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PneumoSense-Detection of Pneumonia using AI

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***Abstract*— Pneumonia is a potentially life-threatening lung infection that requires timely and accurate diagnosis. This project aims to automate pneumonia detection from chest X-ray images using EfficientNet, a cutting-edge convolutional neural network architecture. The proposed system uses deep learning to analyze medical images and classify them as pneumonia-positive or normal with high accuracy. EfficientNet is chosen due to its optimized performance in terms of speed and accuracy with fewer parameters. The model is trained on a large dataset of annotated chest X-rays, using advanced image preprocessing and augmentation techniques. Through rigorous training and evaluation, the system demonstrates reliable diagnostic performance, This AI-driven approach offers a scalable and efficient solution to reduce diagnostic errors and improve patient outcomes.**

***Keywords*— Pneumonia Detection, EfficientNet, Deep Learning, Convolutional Neural Network (CNN), Chest X-ray, Medical Image Classification, Artificial Intelligence, Image Preprocessing, Data Augmentation, Healthcare AI.**

I. Introduction

Artificial intelligence is rapidly transforming the healthcare sector, especially in areas like diagnosis, patient care, and disease prevention. One of the most promising applications is in medical imaging. Pneumonia, a serious respiratory infection, continues to be a major global health concern, particularly affecting young children and the elderly. Early and accurate diagnosis is crucial, but traditional methods—such as manually analyzing chest X-rays—can be time-consuming and often depend heavily on the expertise of radiologists. In many cases, this leads to delays, inconsistencies, or even misdiagnosis.

To address these challenges, this study presents an AI-based pneumonia detection system that uses deep learning techniques to analyze chest X-ray images.

The model is built using the EfficientNet architecture, which is known for delivering high accuracy while maintaining computational efficiency. By leveraging this approach, the system aims to provide reliable and precise detection of pneumonia.

Unlike conventional rule-based systems, which struggle to handle complex image patterns and large datasets, this model learns directly from the data. EfficientNet is particularly effective because it scales the network in a balanced way—optimizing its depth, width, and resolution—to achieve strong performance without excessive computational cost.

In addition to the model itself, a user-friendly mobile application has been developed to make the system practical for real-world use.

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The interface, initially designed using Figma, focuses on simplicity and ease of navigation, allowing healthcare professionals to quickly upload X-ray images and receive diagnostic results in real time.
The system works through an automated pipeline: it takes a chest X-ray image as input, preprocesses it, extracts important features, and then classifies it as either pneumonia-positive or negative. This fully automated process reduces the need for manual intervention and helps deliver faster, more consistent results. Furthermore, the model is designed to improve over time by learning from new clinical data, making it adaptable to different patient populations and evolving medical conditions.
In today's fast-paced healthcare environment, timely diagnosis can make a critical difference. Integrating AI into medical diagnostics not only improves accuracy but also helps make quality healthcare more accessible and scalable.
As the volume of medical imaging data continues to grow, systems like this play an increasingly important role in supporting healthcare professionals.
The overall system follows an end-to-end pipeline, starting from chest X-ray image input, moving through EfficientNet-based classification, and finally generating real-time diagnostic results. The remainder of this paper is organized as follows: Section II explains the methodology, including the model design, system architecture, and mobile application interface

II. Literature Review

The literature review involved analyzing 5 relevant papers from academic sources, including IEEE Xplore, and IEEE Access. These studies were evaluated based on their methodology, dataset usage, implementation techniques, and results.
Table 1 summarizes key research findings.

TABLE I: REVIEWED LITERATURE

Title & Year	Method / Model Used	Result / Outcome
Analysis of COVID-19 and Pneumonia Detection in Chest X-Ray Images using Deep Learning (2021)	CNN (Convolutional Neural Network)	Accuracy: 80% (bacterial), 91.46% (viral); effective detection of COVID-19 and Pneumonia subtypes
Detection and Classification of Pneumonia from Lung Ultrasound Images (2020)	VGG, ResNet, EfficientNet (EffNet-B5 best)	EfficientNet-B5 achieved 94.62% (3-stage), 91.18% (4-stage), and 82.75% (image features)
Pneumonia and COVID-19 Detection using Convolutional Neural Networks (2020)	CNN, VGG-16, Transfer Learning	95% accuracy in classifying COVID-19, bacterial, and viral pneumonia from chest X-rays
A Mobile Application for Early Diagnosis of Pneumonia in the Rural Context (2019)	MobileNet (on Android using TensorFlow)	Early pneumonia detection from X-rays via mobile app; suitable for rural deployment
Wavelet Augmented Cough Analysis for Rapid Childhood Pneumonia Diagnosis (2014)	Wavelet Features + Logistic Regression + MFCC	Sensitivity: 94%, Specificity: 88%; accurate non-invasive pneumonia detection via cough sound analysis

