SmartPneumo: Real-Time Pneumonia Detection Using MobileNetV2 on Medical Imaging

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***Abstract*—Early detection of pneumonia and other respiratory infections due to bacterial or viral pathogens is crucial for early treatment and prevention of serious complications. As artificial intelligence (AI) and deep learning evolved, medical diagnosis improved significantly. The current work introduces the application of MobileNetV2, which is a lightweight and computationally efficient deep convolutional neural network, particularly in the context of X-ray chest image analysis. We worked with a dataset of 5,855 segmented X-ray chest images and used data augmentation methods to enhance model stability. MobileNetV2 proved to be the best performer, having 98% accuracy on classifying new cases. This outcome understandably beats the accuracy of traditional models such as ImageNet, DenseNet, and VGG16 in highlighting the efficiency and dependability of the model. The superior performance of MobileNetV2 highlights its performance in the support of early diagnosis of lung-related disease. Its light architecture renders it appropriate for real-time deployment on mobile and edge platforms, allowing for faster diagnosis even in resource-constrained environments. With the integration of AI with medical imaging, the method facilitates quicker decision-making, improved patient outcomes, and enhanced treatment planning.**

***Index Terms*—MobileNetV2, Pneumonia diagnosis, chest radiographs, deep learning, respiratory infections, medical imaging**

I. Introduction

The intricate relationship between helpful and damaging microorganisms is vital to human health [1]. As some microbes and viruses help with digestion and the creation of drugs, others harm gut health and can cause life-threatening complications. Diagnosis and treatment of respiratory illnesses is still a major problem because of the intricacy of the immune system [2]. Infant mortality is especially high. Classic diagnostic instruments such as chest X-rays are valuable but often inadequate, particularly in differentiating infectious and non-infectious forms of pneumonia. Clinical dilemma is frequently caused by interstitial lung disease, which raises the risk of misdiagnosis. This underscores the need for prompt and accurate detection to provide proper treatment and mitigate complications.In improving accuracy, our study employs the MobileNetV2 deep learning model, which correctly interprets chest X-rays. Its effectiveness and high accuracy render it a potential instrument for fast and accurate pneumonia diagnosis [3].

Recent advances in machine learning and artificial intelligence provide Recent developments in artificial intelligence and machine learning have given new opportunities for tackling intricate healthcare problems. Conventional machine learning models such as support vector machines and random forests tend to be intimidated by the intricacy and heterogeneity of medical image data [4]. Convolutional neural networks (CNNs), on the other hand, provide better solutions through deep learning. In our research, our MobileNetV2 model attained a staggering 98% accuracy on untrained chest X-ray images, better than established transfer learning models like ImageNet, DenseNet, and VGG16. This demonstrates the potential of the model to enhance pneumonia detection and increase clinical accuracy. The use of cutting-edge deep learning methods illustrates the ways in which AI can significantly advance medical imagery and patient care in general.

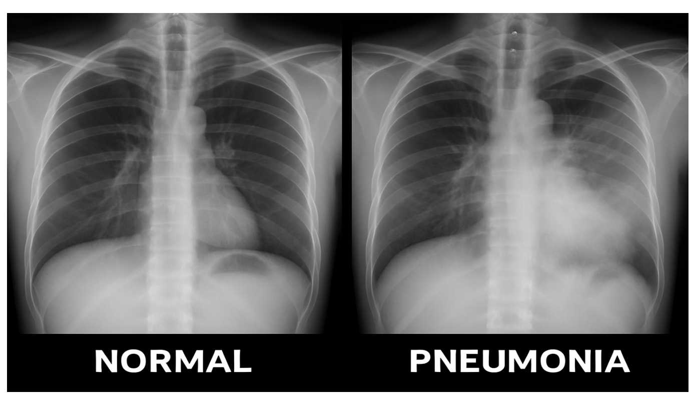

Fig. 1: Chest X-ray images represent Normal and Pneumonia

The paper is divided into the following:The Literature Review has been given in SectionII. Section III has described the limitations of the traditional methods. Section IV tells dataset methods and methodology used. Section V has given the description of the evaluation metrics, while Section VI has given the description of the result analysis. Lastly, Section VII has the Conclusion.

