Pneumonia Detection Using Deep Learning Models With Chest X-rays

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***Abstract*— Pneumonia is a lung infection that makes it difficult to breathe. It occurs when germs such as bacteria and viruses clog the lungs with fluid. This results in symptoms such as cough, fever, and difficulty breathing. To address these issues, this study employs Chest X-rays, which have 5947 X-ray images by DL techniques such as DenseNet201, EfficientNetB0, InceptionV3, AlexNet, and ResNet50 for automatic detection of pneumonia illness, which has 2 classes of normal and pneumonia. The models are trained and tested for detection. DenseNet201 with an accuracy of 97% excellent performance and with good sensitivity and specificity in the ROC curve after it has surpassed more than 50 epochs. EfficientNetB0 has an accuracy of 96%, which is quite decent. The InceptionV3 model also had 96% accuracy. The AlexNet model performed to the extent of around 93%. The ResNet50 model also attained 96% accuracy which is comparable to EfficientNetB0 and InceptionV3. The findings verify that DL is a promising solution for the detection of pneumonia disease, being more efficient and reliable compared to traditional methods. It facilitates correct disease identification, which assists doctors in preventing it.**

Keywords— Deep learning, Identification, Chest X-rays, Disease Detection.

INTRODUCTION

Pneumonia causes about 16% of all under-five deaths globally, and it is the global number one cause of death among under-five children. Two billion people in the world are facing pneumonia disease every year, overall. Pneumonia is an infection of the lungs, which may be brought about by either bacteria or the viruses. Fortunately, this infectious disease is caused due to bacteria or viruses can be treated very effectively using antibiotics and antiviral medicine. Pneumonia is having several kinds like mycoplasma, viral, bacterial, and other forms of pneumonia. Bacterial pneumonia is caused due to bacteria or fungi. It can affect for all ages as who are all addicted to smoking, alcoholic and recent surgery patients, asthma, viral infection, and people with a weak immune system.

Mostly, highly experienced experts use a chest x-ray radiograph to find pneumonia. The diagnosis is then confirmed by medical history, and blood tests usually it appears as an area or patches of increased opacity on chest x-ray radiograph. Especially in rural areas, low-resource countries also have a shortage of trained radiologists. So, computer-aided diagnosis systems are absolutely necessary since they help radiologists promptly distinguish several forms of pneumonia from the collected chest X-ray images. Pneumonia ailment is an efficient way for feature extraction of collecting features from image dataset for diagnostic a persons pneumonia or absence, we used many Deep Convolutional Neural Network transfer learning techniques including AlexNet, DenseNet201, ResNet50, EfficientNetB0, and Inception-V3. We have trained by using chest X-ray image dataset and assessed our models. The models we have trained using deep learning models are evaluated on a number of performance metrics, including accuracy, precision, recall, F1-score, AUC-score, confusion matrix, training and validation accuracy, training and validation loss, and ROC curve.

