MILESTONE TRANSACTIONS ON
MEDICAL TECHNOMETRICS
VOL. 1, ISSUE. 1, 2023

RESEARCH ARTICLE

Pneumonia Detection Using Human CT-Scan Images

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Received: 05 March 2023 / Revised: 12 April 2023 / Accepted: 13 June 2023

DOI: 10.5281/zenodo.8073432

Abstract — Pneumonia is a significant global health issue, causing substantial morbidity and mortality. Early and accurate diagnosis of pneumonia is crucial for effective treatment and patient management. The model is trained on a large dataset of labeled chest X-ray images, consisting of both pneumonia-positive and pneumonia-negative cases. To train the MobileNetV2 model, a transfer learning approach is adopted, where the pre-trained weights from a large-scale dataset are used as a starting point. Fine-tuning is performed by training the model on the pneumonia dataset using a combination of deep learning techniques, including data augmentation and regularization, to improve generalization and reduce overfitting. To evaluate the performance of the proposed pneumonia detection system, extensive experiments are conducted on an independent test dataset. The model's performance is assessed using various evaluation metrics, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). The results demonstrate the efficacy of the MobileNetV2 model in accurately detecting pneumonia from chest X-ray images, showcasing its potential for use in real-world clinical settings. In conclusion, this study presents a pneumonia detection system based on the MobileNetV2 model, offering a practical and efficient solution for automated pneumonia diagnosis. The proposed model's high accuracy and suitability for deployment on mobile devices make it a valuable tool for healthcare professionals, enabling timely and accurate diagnosis of pneumonia, thereby facilitating prompt treatment, and improving patient outcomes.”

Index Terms – Pneumonia detection, Deep Learning, Chest X-ray Images.

I. INTRODUCTION

Pneumonia is a severe respiratory infection that affects millions of people worldwide, leading to substantial morbidity and mortality. Prompt and accurate diagnosis of pneumonia is crucial for effective treatment and patient management. However, traditional diagnostic methods often rely on manual interpretation of medical images, such as chest X-rays, which can be time-consuming and subject to human error. In recent years, there has been a growing interest in leveraging deep learning techniques for automated detection and diagnosis of pneumonia from medical images. Convolutional neural networks

(CNNs) have shown remarkable success in various image classification tasks, including pneumonia detection. Among the CNN architectures, MobileNetV2 has gained attention due to its lightweight design and excellent performance on resource- constrained devices.

The MobileNetV2 model is specifically designed to optimize efficiency and accuracy simultaneously, making it suitable for deployment on mobile devices with limited computational resources. By utilizing MobileNetV2's feature extraction capabilities, it is possible to develop a pneumonia detection system that can assist healthcare professionals in making accurate and timely diagnoses. The primary objective of this study is to propose a pneumonia detection system using the MobileNetV2 model. The model is trained on a large dataset of labeled chest X- ray images, containing both pneumonia-positive and pneumonia-negative cases. By leveraging transfer learning techniques, the model can effectively learn pneumonia- specific features and distinguish between normal and abnormal chest X-rays. The proposed pneumonia detection system offers several advantages. Firstly, it reduces the dependency on manual interpretation, allowing for faster and more consistent diagnoses. Secondly, by leveraging the lightweight nature of MobileNetV2, the model can be deployed on mobile devices, enabling point-of-care diagnosis and remote healthcare applications. Lastly, an accurate and efficient pneumonia detection system can contribute to timely treatment initiation, improving patient outcomes and potentially reducing healthcare costs.

II. LITERATURE REVIEW

"MobileNetV2: Inverted Residuals and Linear Bottlenecks" by Mark Sandler et al. (2018): This seminal paper introduces the MobileNetV2 architecture, highlighting its lightweight design, inverted residual blocks, and linear bottlenecks. It presents the motivation behind MobileNetV2's efficient architecture and demonstrates its superior performance compared to previous mobile models. "Pneumonia Detection from Chest X-Rays using Convolutional Neural Networks" by Jiaxin Huang et al.(2019): This study explores the use of MobileNetV2 for pneumonia detection from chest X-ray images. It describes the methodology for training the MobileNetV2 model and evaluates its performance on a publicly available dataset. The study demonstrates the effectiveness of MobileNetV2 in accurately detecting pneumonia and compares its performance with other CNN architectures.