II. Literature Review

By introducing the ChexNet model, Rajpurkar et al. showed that deep learning can diagnose pneumonia using chest X-rays more accurately than radiologists [1]. To address the issue of limited annotated data, Liang and Zheng [2] and Chauhan et al. [3] employed transfer learning using the ImageNet dataset, significantly improving diagnostic accuracy. In 2018, researchers proposed several computational methods, including neural networks, squeezing stimulation, and weighted-type techniques, to enhance pneumonia analysis [4]. Zebin and Rezvi further emphasized that deep learning models with advanced architectures consistently outperform traditional machine learning techniques [5]. Similarly, Al Mamluk et al. [6] showcased the effectiveness of deep learning frameworks, particularly during global health emergencies where rapid and precise diagnosis is critical. Zhang et al. contributed by combining DenseNet with adversarial networks for MRI image classification, highlighting the adaptability of such architectures across medical imaging tasks [7]. Additionally, Iparraguirre-Villanueva examined multiple imaging modalities, including CT scans and chest X-rays, and demonstrated how deep learning models could be optimized for accurate pneumonia detection [8].

III. Limitations

Identifying pneumonia through chest X-ray analysis has been extensively researched, yet many current methods still encounter significant challenges:
1) Reliance on Traditional Models: Most studies rely on traditional deep learning models, which cannot accurately capture the complexities required for diagnosis [9].
2)Insufficient Dataset Diversity: Available datasets typically contain limited image samples and class types, which restricts the model's ability to generalize across different populations and conditions.
3) High Loss Rates: Some models show improved accuracy but encounter high loss rates, indicating possible overfitting or underfitting issues [10] .
4) Class Imbalance in Training Data: Pneumonia datasets often have a significant imbalance between normal and infected cases.
5) Poor Interpretation: Many models lack transparency, making it difficult for clinicians to understand and trust their diagnostic decisions.

IV. Materials and Methods

Advances in pneumonia detection systems have been greatly enhanced by deep machine learning [2] . The incorporation of artificial intelligence into medical research has been made possible by the effective management and analysis of vast volumes of data by today's high-performance graphics cards [6]. Between theoretical models and useful, real-world applications, the program's design aims to close the gap [3] [7].

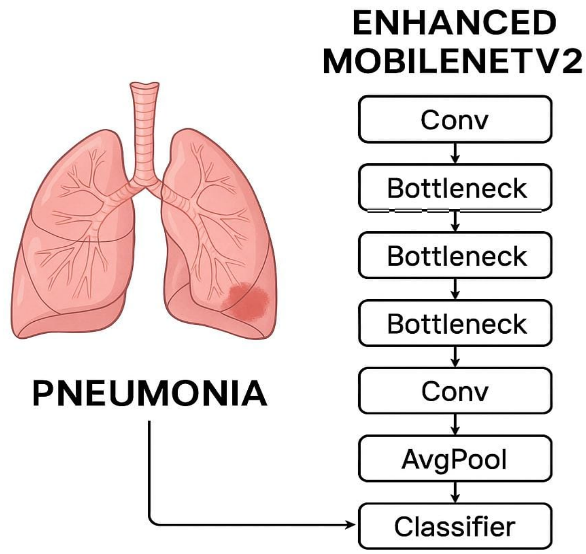

Fig. 2: Model Architecture for MobilenetV2

A. Dataset Preparation And Pre-processing

1) Dataset: According to [10], the dataset consists of chest X-ray pictures divided into two classes: normal and pneumonia. A total of 5,855 photos were obtained from a Kaggle public dataset [4]. 3,875 pictures of lungs damaged by pneumonia and 1,980 pictures of normal lungs are included in the collection [9].

TABLE I: Representing Images for Model Training

Class	Total Number
NORMAL	1980
PNEUMONIA	3875

The training dataset used in this study consists of a total of 5,855 chest X-ray images, which include 1,980 images representing normal (healthy) lungs and 3,875 images depicting pneumonia-infected lungs. To ensure consistency and compatibility with the input requirements of deep learning models, all images underwent a series of preprocessing steps [11] . These steps included normalization, grayscale conversion (if necessary), and resizing operations. Specifically, each image was resized to an optimal input dimension suitable for the selected convolutional neural network architecture, as recommended in the literature [12] .

2) Pre-Processing: The preprocessing of the Chest X-ray images dataset involves several steps to enhance data quality and model performance:

