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Lung Disease Diagnosis Based on MRI Data Using CNN Transfer Learning Method with MobileNetV2 and DenseNet121

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Abstract
Accurate lung disease diagnosis plays a critical role in medical treatment and improving patient outcomes. Conventional diagnostic methods often require experienced radiologists and are time-consuming. This study develops a lung disease diagnosis system based on Magnetic Resonance Imaging (MRI) data using the Convolutional Neural Network (CNN) method with Transfer Learning, specifically utilizing MobileNetV2 and DenseNet121 architectures. The dataset comprises 7,141 MRI images collected from Kaggle and RS Islam Aysha Bogor, classified into nine categories: Bacterial Pneumonia, Covid-19, Normal, Tuberculosis, Pneumothorax, Viral Infection, Asthma, Bronchitis, and Bronchopneumonia. Images were preprocessed to 224×224 pixels with pixel normalization to [0,1]. Four experimental scenarios were evaluated, varying optimizer, learning rate, batch size, and number of epochs. Results showed that MobileNetV2 achieved the best accuracy of 92.14%using RMSprop optimizer, learning rate 0.001, batch size 32, and 40 epochs. DenseNet121 achieved 87.82% accuracy with Adam optimizer under the same configuration. Validation using the confusion matrix yielded an overall accuracy of 91%, precision of 91.37%, recall of 92.25%, and F1-score of 91.79%. The best model was deployed as a web-based application built with Python Flask, enabling automatic image normalization and real-time classification without manual preprocessing. This research demonstrates that CNN-based Transfer Learning is effective for automated lung disease diagnosis with limited datasets.

INTRODUCTION

Lung disease is one of the most serious health problems and a leading cause of morbidity and mortality worldwide. Diseases such as pneumonia, tuberculosis (TB), COVID-19, asthma, bronchitis, and bronchopneumonia affect millions of patients annually and require early and accurate diagnosis for effective treatment [1].

Magnetic Resonance Imaging (MRI) is a widely used medical imaging technique due to its ability to produce high-detail organ images without ionizing radiation. However, interpretation of lung MRI images requires specialized expertise and is often time-consuming, creating risks of delayed diagnosis [2]. According to WHO data, chest radiographs are among the most frequently performed imaging procedures for various pulmonary conditions.

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Convolutional Neural Network (CNN) is a deep learning method that has been extensively applied for image pattern recognition and feature extraction in classification tasks [3]. Transfer learning extends this capability by leveraging pre-trained models (e.g., those trained on ImageNet) and fine-tuning them for specific domains such as medical imaging, enabling high accuracy even with limited datasets [4].

Several previous studies have applied CNN-based methods for lung disease classification with varying results. Previous research combined CNN with SVM for COVID-19 classification using CT-scan images and achieved 97.39% accuracy. Other studies compared VGG-16 and ResNet-50 architectures for COVID-19 and pneumonia detection, reporting accuracy above 85%. CNN with Adaptive Momentum optimization was also successfully applied for pneumonia classification with accuracy reaching 97% [5].

This research develops a web-based lung disease diagnosis system utilizing MobileNetV2 and DenseNet121 transfer learning architectures applied to MRI images, classifying nine disease categories. The system aims to assist medical personnel in delivering faster and more accurate lung disease diagnoses.

RESEARCH METHODS

This research follows a quantitative experimental approach involving six main stages: (1) data collection and analysis, (2) MRI image preprocessing, (3) data visualization, (4) CNN-based classification, (5) system development and implementation, and (6) testing and maintenance.

Dataset

The dataset consists of 7,141 MRI chest images obtained from two sources: Kaggle (6,980 images) and RS Islam Aysha Bogor (161 images). All images are classified into nine categories: Bacterial Pneumonia, Covid-19, Normal, Tuberculosis, Pneumothorax, Viral Infection, Asthma, Bronchitis, and Bronchopneumonia. Additionally, patient diagnostic data from RS Islam Aysha comprising 769 records was used for distribution visualization analysis.