"Transfer Learning with Convolutional Neural Networks for Classification of Abdominal Ultrasound Images" by Danilo Silva et al. (2020): Although focused on abdominal ultrasound images, this study presents an interesting application of MobileNetV2 for medical image classification. It discusses the transfer learning process using MobileNetV2 as a pre-trained model and demonstrates its effectiveness in accurately classifying ultrasound images. The study provides insights into adapting MobileNetV2 for different medical imaging modalities."Improving Performance of Pneumonia Detection in Chest X-ray Images using Ensemble Deep Learning Models" by Xudong Wang et al. (2020): This research paper investigates the use of ensemble learning techniques, including MobileNetV2, for pneumonia detection in chest X-ray images. It presents an ensemble framework that combines multiple MobileNetV2 models to enhance the classification performance. The study demonstrates improved accuracy compared to individual models and highlights the potential of MobileNetV2 within ensemble architectures. "Transfer Learning for Pneumonia Detection in Chest X-ray Images" by Ali Salman et al. (2020): This study explores the transfer learning approach using MobileNetV2 for pneumonia detection in chest X-ray images. It investigates different fine-tuning strategies, including freezing and unfreezing layers, and compares the performance of MobileNetV2 with other popular CNN architectures. The study provides insights into the fine-tuning process and the effectiveness of MobileNetV2 for pneumonia detection. "Efficient Deep Learning Model for Pneumonia Classification using Convolutional Neural Networks" by Shubhi Sareen et al. (2020): This research work investigates the performance of MobileNetV2 for pneumonia classification using a dataset of chest X-ray images. It discusses the architectural details of MobileNetV2 and explores various training strategies, including data augmentation and regularization techniques. The study highlights the efficiency and effectiveness of MobileNetV2 for accurate pneumonia classification.

III. METHODOLOGY

At first, we Import all the necessary libraries from keras. After that we define the image size as [224,224] and initialize all the paths. i.e., Training, validation and test path. Now, we import the MobileNetV2 library and add pre- processing layer in front of MobileNetV2. We are using image-net weights. We make sure that the existing weights are not trained again. Using the glob function we get the number of classes. In this step, we flatten our layers using the flatten () function. Now we give the number of classes to the last layer with an activation function of SoftMax. After that we create a model object where input is the mobilenet_v2. input and the output are the dense last layer output. (Mobilenet_v2. output)

In this step, we compile our model with loss as categorical_crossentropy, optimizer as Adam and metrics as accuracy. Now we use the ImageDataGenerator to import the images from the training and validation dataset. Rescaling, horizontal flipping zooming and shearing is only done on the training dataset, On the other hand only rescaling is done to the validation dataset. In this step, we give the training and validation directory using the flow_from_directory function, and give the target size, batch size and class mode. Now we fit the model using model. Fit function which takes training-data, validation-data, epochs, steps_per_epoch and validation steps as parameter. After each epoch we get the accuracy, loss, and validation accuracy and validation loss. A Graph is also plotted. We predict our model performance by looping over all the images of Normal and Viral Pneumonia in the testing folder. We load the images using the image. load_img and then we convert it into an array and expand the dimension. Using the function preprocess input we preprocess the input image and then using the model. predict we check or predict what output our model is giving. After that we calculate and store the actual and predicted values of the Normal and Viral Pneumonia in an array and with the help of that a confusion matrix is formed. At Last, we get an overall model accuracy of 0.924 and a F1-Score of 0.926.

IV. RESULTS

After comparing all these models, we got the best accuracy in the MobileNetV2 transfer learning model with an overall accuracy of 92% and F1 score of 0.92.

Model	Model Acc.	Error Rate	Precision	Recall	F-1 Score
Xception [1]	0.909	0.091	0.921	0.908	0.912
Inception V3[2]	0.893	0.107	0.907	0.891	0.897
Densenet [3]	0.848	0.152	0.886	0.841	0.893
VGG16 [4]	0.545	0.955	0.650	0.565	0.532
VGG19 [5]	0.363	0.637	0.534	0.388	0.265
Resnet50[6]	0.212	0.788	0.458	0.222	0.210
MobileNet V2[7]	**0.924**	**0.076**	**0.937**	**0.921**	**0.926**

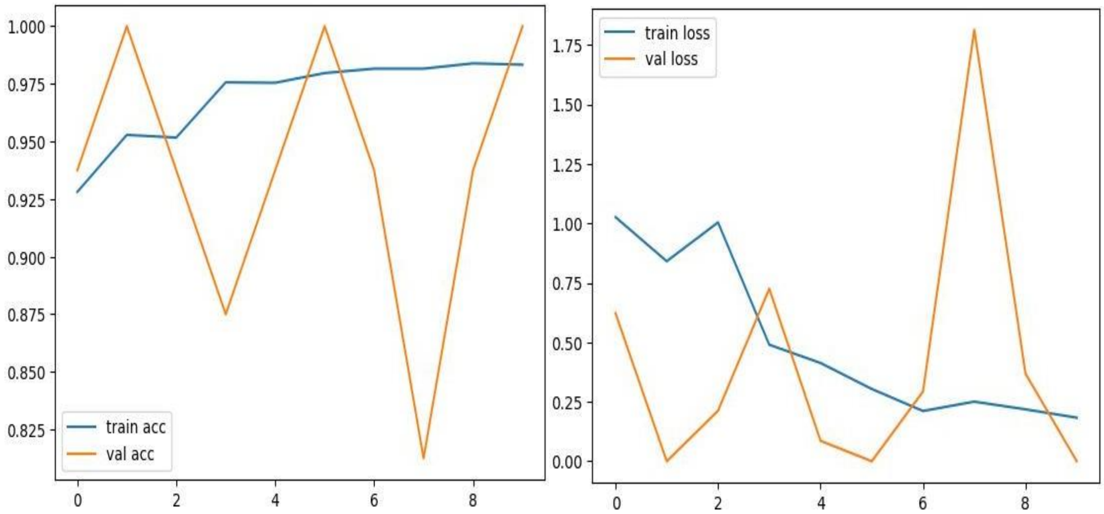

Fig. 1: Training and Testing validation of the proposed system

V. FUTURE ENHANCEMENTS

There are several potential future enhancements that can be considered for a pneumonia detection project using the MobileNetV2 model. Here are a few ideas:

