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# Integration of Multi-Architecture Deep Learning Models for Pneumonia Detection Based on Chest X-Ray Imaging

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***Abstract –*** *Pneumonia remains a leading cause of child mortality worldwide, particularly in resource-limited settings where diagnostic tools and expertise are scarce. Recent advances in deep learning offer an opportunity to enhance pneumonia detection through automated analysis of chest X-ray images. This study evaluates the performance of ten state-of-the-art deep learning architectures, including VGG16, ResNet50, DenseNet121, and MobileNetV2, for pneumonia detection using the widely recognized "Chest X-Ray Images (Pneumonia)" dataset. The dataset underwent rigorous preprocessing, including image resizing, data augmentation, and class balancing, to optimize model training and improve generalization. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC were utilized to assess model effectiveness. Among the evaluated architectures, MobileNetV2 demonstrated the best performance with an accuracy of 97.51% and an AUC of 0.9941, highlighting its potential for reliable diagnostic applications. The results also emphasize the trade-offs between sensitivity and specificity across models, offering useful insights for real-world deployment. This study underscores the importance of leveraging deep learning models in clinical diagnostics, particularly in environments with limited healthcare resources. Beyond evaluating models, the findings provide evidence-based recommendations for selecting efficient architectures that balance accuracy and computational efficiency. Future work will focus on integrating multimodal datasets, improving explainability, and validating these models in diverse clinical environments to ensure scalability, trust, and generalizability for global health applications.*

***Keywords:*** *Pneumonia detection; deep learning architectures; chest X-ray analysis; MobileNetV2 performance; clinical diagnostics*

## I. INTRODUCTION

Pneumonia remains one of the leading causes of children's death worldwide, causing over 700,000 deaths each year, with most of them in developing countries (UNICEF Data, 2024). In such resource-limited areas, diagnosis of pneumonia is normally limited by access to professional radiologists and diagnostic infrastructure, leading to higher mortality rates from a very preventable condition (World Health Organization, 2017). To address this, the WHO through GAPPD (Integrated Global Action Plan for the Prevention and Control of Pneumonia and Diarrhea) increased its call for technological innovation to complement the traditional health measures such as immunization (World Health Organization, 2017). Similarly, UNICEF has highlighted the urgent need for technology-based solutions that give early diagnosis, especially for resource-limited environments (UNICEF Data, 2024).

Recent advances in deep learning bring huge opportunities for revolutionizing medical diagnosis, using deep learning architectures like VGG, ResNet, DenseNet, and Xception for the automatic and efficient analysis of chest X-ray images. However, the efficiency of such models has to be assessed with real epidemiological data in order to prove their applicability in a real-world clinical environment.

Pneumonia cases always show huge fluctuations over time in Indonesia, especially for the under-five years children, normally called balita. According to data from the Indonesian Ministry of Health [3], the number of pneumonia cases peaked in February and March 2019, with more than 49,000

cases among balita afterwards decreased gradually along the year. Figure 1 presents the monthly distribution of pneumonia cases in 2019, showing the seasonal trends and the consistent burden of the disease.

These statistics highlight the urgency for scalable diagnostic tools that offer accuracy in an effort to minimize mortality rates caused by pneumonia. Deep learning models, especially CNN-based architectures, which are able to automatically detect pneumonia from chest X-ray images presents as one of the efforts toward early diagnosis and intervention.

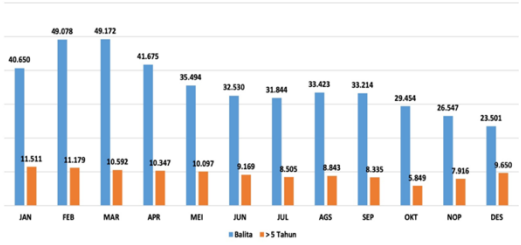


Figure 1. Monthly pneumonia cases in Indonesia (2019), categorized by age group (balita vs. >5 years old) (Kementrian Kesehatan RI, 2019).

