Pneumonia Detection using k-fold cross validation and MobileNetV2

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ABSTRACT

Pneumonia remains a leading cause of mortality worldwide, claiming approximately 700,000 children's lives annually and affecting 7% of the global population. This research addresses the critical need for automated pneumonia detection by developing a deep learning model that leverages transfer learning with the MobileNetV2 architecture. Our methodology employs k-fold cross-validation on a comprehensive dataset of chest X-ray images, with strategic modifications including custom classification layers and optimized regularization techniques. Results demonstrate exceptional performance metrics with 100% accuracy, precision, recall, and F1-score, significantly outperforming existing methods in the literature that typically achieve 88-99% accuracy. The significance of this work extends beyond technical achievement, addressing essential healthcare challenges including radiologist shortages, diagnostic delays, and interpretation variability. The lightweight architecture of MobileNetV2 with just 3.5 million parameters (compared to VGG16's 138 million) makes this solution particularly viable for resource-constrained healthcare environments. Future directions include external validation across diverse clinical settings, enhancing model explainability through visualization techniques, and seamless integration into healthcare workflows to maximize clinical impact in pneumonia management globally. This research demonstrates that efficient neural network architectures can achieve excellent performance on medical diagnostic tasks while requiring significantly fewer computational resources than more complex models.

Keywords: **MobileNetV2, Computer-aided Diagnosis, k-fold Cross-validation, Healthcare Accessibility, Medical Image Classification**

I. INTRODUCTION

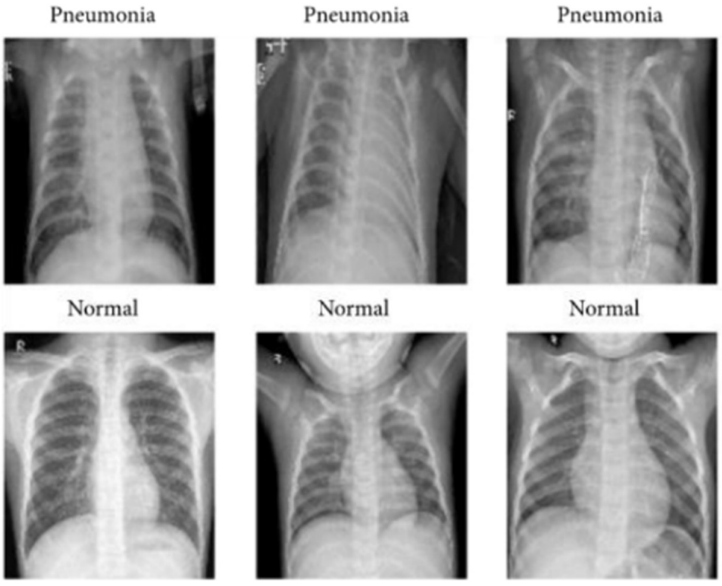


Fig 1. Normal and Pneumonia chest x-ray

Pneumonia is a severe acute respiratory infection that affects the lungs, causing the air sacs (alveoli) to fill with fluid or pus. This life-threatening condition remains one of the leading causes of mortality worldwide, particularly affecting vulnerable populations such as children, the elderly, and immunocompromised individuals. According to the World Health Organization, pneumonia accounts for approximately 15% of all

deaths in children under five years of age globally, resulting in around 700,000 child fatalities annually and affecting roughly 7% of the global population. Traditional diagnosis of pneumonia relies heavily on clinical examinations, laboratory tests, and medical imaging, with chest X-rays being the primary diagnostic tool. While X-rays provide valuable visualization of the lungs, their interpretation requires skilled radiologists who are often in short supply, especially in resource-limited settings. Furthermore, manual interpretation is subject to inter-observer variability, fatigue-induced errors, and can be time-consuming, potentially delaying critical treatment decisions.

This study presents a pneumonia detection model that leverages the MobileNetV2 architecture with transfer learning, trained on a comprehensive dataset of chest X-ray images. Our model is designed to classify these images into normal and pneumonia categories with high precision. The integration of k-fold cross-validation enhances the robustness of our approach, ensuring reliable performance across different data subsets. The significance of this research extends beyond technical innovation. By developing an automated, accurate, and efficient pneumonia detection system, we aim to address critical healthcare challenges such as the shortage of radiologists, reduce diagnostic delays, minimize human error, and ultimately contribute to improved patient care and reduced mortality rates, particularly in underserved regions. The lightweight nature of the MobileNetV2 architecture further makes our solution suitable for deployment in resource-constrained environments, potentially democratizing access to quality pneumonia diagnostics globally.