Table 1. Dataset Distribution by Disease Class

Disease Class	Source	Total Images	Split Ratio
Bacterial Pneumonia	Kaggle + RS Islam Aysha	~800	70:20:10
Covid-19	Kaggle	~900	70:20:10
Normal	Kaggle + RS Islam Aysha	~900	70:20:10
Tuberculosis	Kaggle	~700	70:20:10
Pneumothorax	Kaggle	~700	70:20:10
Viral Infection	Kaggle	~700	70:20:10
Asthma	Kaggle	~450	70:20:10
Bronchitis	Kaggle	~450	70:20:10
Bronchopneumonia	Kaggle + RS Islam Aysha	~491	70:20:10
Total		7,141	

Preprocessing

All MRI images were preprocessed by resizing to 224×224 pixels, which is the standard input size for pre-trained *CNN* architectures such as VGGNet, ResNet, and DenseNet [6]. Each pixel value was then normalized to the range [0,1] by dividing by 255. This normalization maintains algorithm stability and accelerates model convergence during training. Data augmentation techniques were also applied to improve model generalization.

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Data Split

The dataset was divided using a 70:20:10 ratio: 70% for training (4,999 images), 20% for validation (1,428 images), and 10% for testing (714 images). This split ratio was selected to provide sufficient training data while maintaining robust model validation. The larger validation portion enables more reliable monitoring of model performance and helps reduce the risk of overfitting during training [7].

CNN Transfer Learning Architecture

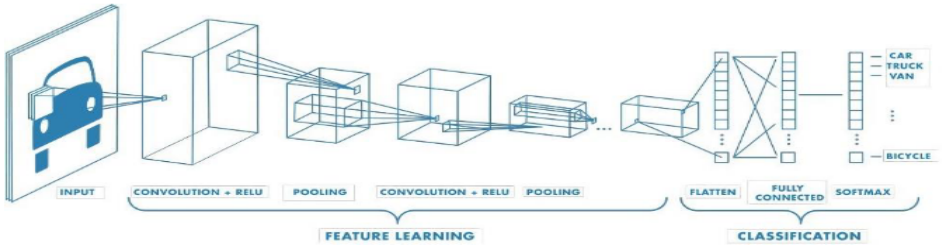

Figure 1. Convolutional Neural Network Method

MobileNetV2 is a lightweight CNN architecture released in 2018 that employs depthwise separable convolutions along with linear bottleneck and shortcut connections between layers. This design reduces computational cost while maintaining high accuracy. Input images (224×224×3) are processed through the pre-trained MobileNetV2 layers, followed by a Global Average Pooling layer that reduces feature maps to 1×1×1280, then classified using a Softmax activation layer outputting nine disease categories.

DenseNet121 is based on the Dense Convolutional Network (*DenseNet*) architecture implementing dense connectivity, where each layer receives feature maps from all preceding layers. This design effectively preserves detailed and complex features with relatively few parameters. The DenseNet121 pipeline produces 7×7×1024 feature maps, compressed via Global Average Pooling (1×1×1024), then classified through Softmax.

Both models use categorical cross-entropy as the loss function for multi-class classification. The final classification covers nine disease categories: Bacterial Pneumonia, COVID-19, Normal, Tuberculosis, Pneumothorax, Viral Infection, Asthma, Bronchitis, and Bronchopneumonia.

CNN Feature Extraction

The CNN classification pipeline consists of two main stages: feature extraction and classification. Feature extraction involves: (1) Convolution Layer — applying 3×3 filters with stride=1 and no padding to detect local patterns; (2) Activation Function (ReLU) — converting negative values to zero to enable learning of complex patterns; (3) Pooling Layer — applying Global Average Pooling to reduce spatial dimensions while retaining key features; and (4) Flattening — converting pooled features into a 1D vector as input to the Fully Connected layer. The Fully Connected layer applies Softmax activation to produce probability distributions across nine disease classes.

Experimental Scenarios

Four hyperparameter tuning scenarios were conducted to optimize the performance of both architectures. Scenario 1 evaluated three optimizers (Adam, RMSprop, and SGD) with fixed parameters of batch size 32, learning rate 0.0001, and 40 epochs. Scenario 2 compared learning rates of 0.001, 0.0001, and 0.00001 using the best optimizer from Scenario 1. Scenario 3 evaluated batch sizes of 32 and 64 using the optimal parameters from previous experiments. Scenario 4 compared different epoch settings (20, 40, and 60 epochs) with the selected hyperparameters.

