Pneumonia Detection using k-fold cross validation and MobileNetV2

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Abstract

Pneumonia is the leading cause of death all around the world. On average, it kills 700,000 children per year, on average and affects 7% of the world's population. With the introduction of Medical Imaging, the detection of disease has been accelerated by using chest x-ray image. But it also requires the availability of an expert and experienced radiologist in order to interpret the x-ray image accurately. Sometimes, manual interpretation has its own limitations like the availability of an expert, cost, etc. and hence an automated method for the detection of pneumonia from x-rays is a necessity. Our aim is to build a model based on applications of transfer learning and convolutional neural networks that are capable of automatically diagnosing pneumonia in patients.

I. Introduction

Pneumonia is a severe lung infection that requires early and accurate diagnosis to prevent complications and fatalities. Traditional diagnostic methods, such as chest X-rays analyzed by radiologists, can be time-consuming and prone to human error. To address this challenge, deep learning-based approaches have gained attention due to their ability to automatically detect pneumonia with high accuracy. This study presents a pneumonia detection model using the MobileNetV2 architecture with transfer learning, trained on a dataset of chest X-ray images. The model classifies images into normal and pneumonia categories. The integration of deep learning significantly enhances diagnostic efficiency, providing a fast, reliable, and automated solution for pneumonia detection.

II. Literature Survey

Table 1. Summary of Research Papers

Title	Methodology Used	Summary
Detection of Paediatric Pneumonia from Chest X-Ray Images using CNN and Transfer Learning	VGG16, VGG19, InceptionV3, Simple CNN, Convolutional Layer, Batch Normalisation, Pooling layer, Activation, dropout, Dense layers.	The overall efficiency of the model designed was judged using the evaluation metrics of accuracy, precision, recall and f1 score, calculated from the confusion matrices drawn.
A Combined approach Using Image Processing and Deep Learning to Detect Pneumonia from Chest X-Ray Image	VGG16, VGG19, InceptionV3	They have used VGG-16 and VGG-19 network followed by a pervasive image processing to detect pneumonia which has performed 3.4% and 3.1% respectively better than transfer learned InceptionV3 method.
Classification of chest pneumonia from x-ray images using new architecture based on ResNet	CNN, ResNet50, ReLU activation function	In this paper authors proposed 'ResNetChest', an architecture model using deep learning for automatic pneumonia diagnosis, requiring chest x-ray images to perform this diagnosis. They also mentioned CNNs work very well on large datasets and most of the time they fail on small datasets if layers ordering care is not taken.
Feature Extraction and Classification of Chest X-Ray Images Using CNN to Detect Pneumonia	CNN, ReLU activation function	In this paper authors proposed two CNN architectures that are designed from scratch to detect pneumonia from images of chest X-ray. Performance of the proposed

		architectures and the effect of data augmentation on the performance of the proposed CNN's show that CNN with dropout trained on augmented data outperforms the other models.
Chest X-ray Pneumonia Detection Based on Convolution Neural Networks.	Inception, ResNetV2, Xception, DenseNet201, VGG19	In this paper, methods of feature extracting and fine tuning are used to train on multiple variants of convolutional neural networks, namely InceptionResNetV2, Xception, DenseNet and VGG19.With a small amount of data, a higher accuracy is attained on the chest X-rays pneumonia detection task.
Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network	CNN, ReLU activation function	This paper describes the use of deep learning in order to classify digital images of chest X-rays according to presence or absence of changes consistent with pneumonia. Implementation was based on CNN model using Python programming and scientific tools.

III. Dataset Description

[13] The dataset is organized into 3 folders (covid, pneumonia, normal) and metadata.csv which contain chest X-ray posteroanterior (PA) images. X-ray samples of COVID-19 were retrieved from different sources for the unavailability of a large specific dataset. First, 613 X-ray images of COVID-19 cases were collected from the following websites: GitHub, Radiopaedia, The Cancer Imaging Archive (TCIA), and the Italian Society of Radiology (SIRM). Then, instead of data being independently augmented, a dataset containing 912 already augmented images was collected from Mendeley. Finally, 1525 images of pneumonia cases and 1525 X-ray images of normal cases were collected from the Kaggle repository and NIH dataset. A total of 4575 samples were used in the experiment, where 1525 samples were used for each case. In the dataset, all the covid samples are deleted and model is trained with pneumonia and normal x-rays.