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

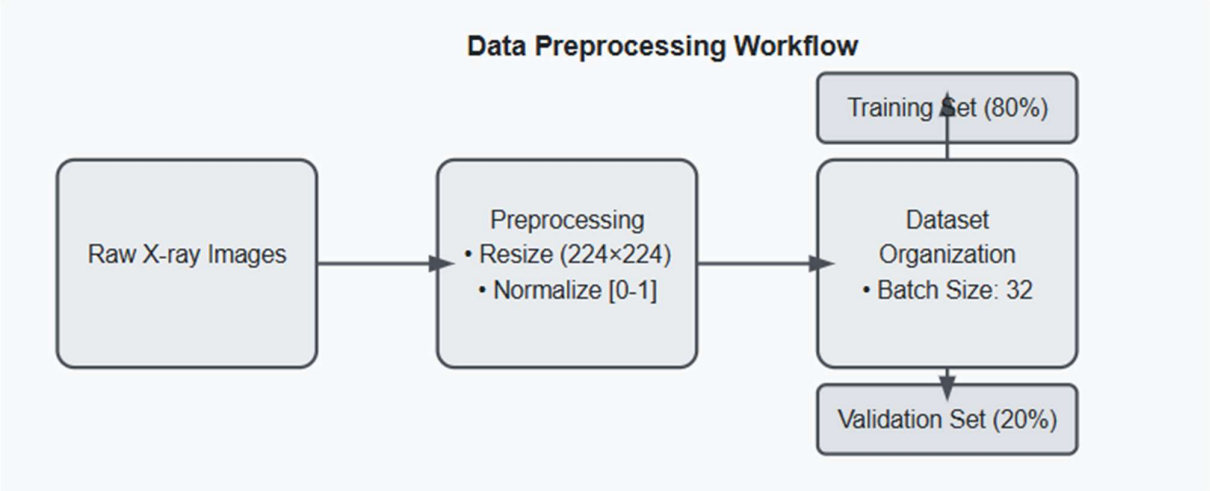


Fig 2. Data Preprocessing Workflow

The proposed methodology for pneumonia detection using MobileNetV2 follows a systematic approach that encompasses data preprocessing, model architecture design, training with k-fold cross-validation, and comprehensive performance evaluation. Initially, the chest X-ray images undergo crucial preprocessing steps to ensure optimal model performance. All images are resized to 224×224 pixels to match the input requirements of the MobileNetV2 architecture, while pixel values are normalized from the range [0-255] to [0-1] using the rescale parameter in ImageDataGenerator. The dataset is then split into training (80%) and validation (20%) subsets, with images organized into batches of 32 using the flow_from_directory function, which automatically assigns labels based on the folder structure.