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Model Evaluation

Model performance was evaluated using a confusion matrix and four metrics: accuracy, precision, recall, and F1-score. The evaluation metrics were calculated using the following equations Accuracy, Precision, Recall, F1-Score. where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative classifications.

System Implementation

The optimized models were converted into .h5 format and deployed as a web-based application using Python Flask. The system performs automatic image normalization before classification, allowing users to obtain lung disease predictions without manual preprocessing.

RESULTS AND DISCUSSION

TABLE 1 presents a comparison between this study and several previous studies [1][5][8]. Although some previous studies achieved higher accuracy using specific datasets and configurations, this research provides advantages through multi-class classification involving nine lung disease categories combined with a complete web-based implementation for real-time diagnosis support.

Table 2. Comparison of Related Research

Researcher	Optimizer	Accuracy	Method
Ramadhani et al. [8]	Adam	88.64%	CNN + SVM
Anggoro et al. [9].	Adam	90.11%	CNN
Berliani et al. [10]	MSE	93.75%	CNN + SVM + NB + DT
Riti et al. [2]	Adam	92.10%	CNN
Andika et al. [5]	Adam	97.00%	CNN
Dimas Ramadhan (2025)	RMSprop	90.39%	Transfer Learning (MobileNetV2)

Compared with previous studies, the proposed approach achieved competitive classification performance despite addressing a more challenging multi-class classification problem. While several previous studies focused on binary classification tasks, such as distinguishing COVID-19 from normal cases, this research classified nine different lung disease categories simultaneously. The increased number of classes introduces greater complexity due to the visual similarity among certain disease patterns. Nevertheless, the MobileNetV2-based transfer learning model achieved an accuracy of 90.39%, demonstrating its effectiveness for multi-class lung disease classification and supporting its potential application in computer-aided diagnosis systems.

Based on the experimental results, MobileNetV2 consistently outperformed DenseNet121 in most testing scenarios. The best MobileNetV2 model achieved an accuracy of 92.14%, while DenseNet121 achieved a peak experimental accuracy of 91.85% during epoch evaluation, while the final selected model achieved 87.82% accuracy under the deployment configuration. This performance difference can be attributed to the architectural characteristics of MobileNetV2, which employs inverted residual blocks and linear bottlenecks to efficiently preserve essential image features while reducing computational complexity.

In addition, MobileNetV2 contains fewer parameters than DenseNet121, making it more suitable for relatively limited medical imaging datasets. The lightweight architecture enables faster convergence during training and reduces the risk of overfitting. Although DenseNet121 benefits from dense connectivity and effective feature reuse, its more complex architecture may require larger datasets to fully exploit its representation capabilities. Therefore, MobileNetV2 demonstrated better generalization performance for the lung disease classification task in this study.

The first experimental scenario evaluated three optimizers—Adam, RMSprop, and SGD—with fixed parameters of batch size 32, learning rate 0.0001, and 40 epochs. As shown in TABLE 3, RMSprop achieved the highest accuracy for MobileNetV2 (88.91%), while Adam was optimal for DenseNet121

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(83.68%). SGD consistently underperformed for both models, particularly with significantly longer training time for DenseNet121 (25 minutes 48 seconds). These results establish RMSprop and Adam as the preferred optimizers for subsequent scenarios. The superior performance of RMSprop in MobileNetV2 can be attributed to its adaptive learning mechanism, which adjusts learning rates individually for each parameter. This capability allows faster convergence and more stable optimization when handling medical image datasets with varying feature complexity. In contrast, SGD showed lower performance due to slower convergence and difficulty in adapting to complex feature distributions within multi-class lung disease classification.

Table 3. Scenario 1 Results — Optimizer Comparison (Avg. Pooling, batch size 32, lr 0.0001, epoch 40)

Model	Optimizer	Accuracy	Loss	Time
MobileNetV2	Adam	0.7525	0.7974	3m 32s
MobileNetV2	RMSprop*	0.8891	0.6104	3m 35s
MobileNetV2	SGD	0.5955	1.1743	3m 25s
DenseNet121	Adam*	0.8368	0.0175	3m 19s
DenseNet121	RMSprop	0.7918	0.7501	3m 27s
DenseNet121	SGD	0.6602	1.0859	25m 48s