I. LITERATURE SURVEY

T. Gabruseva [1] This study employs computational techniques such as squeezing, singleshot detectors, and deep convolutional neural networks to X-ray image detection of pneumonia-affected lung areas. A Pant. [2] This study proposes an AI approach to enhance pneumonia identification from chest X-ray pictures by combining two deep learning models, ResNet 34-based U-Net and EfficientNet B4-based U-Net. The model improves recall and precision while reducing class imbalance problems by utilizing convolutional neural networks and sophisticated loss functions like Dice Loss. Patrik Szepesi [3] A dataset of 5,856 pediatric chest X-ray pictures was used to train and assess this model. Its accuracy was 97.2%, while its precision and recall values were higher than 97%. In contrast to existing deep learning models such as VGG-16, ResNet50, and DenseNet which provide accurate pneumonia classification while guaranteeing computational efficiency. Amit Kumar Jaiswal [4]. The current work suggests a deep learning solution in the form of Mask R-CNN, a strong neural network architecture, to identify and localize pneumonia by chest X-rays with greater performance. Analyzing the capability of artificial intelligence in the analysis of medical images. Hashmi MF. [5] The research introduces a model in which pre-trained deep learning models are employed as feature extractors, while an artificial neural network acts as the ultimate classifier. S. MASAD [6] through the use of convolutional neural networks with classifiers such as random forest, k-nearest neighbor, and support vector machine. 5,852 chest X-ray pictures that were divided into training, validation, and test sets made up the data used in this investigation. With an accuracy of up to 99%, Softmax and SVM were the most accurate classifiers tested. Lal. [7] Deep convolutional neural networks are used by studies such as VGG16, VGG19, Inception-V3, and SqueezeNet for feature extraction, along with classifiers such as SVM, KNN, and ANN. The present model, which is trained on chest X-ray and CT scan data, yields high accuracy with the best results using Inception-V3 and ANN. Bashar A. [8]. Suggest automatic transfer learning using models such as VGG16, VGG19, and DenseNet. The paper shows that image enhancement and data augmentation techniques improve classification accuracy, with VGG16 having the best accuracy of 95.63. S. Basu. [9] It proposes Domain Extension Transfer Learning, this model classes images into four: normal, pneumonia, other diseases, and COVID-19, with an accuracy of 90.13%. The research also uses a Gradient Class Activation Map to see which lung areas affect the model's predictions. A. B. Godbin. [10] The paper discusses some of the top deep learning models like AlexNet, DenseNet, and ResNet to examine their performance in classification models. Wang. [11] It emphasizes the effectiveness of convolutional neural networks particularly SqueezeNet, for feature extraction like neural networks, decision trees, and random forests. The research proves that the classifier with the neural network achieved the highest accuracy of 97.24%, the power of AI in medical imaging. Siddiqi R. [12] The research talks about different solutions, including transfer learning, data augmentation, and visualization methods like Grad CAM to enhance model performance. Convolutional neural networks are important in feature extraction, increasing the accuracy of computer-aided pneumonia detection.

II. PROPOSED METHODOLOGY

This section outlines the methodology used for detecting pneumonia disease using deep learning models. The process includes the dataset used, the feature extraction techniques applied, and a detailed explanation of the models: ResNet50, InceptionV3, EfficientNetB0, DenseNet201, and AlexNet. The methodology is designed to accurately classify binary classes: normal and pneumonia.

A. Dataset used

In this experiment, the dataset is given, with a set of images of X-ray chest images. Normal: The images of the X-ray chest show no signs of disease. Pneumonia: The images of the x-ray chest show the signs of the disease. It provides grayscale images, and the dataset was divided using an 80% 20% split to ensure it is of robust evaluation. The image sizes are standardized by resizing and augmented so that all images in the dataset appear with different angles.

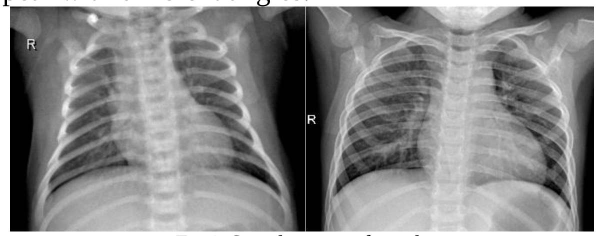


Fig.1. Sample images from dataset

B. Feature Extraction Techniques

Feature extraction is useful to improve the performance of machine learning models by changing raw image data into meaningful patterns that can be classified. In this project, different feature extraction techniques were utilized**:**

Augmentation Technique

By creating training data rather than obtaining new samples, data augmentation can raise the classification accuracy of deep learning models. Here, three different methods of data augmentation-Rotation, Scaling, and Translation were employed to produce enhanced training sets, as shown in the Figure.

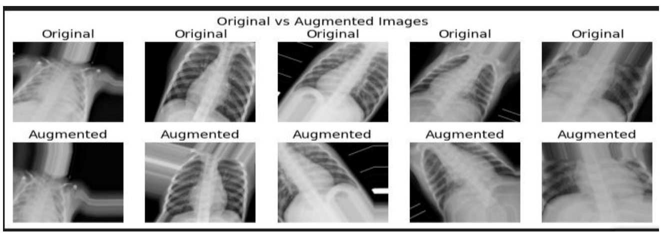


Fig.2. Original vs Augmented Images

C. Types of models used

The models of classification used were ResNet50, InceptionV3, EfficientNetB0, DenseNet201, and AlexNet. Since models are tackled with relatively different methodologies in classification, this has brought on an immensely interesting comparison that can be achieved through the test of performance on the dataset of pneumonia disease.