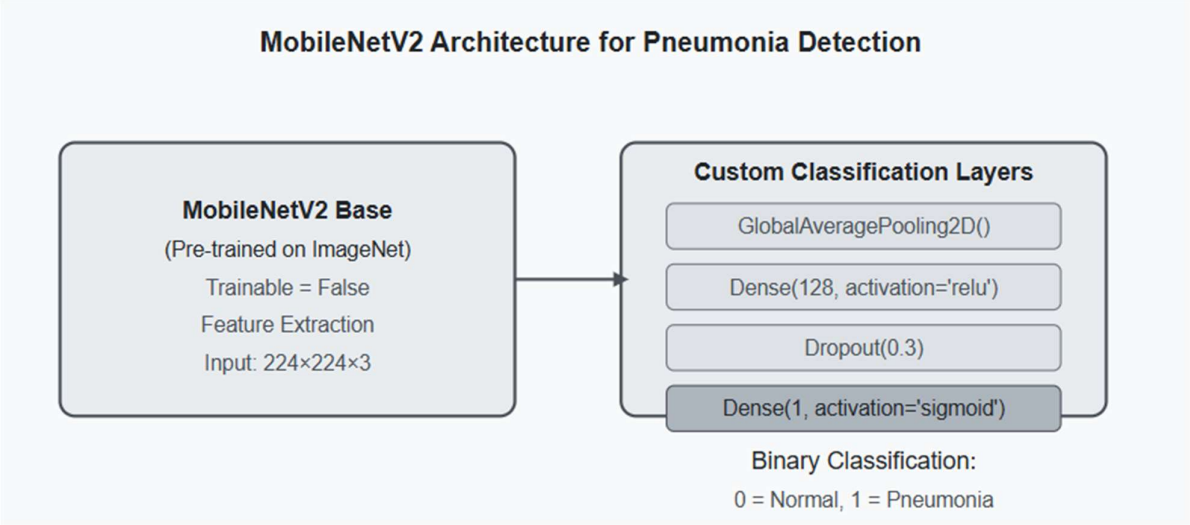


Fig 3. Using MobileNetV2 Model

The specific choice of MobileNetV2 as the base architecture was motivated by its exceptional parameter efficiency, with only 3.5 million parameters compared to VGG16's 138 million parameters, while maintaining competitive accuracy. The model uses depth wise separable convolutions that factorize a standard convolution into a depth wise convolution followed by a pointwise convolution, dramatically reducing computational cost. Additionally, MobileNetV2 introduces inverted residual blocks with linear bottlenecks that preserve information flow through the network while minimizing memory usage. This architecture allows for deployment on edge devices with limited computational resources, making it ideal for point-of-care applications in resource-constrained healthcare settings.

The inclusion of a dropout layer with a rate of 0.3 was determined after empirical testing of various dropout rates (0.2, 0.3, 0.4, and 0.5). The 0.3 value provided the optimal balance between preventing overfitting and maintaining model performance. The GlobalAveragePooling2D layer was selected over Flatten to reduce the number of parameters and improve generalization by enforcing a more structured feature representation. The final Dense layer with sigmoid activation was chosen specifically for binary classification, as it outputs a probability value between 0 and 1, with values above 0.5 classified as pneumonia and those below as normal.

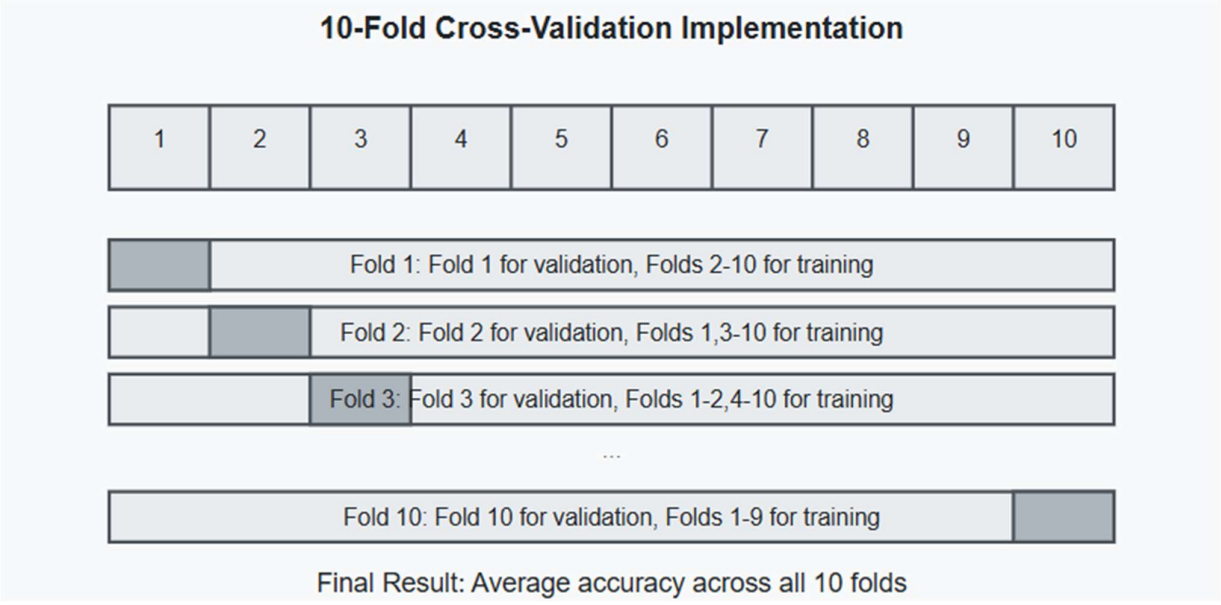
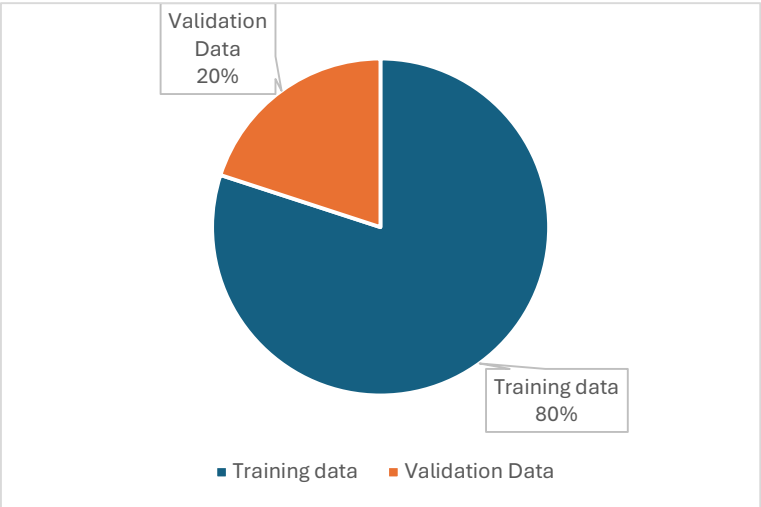