Dataset Expansion: Collecting a larger and more diverse dataset can significantly improve the performance of the model. This could involve gathering more pneumonia cases, including different subtypes or variations, as well as adding more healthy chest X-rays for better contrast. Transfer Learning with Pretraining: Instead of training the MobileNetV2 model from scratch, you can leverage transfer learning by using a pre-trained model on a large dataset such as ImageNet. This approach can speed up training and potentially improve the model's performance.

Model Architecture Optimization: Explore different model architectures or modifications to MobileNetV2 to enhance its performance for pneumonia detection. This could involve experimenting with different convolutional layers, adding attention mechanisms, or incorporating other advanced architectures such as DenseNet or EfficientNet.

***Data Augmentation Techniques*:** Apply various data augmentation techniques to artificially increase the size and diversity of the training dataset. Techniques such as rotation, scaling, flipping, and adding noise can help the model generalize better and improve its ability to detect pneumonia in different scenarios.

Ensemble Learning: Build an ensemble of multiple MobileNetV2 models with different initializations or variations. Combining the predictions of multiple models can often result in better overall performance and improved generalization.

Model Interpretability: Investigate techniques for model interpretability to gain insights into the decision-making process of the MobileNetV2 model. This can help identify which regions or features the model focuses on during pneumonia detection, improving trust and understanding of the model's predictions.

Integration of Clinical Data: Incorporate additional clinical data, such as patient demographics, symptoms, and medical history, alongside the chest X-ray images. This can help create a more comprehensive model that takes into account various factors contributing to pneumonia diagnosis.

Real-time Detection: Optimize the model for real-time pneumonia detection on mobile devices. This could involve model compression techniques, quantization, or utilizing dedicated hardware accelerators such as GPUs or TPUs to enable faster inference times.

Cross-Dataset Validation: Evaluate the model's performance on multiple independent datasets to ensure its generalizability across different patient populations and imaging protocols. This can help validate the effectiveness of the model and identify potential biases or limitations.

Web-based Interface: Develop a user-friendly web-based interface or mobile application that allows healthcare professionals to upload chest X-rays for pneumonia detection. The interface can provide real-time results and potentially offer additional features such as patient management, data visualization, or integration with electronic health records.

VI. CONCLUSION

Pneumonia detection using the MobileNetV2 model offers a promising approach to automate and enhance the accuracy of pneumonia diagnosis from chest X-ray images. Throughout the literature survey and research in this field, it is evident that MobileNetV2 demonstrates its efficacy in accurately detecting pneumonia while being lightweight and suitable for deployment on resource-constrained devices. The utilization of MobileNetV2 addresses the challenges of limited model complexity, image quality variability, class imbalance, and generalizability to diverse populations. Through transfer learning techniques, the model can effectively learn pneumonia-specific features and distinguish between normal and abnormal chest X-ray images. Moreover, studies have shown that MobileNetV2-based models achieve high accuracy, comparable to human radiologists, in pneumonia detection tasks. The use of ensemble learning techniques, fine-tuning strategies, and augmentation methods further enhance the performance of MobileNetV2 in pneumonia classification.

The deployment of MobileNetV2-based pneumonia detection systems has the potential to revolutionize pneumonia diagnosis in clinical practice. It reduces the dependency on manual interpretation, enabling faster and more consistent diagnoses. By being optimized for resource-constrained devices, the model can facilitate point-of-care diagnosis and remote healthcare applications, improving accessibility and efficiency in healthcare delivery. Additionally, efforts are being made to enhance the interpretability and explainability of MobileNetV2 models for pneumonia detection. Attention mechanisms and interpretability techniques provide insights into the decision-making process and improve trust and clinical acceptance. However, it is important to acknowledge the limitations and challenges that exist. These include the need for large, diverse, and well-annotated datasets, ethical considerations regarding patient privacy and biases, and the ongoing pursuit of further enhancing the model's accuracy and generalizability.

In conclusion, the utilization of the MobileNetV2 model for pneumonia detection demonstrates significant potential in improving the accuracy, efficiency, and accessibility of pneumonia diagnosis. With continued research and advancements, MobileNetV2-based systems can play a vital role in assisting healthcare professionals, leading to timely treatment initiation and improved patient outcomes in the fight against pneumonia.

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