BAB 1 INTRODUCTION

Pneumonia is a serious respiratory infection affecting the lungs, caused by bacteria, fungi, and viruses [1]. Streptococcus pneumoniae is particularly prevalent, especially impacting young children and the elderly [2]. Symptoms include fever, cough, difficulty breathing, and chest pain [1]. Globally, pneumonia is a significant health issue, with developing countries facing high child mortality rates due to limited healthcare resources [3]. Chest X-rays are commonly used for diagnosis, but interpreting these images can be challenging, as radiologists' expertise and subjective interpretations vary, leading to inconsistent diagnoses [4]. Convolutional Neural Networks (CNNs) have shown promise in improving diagnostic consistency and accuracy in analyzing chest X-rays, making them a valuable tool in medical imaging.

Despite the advantages of CNNs in medical image analysis, pneumonia detection faces specific challenges. High-performing CNN models, such as DenseNet and VGG, have been effectively applied in pneumonia detection but often require substantial computational power, limiting their deployment in resource-constrained or real-time settings. Darici et al. [5] and Hammoudi et al. [6] demonstrated that DenseNet achieves high accuracy but at a high computational cost, while VGG offers better efficiency but at some accuracy trade-off. These limitations highlight the need for a more efficient model suitable for deployment on limited hardware.

MobileNetV2, introduced by Sandler et al. [7], addresses this need with a lightweight design that reduces computational complexity through depthwise separable convolutions, making it ideal for mobile and embedded systems without compromising accuracy. However, its specific effectiveness in pneumonia detection has not been extensively studied, particularly in terms of balancing accuracy and efficiency in resource-constrained settings. Additionally, while data augmentation techniques like rotation and flipping are commonly employed to enhance model robustness, their specific effects on lightweight models such as MobileNetV2 in medical imaging remain underexplored.

This study addresses these gaps by evaluating MobileNetV2's performance in pneumonia detection with a focus on efficiency and accuracy across different input dimensions. Additionally, it explores the role of data augmentation in improving model robustness and applies hyperparameter tuning to achieve optimal configurations. By systematically analyzing these factors, this research aims to provide a reliable and efficient solution for pneumonia detection suitable for deployment in resource-constrained environments.