Pneumonia Disease Detection using Deep Learning

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***Abstract*— Pneumonia is life-threatening respiratory disease that requires timely diagnosis for effective treatment. Chest X-ray is one of the most commonly used diagnostic tools to detect pneumonia, but interpreting these images manually can be challenging and time- consuming. This project aims to develop an automated system for pneumonia detection using deep learning techniques. Specifically, I explore the performance of three convolutional neural network models: Xception, EfficientNetB4, and EfficientNetV2S, to classify chest X-ray images as either pneumonia-positive or normal. The models were trained and tested on a publicly available chest X-ray dataset. Xception, EfficientNet B4, and EfficientNetV2S are all advanced deep learning models designed for image classification tasks. Xception is a convolutional neural network which helps in reducing the number of parameters while maintaining high accuracy and excels in handling complex patterns. EfficientNet B4 is part of the EfficientNet family, known for its ability to balance accuracy and efficiency by scaling the depth, width, and resolution of the network in a systematic way. EfficientNetV2S is an improved version of EfficientNet, designed to be faster and more efficient, with better performance in terms of accuracy and computational speed, making it ideal for real-time applications.**

INTRODUCTION

Pneumonia is a dangerous respiratory infection that can cause serious health complications or result in death if left undetected and untreated. Chest X-ray imaging is one of the most popular diagnostic techniques used to detect pneumonia; however, human interpretation of X-rays by radiologists tends to be subjective, time-consuming, and susceptible to human error, particularly in high-volume or resource-scarce healthcare environments. The purpose of this project is to solve the problem of automated detection of pneumonia by creating and comparing the performance of three state-of-the-art deep learning models— Xception, EfficientNetB4, and EfficientNetV2S.

I. *SYSTEM ANALYSIS*

Existing System**:** Traditional systems rely on models that work at a slow pace and need powerful computer hardware systems which makes them unsuitable for real-time use or low-resource settings.

Proposed System: The system is intended to classify chest X-ray images as either pneumonia-positive or normal, thereby assisting healthcare professionals in making faster and more reliable diagnostic decisions. This is achieved through the implementation and evaluation of three advanced Convolutional Neural Network (CNN) models: Xception, EfficientNetB4, and EfficientNetV2S.

Advantages:

- Enhances Accuracy and Speed.
- Support Healthcare Professionals

TABLE I
EXISTING WORK OVERVIEW

Title	Authors	Year	Summary
Pneumonia Detection Using CNN based Feature Extraction	Dimpy Varshni et al	2019	This study focused on reducing the manual workload of radiologists by automating pneumonia detection using deep learning.
Pneumonia Detection Using Deep Learning Methods	FaizaMehboob Qaimkhani et al	2022	Aimed to enhance detection accuracy of pneumonia from chest X-rays using advanced deep learning techniques.
Pneumonia Detection Using Convolutional Neural Networks	Puneet Gupta	2021	The paper focused on comparing different CNN architectures to find the best model for pneumonia detection.

II. *SYSTEM DESIGN*

A. *Input*

- Chest X-ray images (grayscale medical images)
- Image class labels: **Normal** or **Pneumonia**

B. *Processing*

- Image resizing (e.g., 299x299)
- Normalization and data augmentation (rotation, flipping, zoom)

- Three deep learning models used: **Xception**, **EfficientNetB4**, and **EfficientNetV2S**
- Pre-trained on ImageNet and fine-tuned on pneumonia dataset
- Trained using training set with validation and testing
- Evaluation using accuracy, precision, recall, F1-score, and confusion matrix

C. Output

- Prediction Label: Whether the input X-ray shows Pneumonia or Normal
- Line graphs displaying how well the model learned during training and validation over several epochs.
- Displays performance metrics such as accuracy, precision, recall, and F1-score.

III. *MODULES DESCRIPTION*

A. Data Preprocessing Module

This module handles the collection, formatting, and cleaning of chest X-ray image data. It includes resizing images to the required input dimensions, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and zooming to increase dataset diversity and prevent overfitting.

B. Model Training Module

This module is responsible for building and training deep learning models. It utilizes transfer learning with pre-trained models such as **Xception**, **EfficientNetB4**, and **EfficientNetV2S**, which are fine-tuned on the pneumonia dataset. The module also includes compilation, optimization (e.g., using Adam optimizer), and regularization (dropout) techniques.

C. Classification and Prediction Module

This module uses the trained model to classify new chest X-ray images as either **Pneumonia** or **Normal**. It processes the input image through the selected model and outputs the prediction along with a confidence score, helping in diagnostic decision-making.