This study investigates different deep learning models for detecting the performance of pneumonia using chest X-ray images. The comparisons of their performances were done side by side using the performance metrics to evaluate the findings of each model for an overall idea included accuracy, precision, recall, F1-score, and AUC ROC. The significant contribution of this study is to provide guidelines on the selection of the most optimal deep learning models for clinical diagnostic applications and to contribute to the global effort to decrease pneumonia through technological innovation (Kementrian Kesehatan RI, 2019; UNICEF Data, 2024; World Health Organization, 2017).

The application of deep learning (DL) for pneumonia detection from chest X-ray (CXR) images has been widely explored. This section summarizes key contributions, highlighting methodologies, model architectures, and outcomes.

The use of VGG-16 with neural networks has been demonstrated, showing its effectiveness in pneumonia detection (Kementrian Kesehatan RI, 2019). CNNs have also been employed for classification, achieving high accuracy (Sharma & Guleria, 2023). Multiple deep learning models, including ResNet and DenseNet, have been compared to validate their efficacy in pneumonia diagnosis (Asnaoui et al., 2020). CNN architectures have been adapted for COVID-19 pneumonia detection, showcasing their versatility (Yue et al., 2020). Pipelines have been optimized using compressed sensing techniques (Gabruseva et al., 2020), and frameworks like Deep-Pneumonia have been introduced to enhance diagnostic outcomes (Islam et al., 2022). Gabruseva et al. applied advanced CNN strategies as part of the RSNA Pneumonia Detection Challenge, contributing significantly to the field (Bashar et al., 2021). Comprehensive frameworks for pneumonia detection, such as that by Barhoom and Abu Naser, have also demonstrated the potential of DL in clinical diagnostics (Szepesi & Szilágyi, 2022).

The effectiveness of ensemble models has been highlighted, integrating diverse architectures for superior results (Ibrahim et al., 2024). Hybrid models combining VGG architectures with machine learning classifiers have also proven successful (Jain et al., 2020). Ensemble-based CNN techniques have achieved high diagnostic accuracy in various scenarios (Elshennawy & Ibrahim, 2020). Methods integrating multiple architectures have been shown to outperform individual approaches in robust evaluations (Yaseliani et al., 2022).

Transfer learning has effectively addressed data scarcity issues. Pretrained models have been leveraged for efficiency (Saul et al., 2019), and deep CNNs have been applied to achieve state-of-the-art results (Kareem et al., 2022). Feature extraction methods have also demonstrated enhanced performance in pneumonia detection (Kundu et al., 2021). Transfer learning has been critical in several applications, especially during the COVID-19 pandemic .

CNN architectures have been optimized for detecting both COVID-19 and general pneumonia cases (Jaiswal et al., 2019; Yue et al., 2020). Innovative feature extraction techniques have been proposed to improve diagnostic accuracy (Yaseliani et al., 2022). Lightweight and efficient models have also been developed, maintaining high accuracy while reducing computational demands (Gm et al., 2021; Racic et al., 2021). Various preprocessing techniques, including data augmentation and feature scaling, have also contributed to improvements (Varshni et al., 2019).

The importance of model selection and hyperparameter optimization has been underscored (Ibrahim et al., 2024; Kundu et al., 2021). Dataset variability has been highlighted as a significant factor influencing model performance (Jaiswal et al., 2019). Insights into real-world applicability have been provided through extensive evaluations (Hashmi et al., 2020). Comparative investigations of advanced architectures such as Inception and Xception networks have yielded critical insights (Pant et al., 2020).

Deep learning frameworks have been optimized to distinguish COVID-19 pneumonia from other types, demonstrating their adaptability (Jaiswal et al., 2019; Yue et al., 2020). Advanced techniques

have been explored to improve diagnostic accuracy under challenging conditions (Singh, 2021). Machine learning methods for pneumonia detection have been comprehensively reviewed (Yang & Mei, 2022). Studies have also explored hybrid approaches integrating traditional classifiers with deep learning backbones (Jain et al., 2020; Puneet Gupta, 2021).