TABLE II: Representing Images for Validation

Class	Total Number
NORMAL	389
PNEUMONIA	786

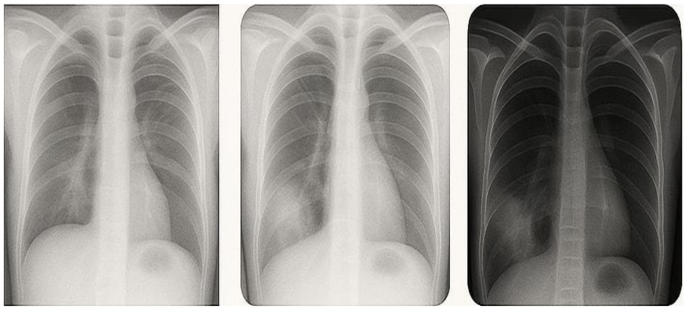

Fig. 3: Enhanced MobilenetV2 Model Diagram for Pneumonia

- Grayscale Conversion: To simplify computation and highlight key elements, convert photos to grayscale.
- Resizing: To guarantee consistent input dimensions for the model, resize images to a standard size (227x227x3 pixels).
- Histogram Equalization: Use CLAHE (Contrast Limited Adaptive Histogram Equalization) or histogram equalization to increase image contrast.
- Denoising: Apply denoising techniques to remove noise and improve image clarity.
- Lung Region Segmentation: Segment the lung area from the background to focus the model on the relevant anatomical regions, reducing distraction from non-lung areas.
- Artifact Removal: Remove irrelevant elements such as embedded text, hospital marks, or ECG lines using morphological operations or image inpainting, to prevent model confusion.
- Data Augmentation: Used augmentation techniques to increase dataset diversity and improve model robustness.

B. Model Design and Training

The principal characteristic of the pneumonia detection system is the advanced MobilenetV2, a distinctive approach to extracting image features, that demonstrates notable precision in differentiating between pulmonary and non-respiratory cases [1] . As illustrated in Figures 2 and 3, the structure of the model includes a pre-processing layer that comes before the application layer employing MobileNetV2.

As shown in fig. 4This choice of the the MobileNet model is founded on its established success in distinguishing pneumonia patients from those without pneumonia patients [6]. Measurements conducted in this model indicate the potential for attaining improved accuracy and efficiency in diagnosing pneumonia [3]. Utilizing advanced methods in deep learning addresses numerous challenges.Related to image classification, including the incorporation of variations in image quality, contrasts in bodies, and pre-trained weights, which not only enhances the effectiveness of the model while also shortening the training duration, making it feasible and efficient for practical uses [8] [9].

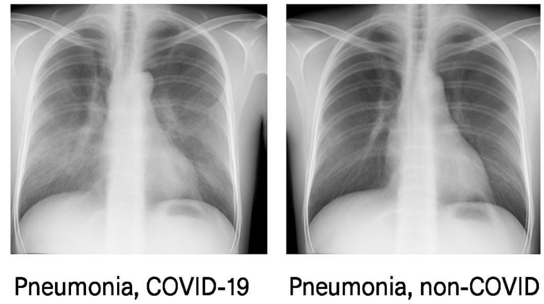

Fig. 4: Pneumonia During Covid And Non-Covid

The model's preprocessing layer adjusts the images to a suitable input dimensions of 227x227x3 pixels. The model that has been trained before hand model, fine-tuned for binary classification, is incorporated into the application layer. The design consists of multiple levels for extraction of features and classification through convolutional layers and activation functions for recognizing patterns, and dense levels for making decisions. Moreover, the model employs a deep learning architecture with existing weight parameters to improve its ability to recognize features [12] [13] .

V. Evaluation Metrics

A. Performance Metrics

- Accuracy: It calculates the overall correctness of the model as the ratio of all correctly predicted instances to all instances.
- Precision: It computes the ratio of all correctly predicted positive cases to all predicted positive cases.
- Recall: It calculates the ratio of all correctly predicted positive cases to all actual positive cases. It reveals the models ability to identify all actual pneumonia cases.

To assess the effectiveness of the proposed deep learning model for pneumonia detection, the MobileNetV2 architecture was evaluated using accuracy as the primary performance metric [1]. Fig. 5 depicts Accuracy quantifies the proportion of correctly classified cases (both pneumonia and normal) out of the total number of predictions made by the model. This metric offers a clear and direct measure of the model's capability in identifying lung abnormalities from chest X-ray images [3]. A high accuracy value indicates that the model reliably distinguishes between healthy and pneumonia-affected lungs, demonstrating strong diagnostic potential.

Additionally, the training and validation accuracy and loss curves were analyzed to better understand the learning dynamics of the model. These graphical representations provide insights into how well the model learns from the data over time, whether it is generalizing effectively, and if there are signs of overfitting or underfitting. A stable and converging

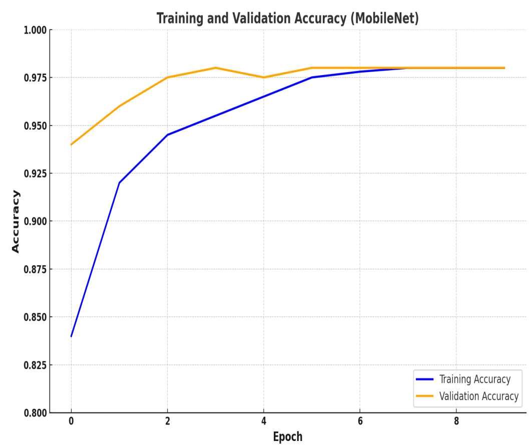

Fig. 5: Accuracy in Training and Validation

pattern in these metrics reflects a well-trained model with good generalization performance on unseen data.