A. ResNet50:

ResNet50 is a residual deep CNN that employs residual learning using skip connections to prevent the vanishing gradient issue. It has 50 layers with batch normalization and ReLU activation, which helps improve stability. Fine-tuned on ImageNet, it is tuned for transfer learning-based pneumonia detection. A sigmoid activation function is beneficial for binary classification (NORMAL and PNEUMONIA). With the depth, ResNet50 trains efficiently. Model Checkpoint stores the top model for utmost accuracy.

B. InceptionV3:

The InceptionV3 is a deep CNN that enhances feature extraction by factorized convolutions and efficient grid size reduction. InceptionV3 is pre-trained on ImageNet and tuned for the detection of pneumonia. Inception module is helpful in multi-scale feature extraction to enhance classification accuracy. A sigmoid activation function at the last layer enables binary classification (NORMAL or PNEUMONIA). Model performance is assessed through ROC curves and AUC scores.

C. EfficientNetB0:

EfficientNetB0 is a lightweight deep model that exchanges accuracy and efficiency with a compound scaling strategy to scale depth, width, and resolution. Pre-trained on ImageNet, and fine-tuned to classify pneumonia in chest X-rays. Fewer parameters than regular CNNs with good accuracy. There is a binary classification supported by a sigmoid activation function (NORMAL or PNEUMONIA). Model checkpoint is saved with the optimal model for the best performance.

D. DenseNet201:

DenseNet201 is a deep network model that facilitates improved gradient flow and feature reuse via dense layer-to-layer connections. Fine-tuned on ImageNet, it is fine-tuned to pneumonia diagnosis using transfer learning. It is less parameter-heavy than ResNet and thus computationally more efficient. To prevent overfitting, it employs Global Average Pooling instead of fully connected layers.A sigmoid activation function supports binary classification (NORMAL or PNEUMONIA).

E. AlexNet:

Image classification using ReLU activation and dropout to have more stable training. It performs binary classification (NORMAL vs. PNEUMONIA) using three fully connected layers with sigmoid activation and five convolutional layers.Data augmentation (flipping, shifting, rotation) helps generalization, whereas dropout mitigates overfitting. AlexNet is computationally intensive despite its success because it contains large fully connected layers. The optimal model is stored by Model Checkpoint to maximize accuracy.

F. Performance Metrics:

- Accuracy: The receiver operating characteristic curve, which graphs the TPR on the Y-axis against the false positive rate on the X-axis, is used to determine accuracy. A tidy summary of the curve's properties in a single number can be found here. AUC values of 0.5 indicate poor accuracy, 0.7 indicate acceptable accuracy, and 0.85 indicate outstanding accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision: This metric measures how many of the positive predictions were correct. A higher precision means that there are fewer false positive errors.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

- Recall: Recall determines how many true positives the model can identify correctly. If recall is high, it means there are fewer false negatives.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

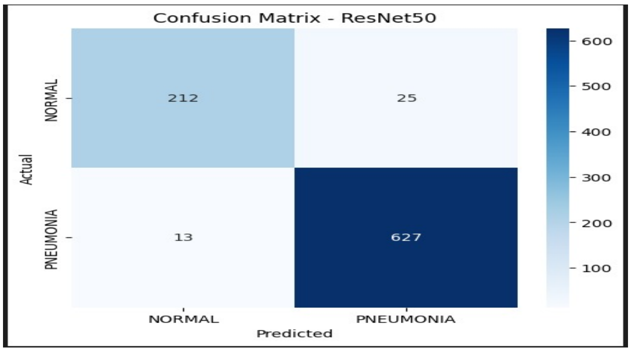
- F1-Score: The F1 score is determined by measuring the precision and recall and enforces the distribution over precision and recall, so that the overall score takes into consideration both precise matching and all the correct matches found.