Using the best optimizers from Scenario 1, three learning rates were tested. TABLE 4 shows that learning rate 0.001 produced the best accuracy for both MobileNetV2 (90.39%) and DenseNet121 (87.82%). Smaller learning rates (0.0001 and 0.00001) resulted in lower accuracy, indicating insufficient convergence within 40 epochs. This confirms that a moderately higher learning rate enables faster and more effective feature adaptation from the pre-trained ImageNet weights. Batch size 32 produced better classification performance compared to batch size 64 because smaller batch sizes provide more frequent weight updates during training. Frequent updates improve model generalization and help avoid local minima. Additionally, smaller batch sizes are more suitable for medical imaging datasets with high feature variation, allowing the model to learn more detailed image characteristics.

Table 4. Scenario 2 Results — Learning Rate Comparison (batch size 32, epoch 40)

Model	Learning Rate	Accuracy	Loss	Time
MobileNetV2	0.001*	0.9039	0.2711	3m 39s
MobileNetV2	0.0001	0.8351	0.6104	3m 35s
MobileNetV2	0.00001	0.8193	0.5290	3m 39s
DenseNet121	0.001*	0.8782	0.4563	6m 04s
DenseNet121	0.0001	0.8368	0.6260	3m 19s
DenseNet121	0.00001	0.8154	0.7528	11m 57s

Two batch sizes (32 and 64) were compared while maintaining the best parameters from previous scenarios. As shown in TABLE 5, batch size 32 consistently outperformed batch size 64 for both architectures. Additionally, batch size 64 resulted in significantly longer training times, particularly for MobileNetV2 (21 minutes 2 seconds vs. 3 minutes 35 seconds). Smaller batch sizes provide more frequent gradient updates, leading to better generalization. The decrease in DenseNet121 accuracy at 60 epochs indicates the occurrence of overfitting, where the model becomes overly specialized to training data and loses generalization capability on unseen data. This phenomenon commonly occurs in deep learning models trained on relatively limited medical datasets. In contrast, MobileNetV2 maintained more stable performance due to its lightweight architecture and efficient bottleneck layers, which reduce excessive parameter learning.

Table 5. Scenario 3 Results — Batch Size Comparison (lr 0.001, epoch 40)

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Model	Batch Size	Accuracy	Loss	Time
MobileNetV2	32*	0.9039	0.3946	3m 35s
MobileNetV2	64	0.8920	0.3042	21m 02s
DenseNet121	32*	0.8782	0.0175	3m 19s
DenseNet121	64	0.8291	0.0235	4m 23s

The effect of training duration was evaluated using 20, 40, and 60 epochs. TABLE 6 shows that for MobileNetV2, the highest accuracy was achieved at 60 epochs (92.14%), while DenseNet121 peaked at 40 epochs (91.85%). DenseNet121 accuracy decreased at 60 epochs (82.91%), suggesting overfitting. MobileNetV2 demonstrated more stable learning curves across extended training due to its efficient bottleneck architecture. High recall performance is particularly important in medical diagnosis systems because it minimizes false negative predictions. In lung disease detection, false negatives may lead to delayed treatment and increased health risks for patients. Therefore, the recall value of 92.25% achieved by MobileNetV2 demonstrates strong potential for assisting early lung disease screening in clinical environments.

Table 6. Scenario 4 Results — Epoch Comparison (batch size 32, lr 0.001)

Model	Epoch	Accuracy	Loss	Time
MobileNetV2	20	0.8953	0.2225	10m 05s
MobileNetV2	40	0.9039	0.3946	3m 35s
MobileNetV2	60*	0.9214	0.2257	29m 41s
DenseNet121	20	0.8782	0.0235	1m 54s
DenseNet121	40*	0.9185	0.0175	3m 19s
DenseNet121	60	0.8291	0.0247	3m 16s

Model Validation

Validation was conducted using the confusion matrix on test data. TABLE 7 presents the comprehensive evaluation metrics for both models under their optimal configurations. MobileNetV2 demonstrated superior overall performance with 91% accuracy, 91.37% precision, 92.25% recall, and 91.79% F1-score. These results indicate that the model reliably identifies lung diseases across all nine classes with minimal false positives and false negatives.