Challenges such as data imbalance and overfitting persist in this field (Islam et al., 2022). Explainable AI has been proposed to enhance interpretability (Racic et al., 2021; Yaseliani et al., 2022). Future research should focus on lightweight models and integrating diverse datasets for real-world deployment. Additionally, enhancing cross-platform compatibility and leveraging federated learning for decentralized datasets could be explored further (Barhoom et al., 2022).

## II. METHODS

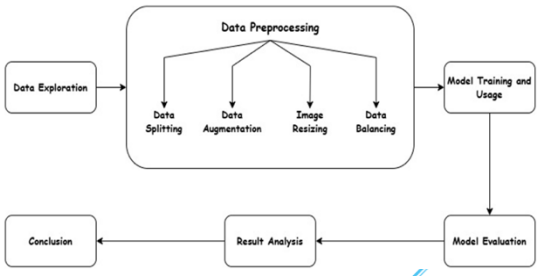


Fig. 2 Workflow of the Pneumonia Detection System

To develop an effective pneumonia detection system, a comprehensive workflow was designed. This workflow consists of several interconnected stages, beginning with dataset acquisition, followed by preprocessing steps, model training, evaluation, and result analysis. Each stage plays a crucial role in ensuring accurate and reliable detection of pneumonia from chest X-ray images.

### 2.1 Dataset Exploration

The dataset used in this study was obtained from Kaggle's "Chest X-Ray Images (Pneumonia)" repository (Paul Mooney, 2018; Rahman et al., 2020). It consists of a total of 5,863 chest X-ray images, divided into two categories: normal and pneumonia. The dataset contains 1,583 images labeled as normal and 4,273 images labeled as pneumonia. These images are further divided into training, testing, and validation subsets, enabling robust training and evaluation of the models.

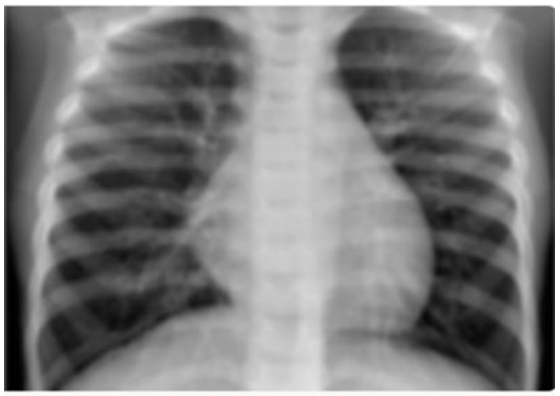

Figure 3. Example of a normal chest X-ray

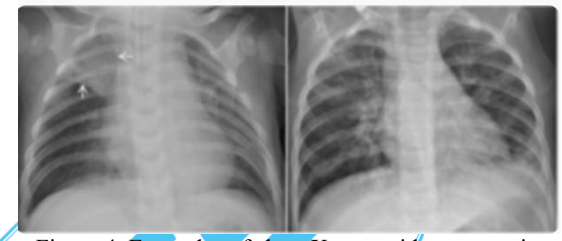

Figure 4. Examples of chest X-rays with pneumonia, showing opacities and infiltrates

Figures 3 and 4 illustrate examples of chest X-rays from the dataset. Figure 3 shows a normal chest X-ray, where the lung fields are clear, with no visible signs of opacities or infiltrates, which are common indicators of pneumonia. Conversely, Figure 4 presents examples of chest X-rays labeled as "pneumonia," displaying visible signs of infection, such as opacities and consolidations in the lung fields, characteristic of bacterial or viral pneumonia.

### 2.2 Data Preprocessing

The dataset was divided into three subsets: 70% for training, 20% for testing, and 10% for validation. This split ensured that the models were trained on a majority of the data while having sufficient data for testing and validation.