$$F_{Score} = \frac{2 * Recall * Precision}{Recall + Precision} \quad (4)$$

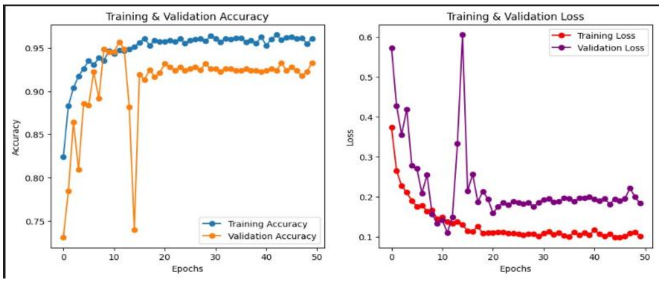
IV. EXPERIMENTAL RESULTS

A. Experimental results for ResNet50

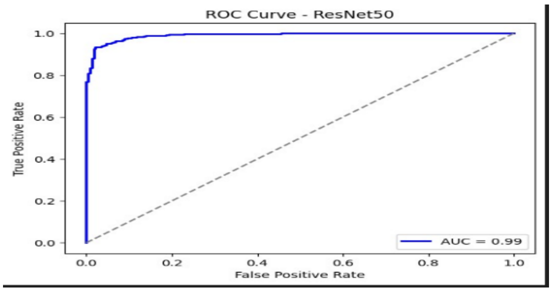
The ResNet50 model showed moderate performance on the test set for pneumonia disease detection. It performed well for all the methods like "Normal" (F1-score: 0.92) and "Pneumonia" (F1-score: 0.97), "Normal" (Recall: 0.89 and "Pneumonia" (Recall: 0.98) and "Normal" (Precision: 0.94) and "Pneumonia" (Precision: 0.96). The overall accuracy was 0.96.



(A)



(B)

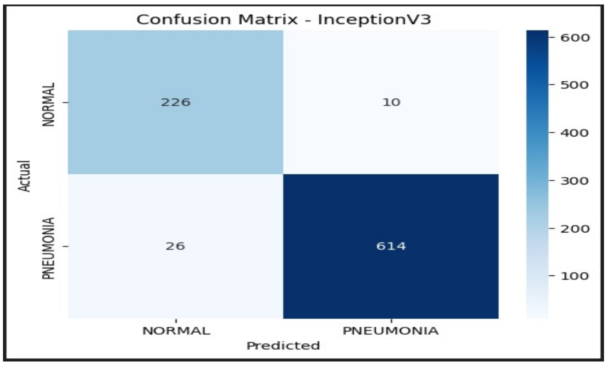


(C)

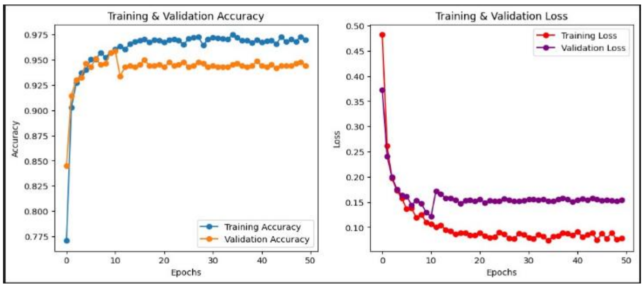
Fig.3. Confusion matrix (A) Training and Validation Accuracy and loss (B) and ROC Curve (C) for ResNet50

B. *Experimental results for InceptionV3*

The InceptionV3 model showed moderate performance on the test set for pneumonia disease detection. It performed well for all the methods like "Normal" (F1-score: 0.93) and "Pneumonia" (F1-score: 0.97), "Normal" (Recall: 0.96) and "Pneumonia" (Recall: 0.96) and "Normal" (Precision: 0.90) and "Pneumonia" (Precision: 0.98). The overall accuracy was 0.96.



(A)



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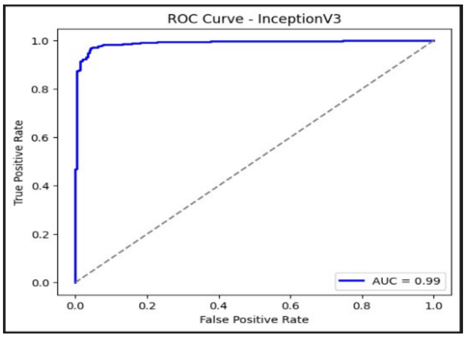
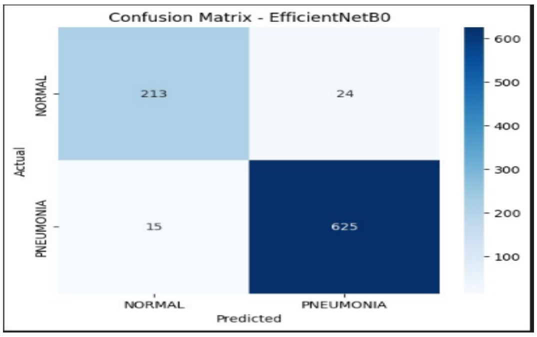