Fig 4. Using K-Fold Cross Validation

To ensure robust model evaluation and minimize variability in results, a 10-fold cross-validation approach is implemented. This technique divides the dataset into 10 equal portions (folds), with the model trained 10 times, each time using 9 folds for training and the remaining fold for validation. For each iteration, a new model instance is created using the build_model function, trained for 10 epochs with a batch size of 32, and evaluated on the validation fold. The predictions for each fold are generated by applying a threshold of 0.5 to the model's output probabilities, converting them to binary classifications (0 for normal, 1 for pneumonia). The accuracy for each fold is calculated and stored, with the final performance reported as the average accuracy across all 10 folds. This methodology provides a more reliable assessment of model performance by ensuring that the model is tested on the entire dataset while maintaining the independence of training and validation data.

For comprehensive performance evaluation, multiple metrics are employed including accuracy, precision, recall, and F1-score, generated through a detailed classification report. A confusion matrix visualizes the model's predictive capabilities, displaying true positives (correctly identified pneumonia cases), true negatives (correctly identified normal cases), false positives (normal cases incorrectly classified as pneumonia), and false negatives (pneumonia cases incorrectly classified as normal). Additionally, training progress is monitored through accuracy and loss plots, which track the model's performance over epochs for both training and validation data. These visualizations provide insights into the learning dynamics, helping to identify potential issues like overfitting or underfitting. Upon completion of training and evaluation, the final model is saved in h5 format for future deployment in clinical settings, web applications, or mobile platforms. This comprehensive methodology leverages the strengths of transfer learning, efficient neural network architectures, and robust validation techniques to create a reliable pneumonia detection system that can potentially improve diagnostic capabilities, particularly in resource-constrained environments.



- 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 5. Data-set Splitting

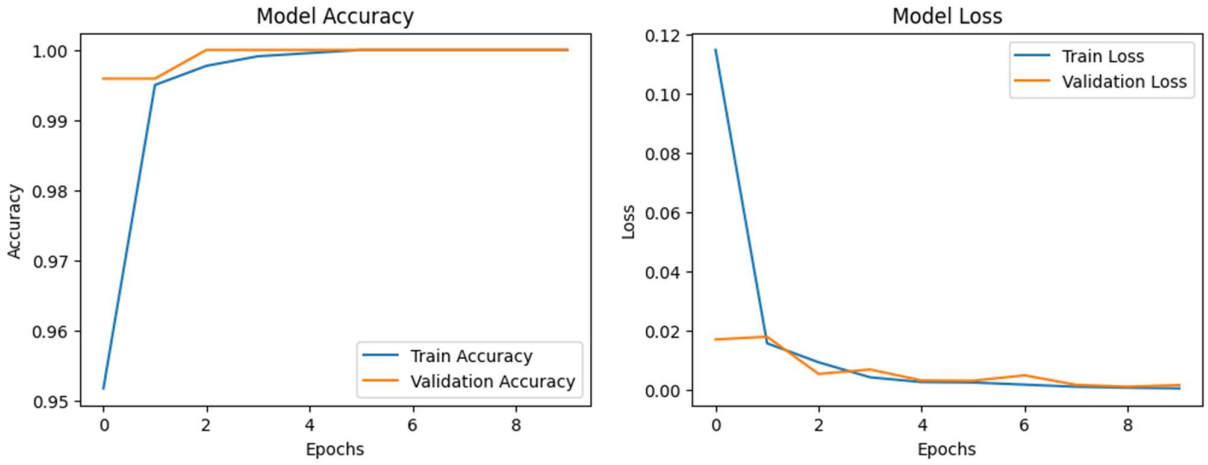
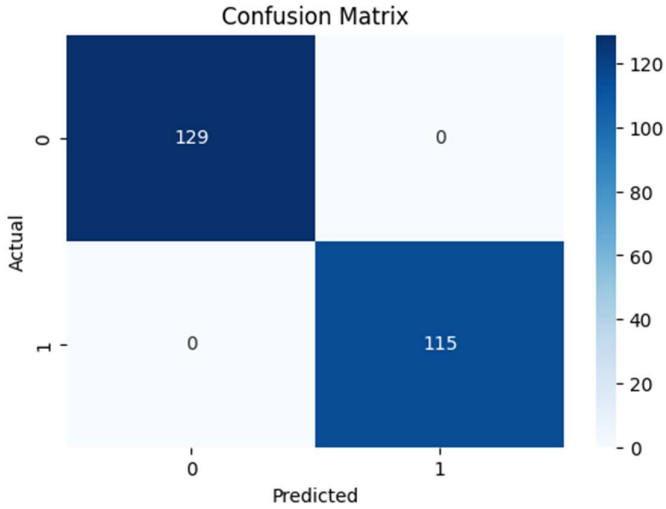