D. Performance Evaluation Module

This module evaluates the accuracy and reliability of the model using standard metrics such as **accuracy**, **precision**, **recall**, **F1-score**, and **confusion matrix**. It helps in identifying the best-performing model for deployment.

E. Output and Visualization Module

This module visualizes results and model performance. It generates graphs such as training/validation accuracy & loss curves, ROC curves, and confusion matrices using tools like **Matplotlib** and **Seaborn**. These visual aids help in understanding how well the model is performing.

IV. *SYSTEM ARCHITECTURE*

The system architecture for pneumonia detection is designed using a layered deep learning approach to ensure efficient image processing, accurate classification, and user-friendly result interpretation.

A. Key Layers:

Input Layer (Data Acquisition Preprocessing): The system starts by acquiring chest X-ray images from a public dataset. These images undergo preprocessing, which includes resizing, normalization, and data augmentation (like rotation and flipping). This ensures consistency and quality before feeding the data into the deep learning models.

Processing Layer (Model Training Prediction): The preprocessed images are passed into deep learning models based on Convolutional Neural Networks. In this system, three powerful architectures—Xception, EfficientNetB4, and EfficientNetV2S—are utilized. Each model processes the input image and outputs predictions indicating whether pneumonia is present or not.

Decision Layer (Classification and Output Analysis): Each model classifies the X-ray image as either Pneumonia or Normal. These predictions can be compared to choose the best-performing model

Output Layer(Visualization Interpretation): The results include the accuracy score, precision, recall, F1-scorce and optionally, visualizations such as confusion matrices to help doctors or users better understand the system's decision.

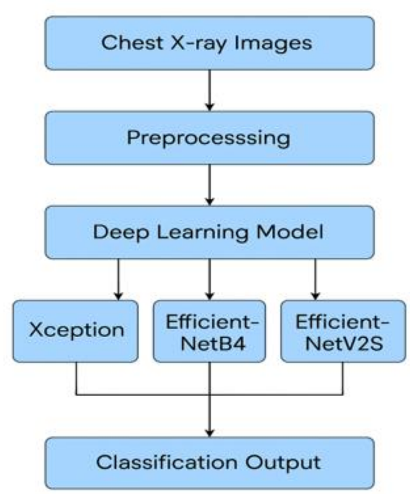

Fig. 1. System Architecture Flow

V. DEEP LEARNING MODELS USED

The Pneumonia Detection System leverages three deep learning models across Convolutional Neural Networks to identify either pneumonia-positive or normal conditions in chest X-ray images. The deep learning models for image classification use Convolutional Neural Networks (CNNs) with established reputation in the field because of top accuracy rates together with fast feature extraction and powerful classification capabilities.

A. Xception

Purpose: Image classification for pneumonia detection.

Function: Uses depthwise separable convolutions to extract complex features from X-ray images while reducing the number of parameters. It processes features through entry, middle, and exit flow layers for effective pattern learning.

Advantages: High accuracy, efficient model size, and excellent at capturing fine details in medical images.

B. EfficientNetB4

Purpose: Accurate pneumonia detection with optimized performance.

Function: Scales the model's depth, width, and resolution using a compound scaling method. It uses MBConv blocks and swish activation to efficiently learn from image data.

Advantages: Balanced trade-off between speed and accuracy, effective with fewer resources, and suitable for high-resolution medical image analysis.

C. EfficientNetV2S (EfficientNet Version 2 – Small)

Purpose: Fast and lightweight pneumonia detection for real-time use.

Function: An improved version of EfficientNet, it combines fused MBConv layers and progressive learning strategies to achieve faster training and better accuracy on smaller datasets.

Advantages: Very fast, lower training time, optimized for real-time prediction, and ideal for deployment on devices with limited resources.

VI. IMPLEMENTATION

Technologies Used:

- Language: Python
- Libraries: TensorFlow, Keras, NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn
- Models Used: Xception, EfficientNetB4, EfficientNetV2S (via Keras Applications / TensorFlow Hub)
- Development Environment: Jupyter Notebook, Google Colab
- Dataset Source: Combined pneumonia chest X-ray datasets from Kaggle.