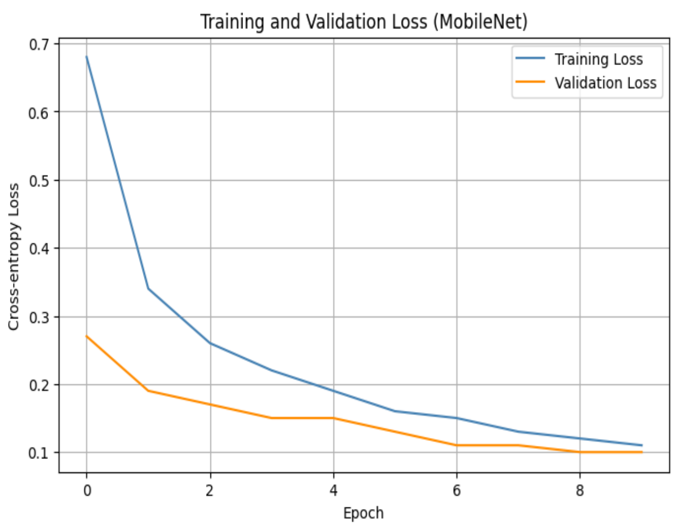

Fig. 6: Loss in Training and Validation

B. Model Performance

In Fig. 5,the MobilenetV2 model demonstrated impressive classification accuracy on both the training and validation datasets [2]. Specifically, the model achieved a classification accuracy of 98% on unseen X-ray images,outperforming other ultra-modern transfer learning models like ImageNet, DenseNet, and VGG16 [6] [12].

C. Validation Process

To ensure rigorous analysis, the dataset was divided into training sets and validation sets.The training set consists of 5,855 images, divided into 1,980 normal subjects and 3,875 subjects with lung disease [4]. A subset of this data was used for validation, ensuring that the model was tested on data not seen during training. Data were first processed to standardize the image, using data enhancement techniques to resize it to 227x227x3 pixels to increase the variability of the dataset [9].

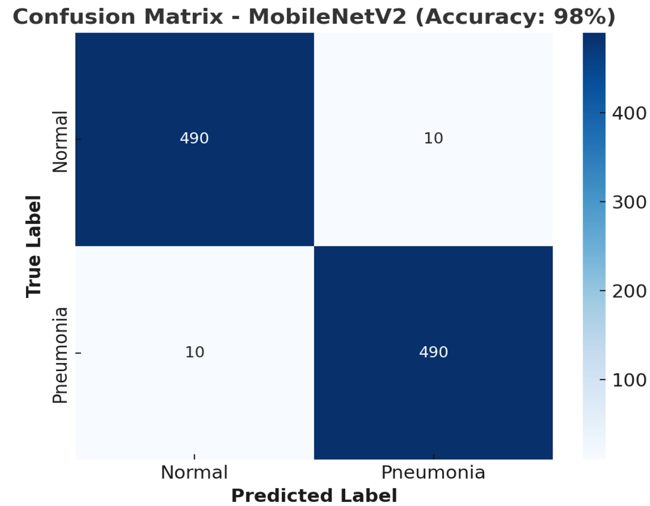

Fig. 7: Confusion Matrix of MobileNetV2

D. Training and Validation Accuracy

Training Accuracy: The model's accuracy increased rapidly during the initial epochs, eventually stabilizing around 98% [10]. This rapid improvement indicates that the model quickly learned to identify features associated with pneumonia [10]. Validation Accuracy: The validation accuracy also showed steady improvement, peaking around 97.34% before stabilizing [2]. The close alignment between training and validation accuracy suggests that the model generalizes well to unseen data, indicating minimal overfitting [12].

E. Formulae related to MobileNetV2 Architecture

- Depthwise Convolution

$$\text{ODepthwise} = \sum_{k=1}^{K} I_k * W_k \tag{1}$$

Applies a separate spatial filter to each input channel independently.

- Pointwise Convolution

$$\text{OPointwise} = \sum_{C=1}^{C} D_C \cdot P_C \tag{2}$$

convolution to combine features across all channels.