(C)

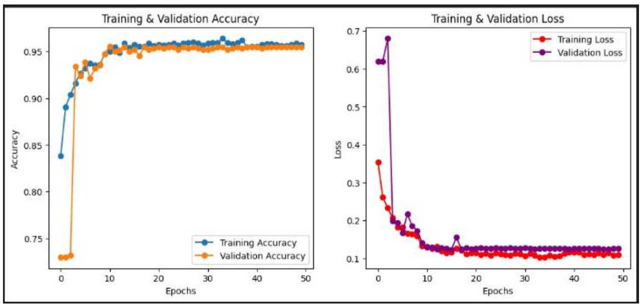
Fig.4. Confusion matrix (A) Training and Validation Accuracy and loss (B) and ROC Curve (C) for InceptionV3

C. *Experimental results for EfficientNetB0*

The EfficientNetB0 model showed moderate performance on the test set for pneumonia disease detection. It performed well for all the methods like "Normal" (F1-score: 0.92) and "Pneumonia" (F1-score: 0.97), "Normal" (Recall: 0.90) and "Pneumonia" (Recall: 0.98) and "Normal" (Precision: 0.93) and "Pneumonia" (Precision: 0.96). The overall accuracy was 0.96.



(A)



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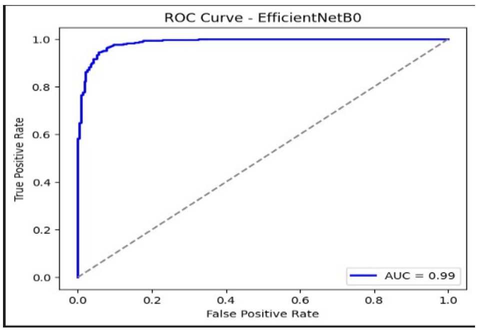
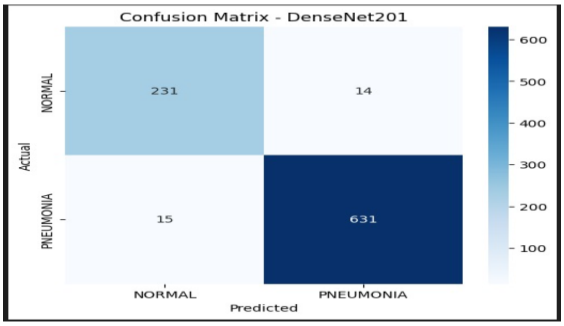


(C)

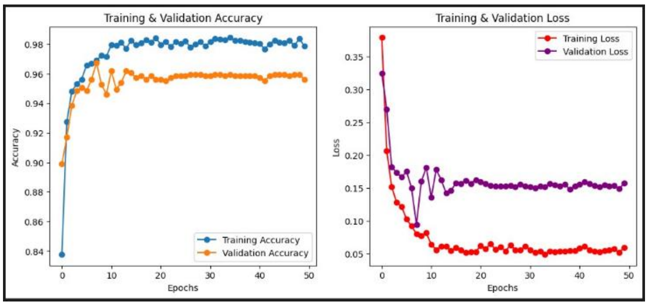
Fig.5. Confusion matrix (A) Training and Validation Accuracy and loss (B) and ROC Curve (C) for EfficientNetB0

D. Experimental results for DenseNet201

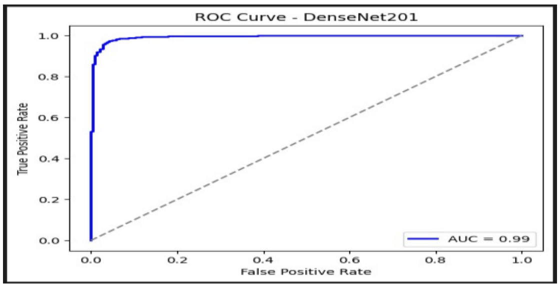
The DenseNet201 model showed Excellent performance on the test set for pneumonia disease detection. It performed well for all the methods like "Normal" (F1-score: 0.94) and "Pneumonia" (F1-score: 0.98), "Normal" (Recall: 0.94) and "Pneumonia" (Recall: 0.98) and "Normal" (Precision: 0.94) and "Pneumonia" (Precision: 0.98). The overall accuracy was 0.97.