VII. TESTING AND EVALUATION

Test Cases:

- Input: Chest X-ray image of a patient with confirmed pneumonia → Output: Classified as *Pneumonia Positive* Input: Normal chest X-ray image → Output: Classified as *Pneumonia Negative*

Performance Metrics:

- Accuracy
- Recall
- Precision
- F1-Score

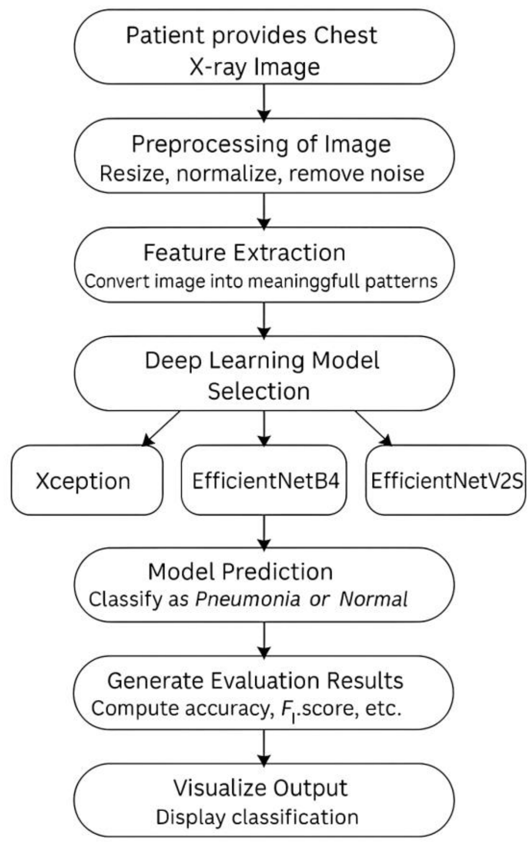

Fig. 2. Process Flow Chart

VIII. DATASET OVERVIEW

The dataset used in this project is a custom, recently developed pneumonia detection dataset, created by combining four publicly available chest X-ray datasets from Kaggle. Each of these individual datasets was originally designed for the purpose of chest X-ray analysis and pneumonia detection, providing high-quality, labeled images of both pneumonia-positive and normal cases. By merging these datasets, a more diverse, balanced, and comprehensive dataset was formed, encompassing a wider range of patient demographics, imaging conditions. The size of data set is 5.49 GB.

Key Attributes:

Image Data: Chest X-ray images with associated metadata (e.g., resolution, orientation, image quality).
Model Predictions: Classification label (Normal, Pneumonia).
Model Performance: Accuracy, precision, recall and F1score.
Comparative Evaluation: Performance metrics comparison among models like Xception, EfficientNetB4, and EfficientNetV2S.

A. Dataset Classes:

Image Information: X-ray Image ID, Image Type, Image Size, Image Quality
Model Output: Predicted Class (Normal/Pneumonia).
Evaluation Metrics: Accuracy, Precision, Recall and F1-Score.
Model Comparisons: Model Name (Xception, EfficientNetB4, EfficientNetV2S), Evaluation Scores, Best Performing Model