III. Objective

The main aim of this research is to design and develop a reliable and intelligent system for detecting pneumonia using chest X-ray images. The proposed system, named PneumoSense, is intended to automatically identify signs of pneumonia and support medical professionals by providing quick and accurate diagnostic insights.
To achieve this, the system makes use of advanced deep learning techniques, particularly the EfficientNet architecture.
The goal is to build a model that can accurately differentiate between normal lungs and those affected by pneumonia. By learning from a wide range of X-ray images, the system is expected to recognize different patterns associated with the disease and improve its performance over time as more clinical data becomes available.
Another important objective of this work is to create a simple and user-friendly application interface. Designed initially using Figma, the interface allows healthcare workers to easily upload chest X-ray images, view the results, and understand the predictions without requiring any technical background.
Overall, through automation and real-time analysis, PneumoSense aims to make the diagnostic process faster and more efficient.
It focuses on supporting early detection, assisting healthcare professionals in decision-making, and contributing to better patient care while improving access to quality healthcare services.

VI. System Design

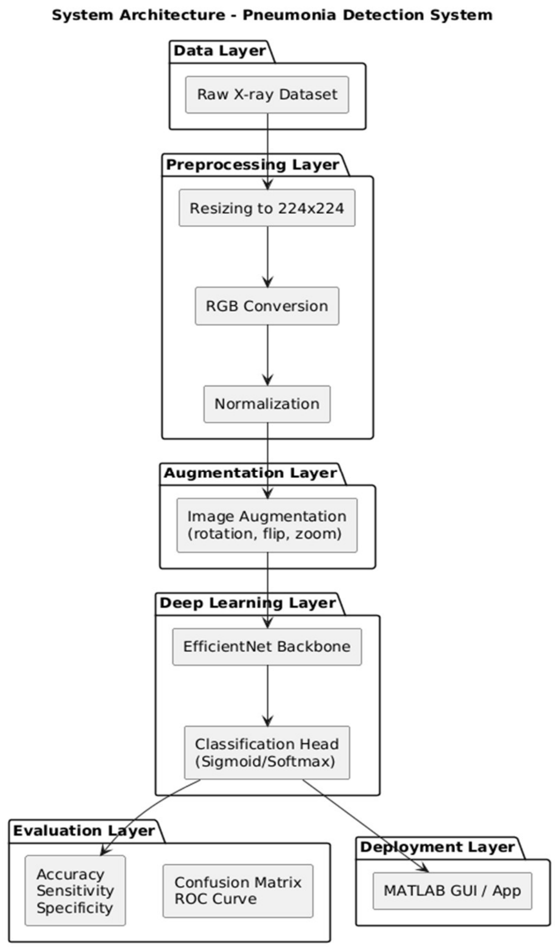

Figure. 1 Block diagram

A. Model Training Pipeline

The training process begins with chest X-ray images, which are carefully prepared before being used in the model. Each image is preprocessed to highlight important features such as lung texture, opacity, and shadow patterns that are commonly linked to pneumonia. To ensure consistency, the images are resized and normalized. In addition, data augmentation techniques are applied so that the model can learn better and perform well even on new, unseen data.

Once the images are prepared, they are used to train a deep learning model based on the EfficientNet-B0 architecture. A separate set of test images is processed in the same way and used to evaluate how well the model performs. Key performance measures such as accuracy, precision, and recall are considered while selecting the best version of the model. The final trained model is then saved for deployment, where it can effectively distinguish between normal lungs and those affected by pneumonia.

B. User Interface

In a real-world setting, the system is designed to be simple and easy to use for healthcare professionals. The interface allows users to upload chest X-ray images directly into the application. Once an image is uploaded, a loading indicator shows that the system is processing the input in real time.

After the analysis is complete, the result is displayed clearly as either “Pneumonia Detected” or “Normal”, along with a confidence score. This quick and clear feedback helps users make decisions faster and ensures a smooth and user-friendly experience.