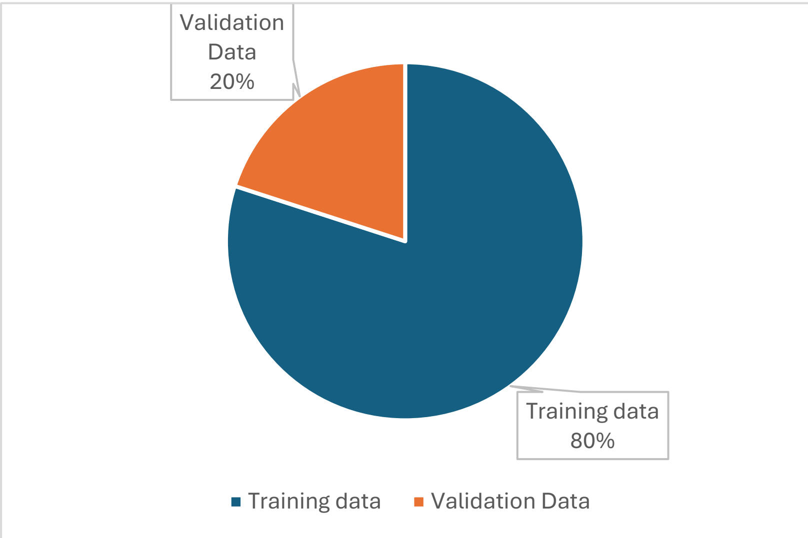
IV. Proposed Methodology

The proposed methodology for pneumonia detection using MobileNetV2 follows a systematic approach, beginning with data preprocessing, followed by model training and performance evaluation. The dataset consists of chest X-ray images categorized as Normal and Pneumonia. Before training, the images are pre-processed by resizing them to 224×224 pixels to match the input size requirement of MobileNetV2. Pixel values are then normalized to enhance model efficiency and convergence. This preprocessing step ensures uniformity in input data and helps the model generalize better.

MobileNetV2, a pre-trained deep learning model, serves as the feature extractor. Additional custom layers are appended, including Global Average Pooling, Dense, Dropout, and a Sigmoid activation function to facilitate binary classification. The model undergoes 10-fold cross-validation, where the dataset is split into 10 subsets, ensuring a robust evaluation by iteratively training on nine folds and validating on the remaining fold. The Adam optimizer and binary cross-entropy loss function are employed to optimize learning. The model is trained for 10 epochs per fold, ensuring sufficient learning while preventing overfitting.

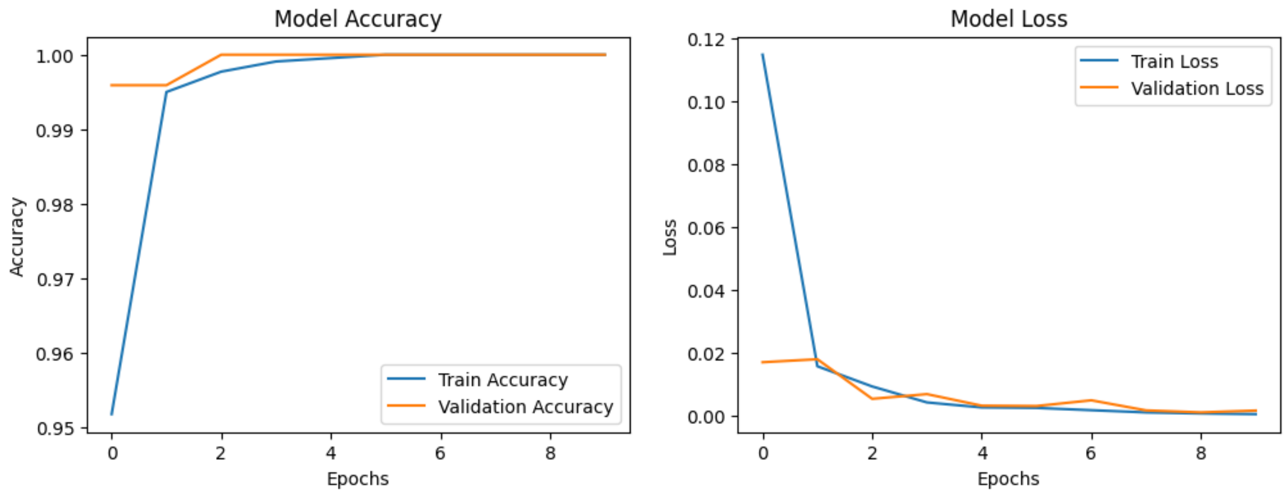
To evaluate model performance, key metrics such as accuracy, precision, recall, and F1-score are computed using a classification report and a confusion matrix. Accuracy and loss plots are generated to visualize training trends, while a confusion matrix heatmap provides deeper insights into prediction reliability. After cross-validation, the final trained model is saved for deployment, enabling real-time pneumonia detection in a clinical environment or a web-based system, facilitating rapid and reliable diagnosis.