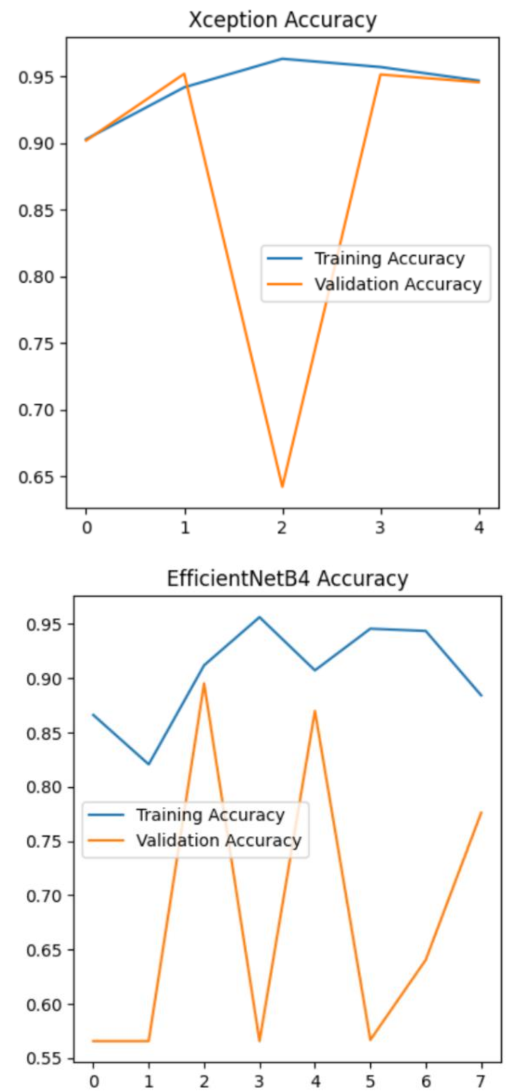

Fig. 3. Accuracy Graph for Xception and EfficientNetB4

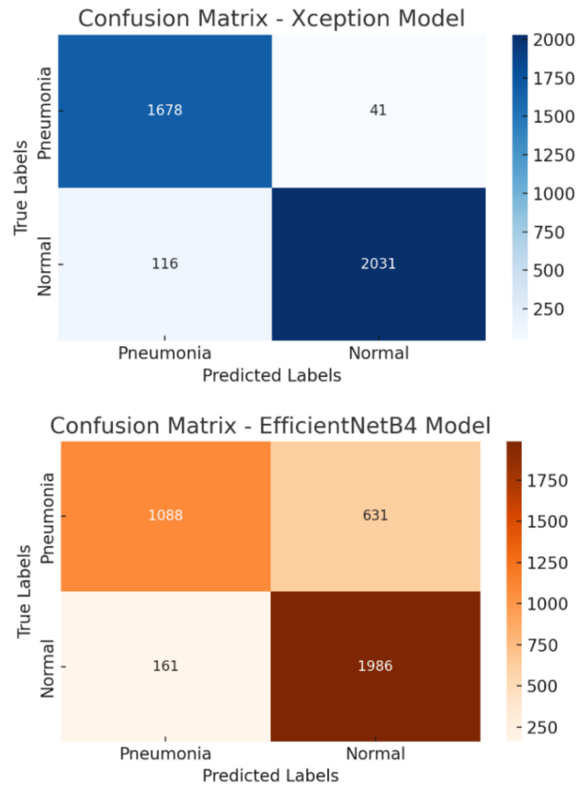

Fig. 4. Confusion Matrix for Xception and EfficientNetB4

IX. Conclusion and Future Scope

Future Scope: In the future, this pneumonia detection system can be improved in many ways. Multiple innovative methods exist for improving the pneumonia detection system and its practicality throughout future development. The system enables easy uploading of chest X-rays from hospital systems to provide doctors with prompt analysis during examinations. The system's direct connection to hospital systems would create time efficiencies which enhance emergency decision-making processes. The current model focuses on binary classification (pneumonia vs. normal). The system requires additional data processing and minor updates to identify major lung conditions such as tuberculosis, lung cancer alongside the current functionality of detecting COVID- 19. The system will become more effective and useful for medical professionals when implemented. A necessary update to the system consists of adding information about patient demographics together with symptoms and recorded health background data. The system achieves better and individualized predictions through the incorporation of supplemental information. The system should receive modifications to make it run efficiently. Doctor system confidence can increase through visual descriptions that show which part of the lung contains the detected issue. The enhanced system interpretation helps medical professionals understand the basis of their diagnoses better. We can achieve a model that serves all populations equally by applying more extensive training to a wider variety of clinical datasets. Such modifications will enable better accuracy and reliability for implementing the system in actual hospitals worldwide.

Conclusion: The project shows how deep learning can develop automated pneumonia detection through X-ray images despite attaining different accuracy levels. The system employed Xception and EfficientNet B4 with EfficientNet V2S so it could recognize pneumonia-positive or normal X-rays with different levels of precision. Deep learning effectively enables automatic pneumonia detection through chest X-ray images according to the project results. Three advanced convolutional neural network (CNN) architectures namely Xception and EfficientNetB4 and EfficientNetV2S enabled the system to perform classification of chest X-rays between pneumonia-positive and normal cases with different levels of accuracy. The Xception model demonstrated the most effective results reaching 95% accuracy when compared to the remaining models by correctly recognizing most of the images. Xception demonstrates high diagnostic accuracy of deep learning techniques making it valuable for medical diagnosis operations dealing with heavy caseloads and radiologist staffing shortages. This system provides two essential benefits through its automatic operation by preventing human mistakes while operating efficiently. Expert medical professionals become less crucial due to this system because it provides valuable service to rural and underdeveloped areas. The system consumes fewer computing resources and saves time because it operates through transfer learning models and relies on publicly available databases. AI deep learning technology proved its capability to assist medical diagnosis through early disease detection specifically in cases of pneumonia. Future optimization will lead to enhanced system capabilities that healthcare institutions could implement for doctor assistance in preventing patient deaths.

X. *REFERENCES*

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