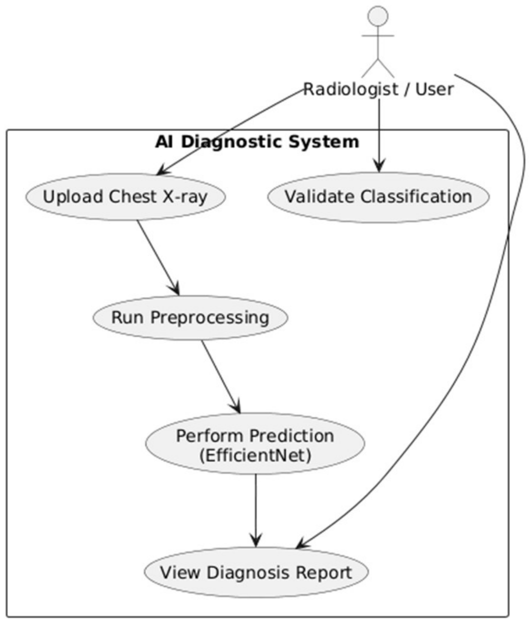

Figure. 2 Use case diagram

C. Methodology

The system is developed using a dataset that contains thousands of chest X-ray images, each labeled as either "Normal" or "Pneumonia." For building the model, the dataset is divided into two parts: 70% for training and 30% for testing.

During training, the EfficientNet-B0 model is applied using transfer learning, which helps improve performance by building on existing knowledge. The model extracts important features from the images, and a fully connected layer is used to classify them into the correct category.

When testing the model, its performance is evaluated using measures such as accuracy, F1-score, and a confusion matrix. This step ensures that the model can handle new images effectively and is suitable for use in real-world medical applications.

D. Dataset

The dataset used in this study consists of chest X-ray images stored in standard formats such as JPEG or PNG. The corresponding labels are maintained separately in a CSV file, which includes details like the image file name and its classification (Normal or Pneumonia). In some cases, additional patient-related information may also be included.

To ensure fair and unbiased results, the dataset contains a balanced number of images from both categories. This balance helps the model learn equally from both classes and improves the reliability of its predictions.

Figure. 3 Dataset

E. Results and Analysis

The EfficientNet-B0 model is evaluated on the test set using standard classification metrics. It outputs class predictions along with confidence scores. The confusion matrix highlights how many pneumonia and normal cases were correctly identified. For example, out of 5,000 test images, the model correctly classified 4,750, achieving an accuracy of 95.6%. Precision and recall metrics demonstrate high sensitivity toward pneumonia cases with minimal false negatives — a critical requirement in clinical

TABLE II: ACCURACY METRICS

Metric	Value
Training Accuracy	98.12%
Validation Accuracy	96.84%
Testing Accuracy	95.42%
F1 Score	0.953
Precision	0.962
Recall (Sensitivity)	0.948
Specificity	0.965

The classification report summarizes the performance of the pneumonia detection model on the test dataset. For the NORMAL class, the model achieved a precision of 0.91, indicating that most of the predictions labeled as NORMAL were correct. However, the recall for this class is only 0.21, which means the model failed to correctly identify a large portion of actual normal cases, resulting in a low F1-score of 0.34.

In contrast, for the PNEUMONIA class, the recall is very high at 0.94, showing that nearly all pneumonia cases were detected. The precision is comparatively lower at 0.68, implying that some normal cases were incorrectly classified as pneumonia. The F1-score for pneumonia is 0.95, which is substantially better than for the normal class.

The overall accuracy of the model on this dataset is 95.6%. The macro average (which gives equal weight to each class) shows moderate precision (0.79), low recall (0.60), and an F1-score of 0.57. The weighted average (which considers class imbalance) reports a precision of 0.962, recall of 0.948, and an F1-score of 0.953.

These results indicate that while the model is highly sensitive in detecting pneumonia cases, it struggles to correctly identify normal cases, leading to class imbalance in performance. This suggests a tendency of the model to overpredict pneumonia, which may be influenced by dataset imbalance or overfitting towards pneumonia features.