(A)



(B)

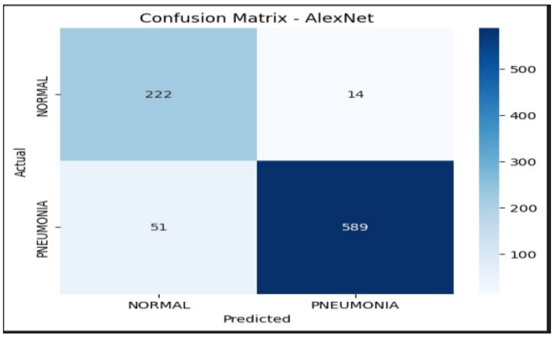


(C)

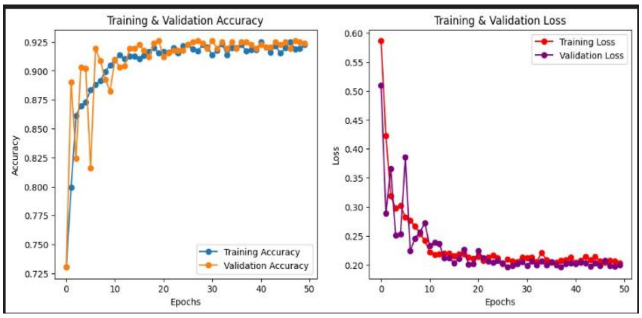
Fig.6. Confusion matrix (A) Training and Validation Accuracy and loss (B) and ROC Curve (C) for DenseNet201

E. Experimental results for AlexNet

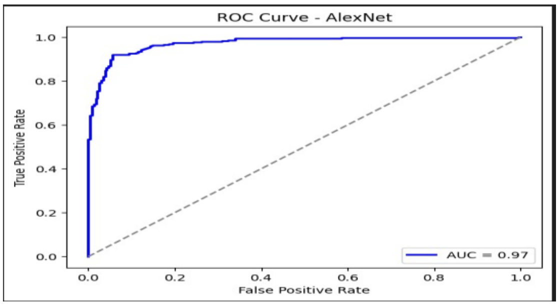
The AlexNet model showed low performance on the test set for pneumonia disease detection. It performed well for all the methods like "Normal" (F1-score: 0.87) and "Pneumonia" (F1-score: 0.95), "Normal" (Recall: 0.94) and "Pneumonia" (Recall: 0.92) and "Normal" (Precision: 0.81) and "Pneumonia" (Precision: 0.98). The overall accuracy was 0.93.



(A)



(B)



(C)

Fig.7. Confusion matrix (A) Training and Validation Accuracy and loss (B) and ROC Curve (C) for AlexNet

TABLE. PERFORMANCE ANALYSIS OF PROPOSED MODELS

Model	Types	Precision	Recall	F1-Score	Support	Accuracy
Dense Net201	Normal	0.94	0.94	0.94	245	0.97
	Pneumonia	0.98	0.98	0.98	646	
Efficient NetB0	Normal	0.93	0.90	0.92	237	0.96
	Pneumonia	0.96	0.98	0.97	640	
InceptionV3	Normal	0.90	0.96	0.93	237	0.96
	Pneumonia	0.98	0.96	0.97	640	
AlexNet	Normal	0.81	0.94	0.87	236	0.93
	Pneumonia	0.98	0.92	0.95	640	
ResNet 50	Normal	0.94	0.89	0.92	237	0.96
	Pneumonia	0.96	0.98	0.97	640	

V. CONCLUSION

This study aimed at the detection of pneumonia disease by developing and testing DL models using a dataset of chest X-ray images, consisting of two different classes: Normal and Pneumonia. By a systematic process of feature extraction, and model training, we were able to successfully apply five different algorithms ResNet50, InceptionV3, EfficientNetB0, DenseNet201, and AlexNet. Our work proves that the DenseNet201 model with an overall accuracy of around 97% in testing. The experimental results also indicated that EfficientNetB0, InceptionV3, and ResNet50 attained good accuracies of 96% and AlexNet attained minimum accuracy of 93%. The successful implementation of these models indicates that with the assistance of AI features these can be implemented for medical purposes. Future work should investigate the incorporation of more varied datasets and other feature extraction methods to further enhance classification accuracy.

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