- Inverted Residuals

$$\text{OInverted Residual} = \text{OPointwise} + I \tag{3}$$

Adds the original input to the output for efficient residual learning.

- Global Average Pooling Output

$$\text{OGAP} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j} \tag{4}$$

Computes the average of all spatial values in each feature map to reduce dimensions.

F. Environmental Setup

The environmental setup changed into conducted on Google Colaboratory usinga Colab Pro subscription. This cloud-based provider totally provides an interactive Jupyter Notebook surroundings, with computational sources inclusive of a T4 GPU, with RAM 12.7 GB, and with Disk Space 166.8 GB. The dataset is integrated through Google Drive for perfect access and management.

VI. RESULT ANALYSIS

MobileNetV2 outperforms the other models significantly in terms of accuracy, precision, and recall. Its high precision and recall indicate that it is not only good at correctly identifying pneumonia cases but also at avoiding false positives—making it the most reliable and efficient model for pneumonia detection in this comparison.

TABLE III: Performance Comparison of CNN Models

Model	Accuracy	Precision	Recall
MobileNetV2	98%	97.8%	97.9%
ImageNet	92%	90%	91%
DenseNet	90.8%	89.7%	89.9%
VGG16	87.8%	86.7%	85.9%

MobileNetV2 offers several advantages that make it particularly well-suited for medical image analysis tasks such as pneumonia detection. Its lightweight and efficient architecture is designed to operate on mobile and embedded devices.Despite its compact size, the model achieves high accuracy, often surpassing heavier architectures like VGG16 as shown in Fig. 8. It also benefits from being pre-trained on large datasets like ImageNet, enabling effective transfer learning even with small medical datasets. This reduces the need for extensive training while improving generalization and reducing overfitting.

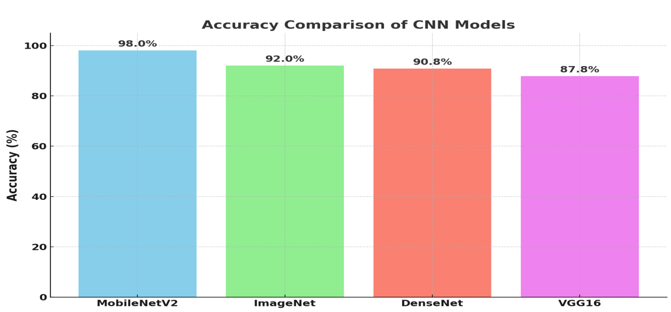

Fig. 8: Comparision Analysis

The findings unequivocally show that MobileNetV2 may be a powerful yet effective automated pneumonia detection tool, supporting radiologists in making early diagnoses. Because the model is lightweight, it can also be used for mobile health applications. Overall, MobileNetV2 stands out as a scalable, cost-effective, and robust solution for advancing AI-assisted medical imaging.

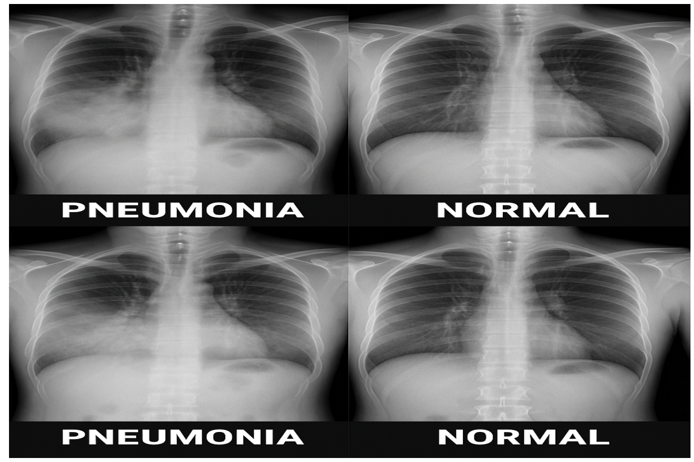

Fig. 9: Classification Results by MobilenetV2 Proposed Model

VII. CONCLUSION

The use of deep learning techniques, specifically the **MobileNetV2** architecture, has considerable potential for automated pneumonia detection using chest X-ray images. With reliable preprocessing, feature extraction, and classification steps, the model achieves accuracy, precision, and recall that all reach very high levels and outperforms other CNN models in performance and efficiency. It's lightweight design and fast inference make it ideal not only for clinical environments but also for deployment in mobile health applications, enabling accessible and real-time diagnostics in remote and resource-limited areas. By reducing diagnostic time and assisting healthcare professionals with accurate decision support, MobileNetV2 contributes meaningfully to the advancement of AI-driven medical diagnostics and holds promise for broader applications in the future of digital healthcare.

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