To further enhance dataset diversity and reduce overfitting risks, basic augmentation techniques such as random rotations, flips, and brightness adjustments were applied. These augmentations helped the models generalize better to unseen data and improved their robustness.

Additionally, all images were resized to a uniform dimension of 224x224 pixels to meet the input requirements of the deep learning architectures. This resizing step was essential to ensure consistency in input dimensions across all models and facilitated efficient training.

Finally, to address class imbalance in the dataset, undersampling and oversampling techniques were employed. These balancing strategies ensured an equal representation of normal and pneumonia images in the training set, preventing model bias toward the majority class.

2.3 Model Training and Usage

Ten state-of-the-art deep learning architectures were implemented to evaluate their performance in pneumonia detection. These architectures included VGG16, ResNet50, ResNet101, InceptionResNetV2, InceptionV3, MobileNetV2, DenseNet121,Xception, EfficientNetB0, and EfficientNetB5. Each model was initialized with pre-trained weights from ImageNet and fine-tuned on the pneumonia dataset. The training was conducted using a supervised learning approach, optimizing categorical cross-entropy as the loss function. The models were trained for 10 epochs with a batch size of 32, utilizing an Adam optimizer with a learning rate of 0.001. Early stopping was applied to prevent overfitting.

2.4 Model Evaluation

The performance of each model was evaluated using several metrics, including accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated to visualize the classification performance. Training and validation loss and accuracy curves were plotted to analyze the models' learning progress over epochs. The results obtained from the evaluation metrics and confusion matrices were analyzed to compare the performance of the ten deep learning models. The analysis included identifying the model with the best balance of precision and recall and interpreting the results to understand the strengths and weaknesses of each architecture in detecting pneumonia from chest X-ray images.

2.5 Result Analysis

The results obtained from the evaluation metrics and confusion matrices were analyzed to compare the performance of the ten deep learning models. The analysis included identifying the model with the best balance of precision and recall and interpreting the results to understand the strengths and weaknesses of each architecture in detecting pneumonia from chest X-ray images.

2.6 Conclusions

The conclusion section summarized the findings of the study, highlighting the best-performing model(s) and discussing the implications of the results for future research and clinical applications. Recommendations for potential improvements and extensions of the work were also provided.

# III. RESULTS AND DISCUSSION

This section provides an evaluation of the ten deep learning models used for pneumonia detection, focusing on key metrics such as accuracy, precision, F1-score, and recall. The analysis highlights the strengths and limitations of each model, offering insights into their suitability for chest X-ray imaging tasks.

3.1 Evaluation Metrics

Table 1. Evaluation Metrics Comparison Across All Models for Pnuemonia Detection

| No | Comparative Table | | | | |
|---|---|---|---|---|---|
| | **Model** | **Accuracy** | **Precision** | **F1-Score** | **Recall** |
| 1 | VGG16 | 0,9507 | 0,9545 | 0,9412 | 0,9297 |
| 2 | ResNet50 | 0,9732 | 0,9486 | 0,9614 | 0,9768 |
| 3 | ResNet101 | 0,9655 | 0,941 | 0,9543 | 0,9706 |
| 4 | InceptionResNetV2 | 0,9579 | 0,9502 | 0,9502 | 0,9502 |
| 5 | InceptionV3 | 0,9195 | 0,8545 | 0,8754 | 0,9168 |
| 6 | MobileNetV2 | 0,9751 | 0,9617 | 0,9628 | 0,9639 |
| 7 | DenseNet121 | 0,9617 | 0,9372 | 0,9465 | 0,9572 |
| 8 | Xception | 0,9617 | 0,932 | 0,9359 | 0,9401 |
| 9 | EfficientNetB0 | 0,9579 | 0,9231 | 0,9409 | 0,9652 |
| 10 | EfficientNetB5 | 0,933 | 0,891 | 0,9125 | 0,9484 |