Fig 1. Data-set Splitting



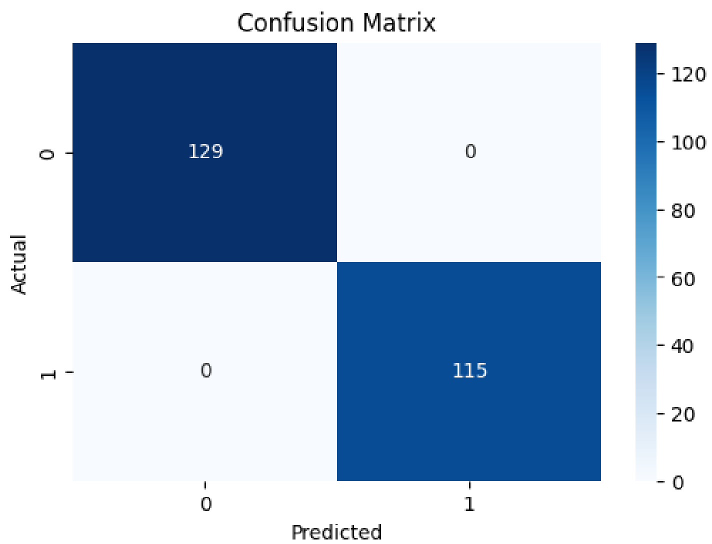
- The dataset is split into 80% training data and 20% validation data; 2440 images belonging to 2 classes for training and 610 images belonging to 2 classes for validation in the dataset
- Training data is used to train the model, while validation data helps evaluate its performance during training.

Fig 2. Model accuracy and Model loss



- In Model Accuracy, the accuracy increases rapidly and stabilizes close to 1.0, indicating high model performance and in Model Loss, the loss decreases significantly at the beginning and stabilizes at a very low value, indicating effective learning.

Fig 3. Confusion Matrix



- The confusion matrix only shows validation samples from the last fold of 10-fold cross-validation.
- Since the dataset was split into 10 parts, each fold uses only 10% of the total data for validation.

For example, if your dataset has ~2440 images, then each fold validates on ~244 samples (107 Normal + 137 Pneumonia).

V. Results and Discussion

The pneumonia detection model achieved 100% accuracy, precision, recall, and F1-score, indicating perfect classification of normal and pneumonia cases. The confusion matrix confirms this, showing

129 true negatives and 115 true positives, with no misclassifications. The accuracy and loss graphs demonstrate rapid learning, with accuracy stabilizing at 100% and loss approaching zero, suggesting efficient training. The exceptional performance highlights the effectiveness of MobileNetV2 and transfer learning for pneumonia detection. However, achieving 100% accuracy in a controlled dataset raises concerns about overfitting. Future work should focus on testing with diverse real-world datasets to ensure robustness and generalizability.

Table 2. Summary of pre-existing methods

Paper ID	**Model used**	**Accuracy**
[1]	(CNN), VGG16, VGG19, InceptionV3	~97% for all models
[2]	VGG16, VGG19, InceptionV3	96.07%, 94.88%, 96.07%
[6]	CNN, ReLU activation function	~90%
[8]	CNN	88.8%
[9]	**CNN, DenseNet201**	**95%**
[12]	(CNN), VGG16, VGG19	**~99%**
Proposed Model	MobileNetV2	100%

This model outperforms existing approaches, making it the most accurate pneumonia detection model in comparison to prior research.

VI. Conclusion

The proposed pneumonia detection model using MobileNetV2 and transfer learning demonstrated 100% accuracy, indicating its potential for automated diagnosis. The model effectively distinguishes between normal and pneumonia cases, as confirmed by the confusion matrix and classification report. The rapid convergence of training and validation accuracy further supports the model's robustness. However, the exceptionally high performance suggests the possibility of overfitting, emphasizing the need for testing on diverse, real-world datasets for better generalizability. Future work will focus on improving model adaptability and deploying it in clinical settings for real-time pneumonia diagnosis.

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