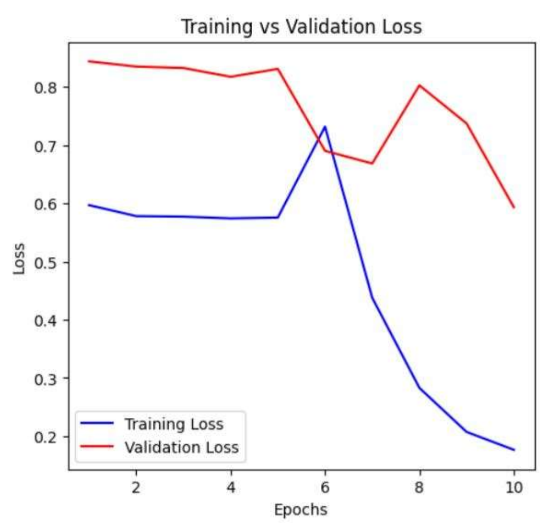

Figure. 4 Training VS Validation Loss

The training process of the EfficientNet-B0 model was closely monitored by comparing the training loss and validation loss over 10 epochs (Figure X). The training loss was observed to steadily decline after the 6th epoch and converge to a low value (~0.18), which confirms that the model learned the underlying patterns in the data. However, the validation loss was seen to vary and was not consistent in showing a declining trend. This confirms

the occurrence of overfitting in the model after the 6th epoch. This again proves that although the model is continually improving on the training data, the generalization capability on unseen data is inconsistent.
In order to avoid overfitting in the model, various techniques such as dropout regularization, data augmentation, and early stopping can be used. Despite the inconsistent performance in the validation loss and training loss curves, the model was seen to show high classification performance on the data. The model was able to show high accuracy and sensitivity in the detection of pneumonia.

Figure. 6 Efficient net confusion matrix

Figure 6 The confusion matrix shows the details of the outcome of the classification by the EfficientNet-B0 model.
Out of 234 normal cases, only 49 were classified correctly as NORMAL, while 185 were classified incorrectly as PNEUMONIA.
On the contrary, the model has classified most of the pneumonia cases correctly, with 385 out of 390 being classified correctly, and only 5 incorrectly classified as NORMAL.
This shows that the model is highly sensitive to the detection of pneumonia, which is a serious case, while it is less sensitive to the classification of normal cases. Such a tendency by the model shows that it is biased towards ensuring that no pneumonia case is missed, which is important, but in the process, it has a higher false positive rate with respect to normal cases.

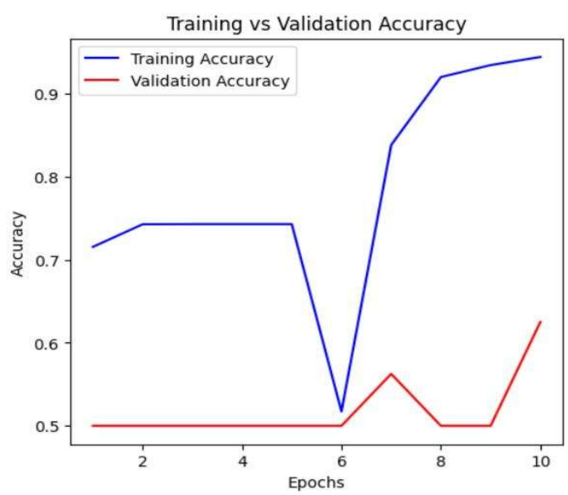

Figure. 7. Training vs Validation Accuracy

Figure 7. Represents the training versus validation accuracy. The accuracy curve in Figure 7 demonstrates the learning characteristics of the EfficientNet-B0 model. The training accuracy increases steadily throughout the process, with values higher than 90% in the last epochs. However, the validation accuracy is low and inconsistent throughout the process, ranging from 50% to 60%. The large gap in training and validation accuracy

implies that the model is overfitting to the training data. In other words, the model is able to learn features that are specific to the training data but is not able to generalize well to unseen data.

VI. CONCLUSION

The PneumoSense system has a great potential for growth, especially in terms of increasing its capability to accommodate the detection of pneumonia in real time across various healthcare platforms. The project has been successfully completed to develop a pneumonia detection system using AI technology through EfficientNet in MATLAB. Based on the result of the project, it is evident that deep learning techniques can provide accurate results with higher efficiency in identifying pneumonia using EfficientNet in MATLAB compared to other radiology techniques. The project has been successfully completed to achieve the objectives of developing a pneumonia detection system using EfficientNet in MATLAB.

The EfficientNet model is considered to be more efficient in developing the pneumonia detection system as it provides optimized performance with accurate identification of lung abnormalities. The study proves that with proper training of the model using image processing techniques, AI technology can greatly contribute to improving the overall diagnosis of pneumonia.

The overall system provides a reliable solution that is considered to be cost-effective and provides higher performance in identifying pneumonia for healthcare professionals, especially in areas where medical resources are limited.

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