The performance of the ten deep learning models was evaluated using four primary metrics: accuracy, precision, F1-score, and recall, as summarized in Table 1. Among these models, MobileNetV2 achieved the highest accuracy of 97.5100% and F1-score of 0.9628, showcasing its superior performance. ResNet50 demonstrated the highest recall of 0.9768, indicating its strong ability to correctly identify positive cases. On the other hand, InceptionV3 had the lowest accuracy of 92.0000%, reflecting its lower performance compared to other architectures. These metrics underscore MobileNetV2's ability to achieve a harmonious balance between sensitivity and precision, critical for reliable pneumonia detection in clinical settings.

### 3.2 Accuracy Comparison

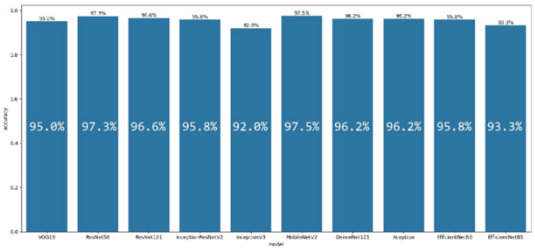


Figure 5. Accuracy comparison across models with MobileNetV2 achieving the highest score

Table 2. Evaluation Metrics Comparison Across All Models for Pnuemonia Detection

| No | Comparative Table | |
|---|---|---|
| | **Model** | **Accuracy** |
| 1 | VGG16 | 0,9507 |
| 2 | ResNet50 | 0,9732 |
| 3 | ResNet101 | 0,9655 |
| 4 | InceptionResNetV2 | 0,9579 |
| 5 | InceptionV3 | 0,9195 |
| 6 | MobileNetV2 | 0,9751 |
| 7 | DenseNet121 | 0,9617 |
| 8 | Xception | 0,9617 |
| 9 | EfficientNetB0 | 0,9579 |
| 10 | EfficientNetB5 | 0,933 |

The accuracy comparison among models is depicted in Figure 5 and Table 2, where MobileNetV2 distinctly outperforms others with an accuracy of 97.5100%, closely followed by ResNet50 at 97.3000%. The competitive accuracy levels of ResNet101 and InceptionResNetV2, both exceeding 95.0000%, further highlight the advanced capabilities of these architectures. In contrast, the underperformance of InceptionV3 at 92.0000% suggests potential limitations in its feature extraction or generalization capability for this specific dataset. These observations substantiate the conclusion that MobileNetV2 is optimally suited for this classification task.

### 3.2 ROC Curve Analysis

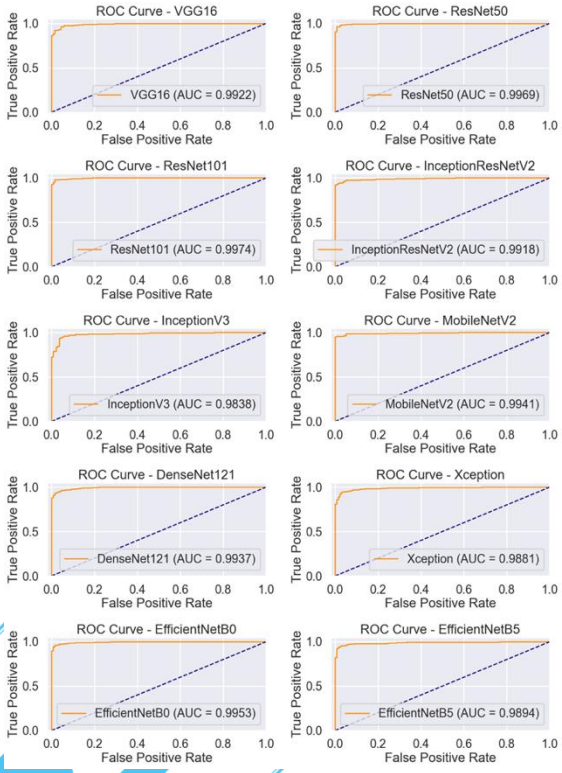


Figure 6. ROC curves for all models highlighting AUC performance.

