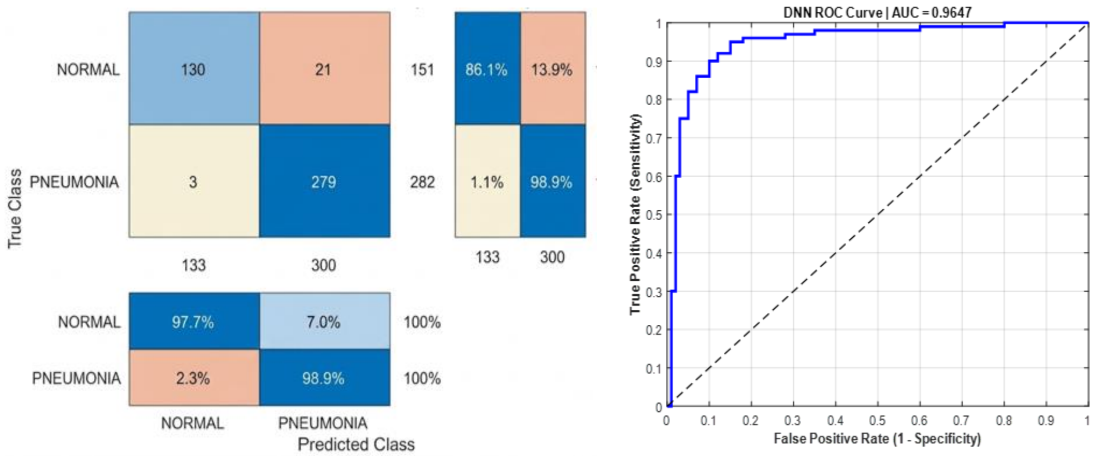

Figure 10: Confusion matrix and ROC for pneumonia detection using DNN model

A Comparative Analysis on pre-trained model with proposed DNN model has been tabulated as in table 3 and the same has been plotted in figure 11 for the detection of pneumonia. All the models do a great job in detecting the presence of pneumonia in the X-ray. The results indicate that proposed model is moderately better than that of the pre-trained by considering the parameters like accuracy, mAp, F1-Score, Precision, and recall. Between the pre-trained models efficientNetB0 attained an accuracy of 89.2% and lowest accuracy of 82.2% in VGG-19 model. Among the DL models Proposed model achieved highest accuracy of 92.0% in comparison with all other model.

Table 3: Comparison of proposed Model with pre-trained models

Performance Metric	Proposed DNN	EfficientNet-B0	ResNet-50	VGG-19
Accuracy	0.920	0.892	0.857	0.822
Recall	0.940	0.910	0.873	0.850
Specificity	0.880	0.853	0.820	0.767
Precision	0.940	0.925	0.907	0.879
Negative Predictive Value	0.880	0.826	0.764	0.719
F1-Score	0.940	0.918	0.890	0.864
False Positive Rate	0.120	0.147	0.180	0.233
Area Under Curve	0.965	0.913	0.905	0.825
MCC	0.820	0.758	0.681	0.605
KAPPA	0.820	0.757	0.680	0.604

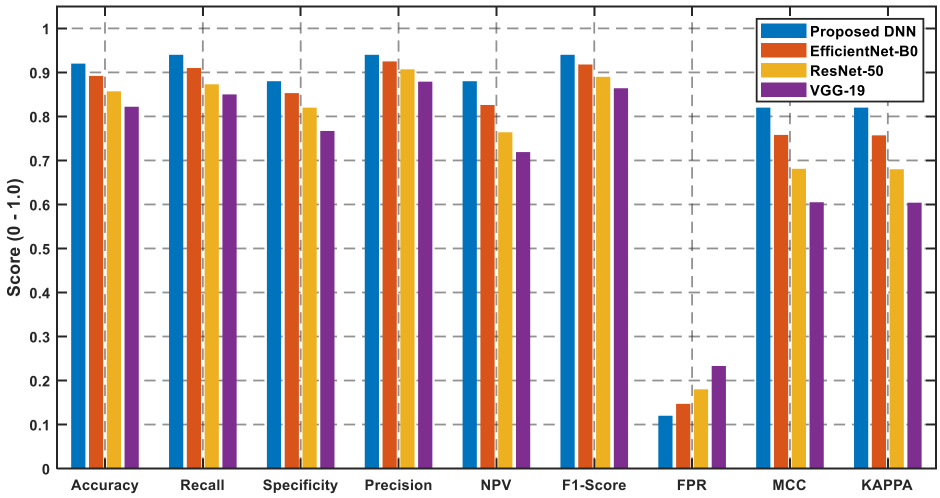

Figure 11: Performance Comparison of proposed Model with pre-trained models

CONCLUSION

The proposed research is carried out to demonstrate the efficacy and accuracy of pneumonia diagnosis using pre-trained and proposed DL on chest X-ray image datasets. Because of the promising results of deep learning methods, the publically available dataset was used in this work to detect the presence of pneumonia.

In the research highest accuracy of 89.2% from efficientNetB0 was observed among the pre-trained models. In the proposed approach highest accuracy of 92.0% has been obtained in the identification of pneumonia using proposed DNN. In both the case ROC-AUC value more than 0.99 has been achieved. Overall, proposed DNN provides the best performance among the data towards the detection of pneumonia. From the results it concludes that proposed model is significantly better than that of the pre-trained models. According to the developers, the suggested diagnostic system provides top doctors an accurate and rapid diagnosis. Future work can focus on optimizing model against data capacity and time complexity for faster processing system.

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