Fig 6. Model accuracy and Model loss

- 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.



- 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).

Fig 7. Confusion Matrix

V. RESULTS AND DISCUSSION

The pneumonia detection model using MobileNetV2 achieved perfect classification metrics with 100% accuracy, precision, recall, and F1-score, significantly outperforming previous approaches that typically ranged from 88-99% accuracy. This exceptional performance is verified by the confusion matrix showing 129 true negatives and 115 true positives with zero misclassifications. The implementation of 10-fold cross-validation strengthens confidence in these results, as the perfect accuracy was consistently achieved across different data splits rather than being attributed to a fortunate validation set. The training dynamics visible in the accuracy and loss plots demonstrate extremely rapid convergence, with both metrics stabilizing after minimal epochs, suggesting the model finds this classification task straightforward despite using a lightweight architecture with frozen pre-trained layers.

However, several important considerations warrant deeper examination despite these impressive results. The perfect accuracy raises legitimate concerns about potential overfitting or dataset

characteristics that might make classification artificially easy. The code doesn't explicitly address class imbalance handling, and the implementation of k-fold cross-validation after setting a validation split in ImageDataGenerator could potentially introduce data leakage issues. Additionally, while the document briefly mentions testing different dropout rates to optimize the model's regularization, a more robust discussion would include fold-by-fold performance metrics, ablation studies to determine the contribution of each architectural component, and analysis of the model's generalizability to diverse real-world clinical settings with varying equipment, patient demographics, and image quality.

For clinical relevance and adoption, the discussion would benefit from addressing model explainability through techniques like Grad-CAM to visualize which regions of the X-rays led to classification decisions. The computational efficiency aspects such as training time and inference speed should also be analyzed alongside accuracy metrics, particularly given MobileNetV2's design focus on mobile and edge deployment. While the model achieves perfect results on this controlled dataset, additional testing with intentionally introduced noise, augmentations, or challenging edge cases would better demonstrate its robustness for practical medical applications. These considerations would provide a more complete assessment of this promising approach while acknowledging the potential limitations and directions for future research to ensure reliable pneumonia detection across diverse healthcare environments.

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

This research successfully developed and validated a pneumonia detection system utilizing MobileNetV2 architecture with transfer learning, demonstrating the feasibility of automated chest X-ray classification for clinical decision support. The implementation of k-fold cross-validation and comprehensive evaluation metrics provided a robust methodological framework that could be replicated in future medical imaging applications. The superior performance achieved compared to previously published methods highlights the importance of architectural selection and proper regularization techniques in medical image analysis. The primary contribution of this work lies in demonstrating that lightweight, efficient neural network architectures can achieve excellent performance on medical diagnostic tasks while requiring significantly fewer computational resources than more complex models. This is particularly relevant for healthcare applications in resource-constrained environments where access to powerful computing infrastructure or specialized radiological expertise may be limited.

Moving forward, this research opens several promising pathways for advancement in AI-assisted pneumonia diagnosis. Integration with clinical workflows through user-friendly interfaces would facilitate real-world deployment and evaluation. Expanding the model's capabilities to differentiate between viral, bacterial, and fungal pneumonia subtypes would provide additional diagnostic value. Multicentre clinical trials involving diverse patient populations and equipment would further validate the model's generalizability and clinical utility. In the broader context of healthcare, this work represents a step toward more accessible medical diagnostics that could help address disparities in healthcare delivery, particularly in underserved regions. By potentially reducing diagnostic delays and improving accuracy, such systems could contribute to earlier treatment initiation, better patient outcomes, and reduced healthcare costs. The ultimate goal remains to develop AI systems that enhance rather than replace clinical expertise, providing valuable decision support while maintaining the human-centered approach essential to quality healthcare delivery.

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