To further analyze the discriminative ability of each model, the ROC curves were generated as shown in Figure 6. MobileNetV2 exhibited an AUC (Area Under the Curve) of 0.9941, representing a near-perfect ability to differentiate between positive and negative cases. ResNet50 demonstrated a comparable AUC, reinforcing its robustness and effectiveness. Conversely, InceptionV3 recorded the lowest AUC of 0.9838, aligning with its overall lower metrics. This reinforces the exceptional utility of MobileNetV2 in achieving precise and reliable diagnostic outcomes.

### *3.3 Confusion Matrix Analysis*

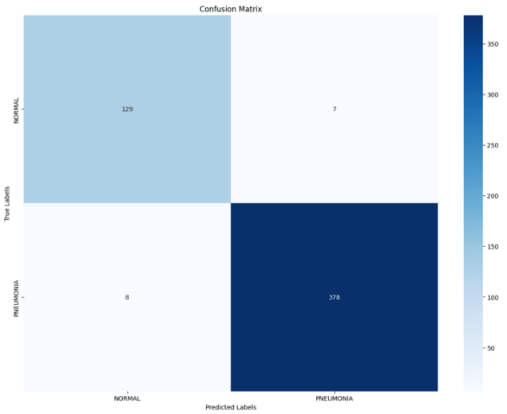


Figure 7. Confusion matrix for MobileNetV2 showing true and false predictions.

The confusion matrix for MobileNetV2, presented in Figure 7, provides granular insights into its classification performance. The model correctly identified 378 pneumonia cases (true positives) and 129 normal cases (true negatives), with minimal misclassifications: 7 false positives and 8 false negatives. These results underscore the model's high sensitivity and specificity, essential for minimizing diagnostic errors in real-world clinical applications. This performance highlights MobileNetV2's reliability in reducing false negatives, a critical factor in life-threatening conditions like pneumonia.

### 3.4 Training Process Analysis


Figure 8. Training and validation metrics for MobileNetV2 across epochs

The training process of MobileNetV2, depicted in Figure 8, demonstrates consistent and robust improvement over epochs. The training accuracy steadily increased to approximately 96.4000%, while the validation accuracy remained above 96.0000%, indicative of effective generalization to unseen data. The convergence of training and validation loss curves further emphasizes minimal overfitting, ensuring the model's reliability in diverse clinical datasets. These trends validate the efficiency of the training regime employed and the architecture's ability to adapt effectively to the task.

## IV. CONCLUSION

This study highlights the pivotal role of deep learning in addressing global health challenges, particularly in diagnosing pneumonia from chest X-ray images. Among the evaluated models, MobileNetV2 emerged as the optimal architecture, achieving the highest accuracy (97.5100%) and AUC (0.9941), alongside robust F1-score and balanced sensitivity and specificity. These findings emphasize MobileNetV2's capability to deliver precise and reliable diagnoses, particularly in resource-constrained settings.

By leveraging the "Chest X-Ray Images (Pneumonia)" dataset from Kaggle, this research contributes evidence-based insights into model performance, supporting the adoption of AI-driven diagnostics. The integration of such advanced technologies aligns with global health initiatives, such as those by WHO and UNICEF, to reduce preventable deaths through early and accurate disease detection.

Future research should explore the integration of these models into real-world clinical workflows, addressing challenges such as interpretability, data privacy, and scalability. Moreover, extending the analysis to include multimodal datasets, such as combining X-ray images with patient metadata, could further enhance diagnostic accuracy. Collaboration with healthcare providers to validate these models on diverse populations and settings will be essential for ensuring their effectiveness and generalizability in real-world applications.

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