Table 7. Model Validation Results Using Confusion Matrix

Metric	MobileNetV2	DenseNet121	Description
Accuracy	90.39%	87.82%	Overall correct prediction ratio
Precision	91.37%	64.00%	Positive prediction accuracy
Recall (Sensitivity)	92.25%	77.20%	True positive detection rate
F1-Score	91.79%	70.00%	Harmonic mean of Precision & Recall

The evaluation metrics obtained from the confusion matrix indicate that MobileNetV2 achieved strong classification performance across all disease categories. The model obtained a precision of 91.37%, suggesting that most positive predictions were correctly classified. High precision is important in medical diagnosis because it minimizes the occurrence of false positive predictions, which may lead to unnecessary medical examinations and treatments.

Furthermore, MobileNetV2 achieved a recall value of 92.25%, indicating its ability to correctly identify the majority of disease cases. Recall is considered one of the most critical metrics in medical applications

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because a low recall value may result in false negative predictions, where diseased patients are incorrectly classified as healthy. Such errors can delay treatment and potentially worsen patient outcomes.

The model also achieved an F1-score of 91.79%, demonstrating a balanced relationship between precision and recall. These results confirm that the proposed MobileNetV2-based transfer learning approach is capable of providing reliable support for automated lung disease screening and classification.

Training Stability Analysis

Training and validation performance were analyzed to evaluate model stability and overfitting tendencies. The 70:20:10 dataset split provided stable validation results and enabled effective monitoring during model development. MobileNetV2 showed more consistent learning behavior across training scenarios due to its lightweight architecture and efficient feature extraction mechanism. In contrast, DenseNet121 experienced performance degradation at extended training epochs, indicating potential overfitting when trained on a relatively limited medical image dataset.

Web Application Implementation

The optimized MobileNetV2 model was deployed as a web-based lung disease classification system using Flask. The application supports image uploading, automatic pixel normalization to the range of [0,1], and disease classification without requiring manual preprocessing. Functional testing confirmed that the main components, including image input, preprocessing, and prediction processes, operated correctly.

Model Strengths and Limitations

The proposed web-based classification system has the potential to assist healthcare professionals in the preliminary screening of lung diseases. By providing automated image classification, the system can reduce diagnostic workload and support faster decision-making processes. Although the model is not intended to replace medical experts, it can serve as a decision-support tool, particularly in healthcare facilities with limited access to experienced radiologists. Furthermore, the web-based implementation increases accessibility and enables real-time disease classification through a user-friendly interface.

Model Strengths and Limitations

The proposed transfer learning approach demonstrated advantages in terms of efficient training, competitive classification performance, and reduced computational requirements by utilizing pre-trained ImageNet features. MobileNetV2 achieved better generalization performance compared to DenseNet121 while requiring fewer computational resources.

However, several limitations remain. The model performance was influenced by hyperparameter selection, and some visually similar disease classes may still lead to classification errors. In addition, imbalance among several disease categories and limited data sources may affect model generalization. Future studies should evaluate larger multi-center datasets and explore advanced architectures such as EfficientNet, ConvNeXt, and Vision Transformer (ViT) to improve robustness.

CONCLUSION

This research successfully developed a CNN-based Transfer Learning system for lung disease classification from MRI images across nine disease categories: Bacterial Pneumonia, COVID-19, Normal, Tuberculosis, Pneumothorax, Viral Infection, Asthma, Bronchitis, and Bronchopneumonia. MobileNetV2 achieved the best overall accuracy of 90.39% with precision 91.37%, recall 92.25%, and F1-score 91.79%, using RMSprop optimizer, learning rate 0.001, batch size 32, and 40 epochs with the 70:20:10 data split. DenseNet121 achieved 87.82% accuracy using the Adam optimizer under the same experimental configuration. Although MobileNetV2 achieved 92.14% accuracy during epoch experimentation, the final deployed model used the configuration with stable validation accuracy of 90.39%.

The 70:20:10 data split ratio provided stable validation performance and contributed to reducing overfitting during model training. Transfer learning demonstrated effectiveness in achieving high classification accuracy despite the limited size of medical imaging datasets. The best model was deployed

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as a web-based application using Python Flask, enabling real-time lung disease prediction without manual preprocessing. Future research should consider: (1) expanding the dataset with images from more hospitals to improve model generalization; (2) systematic hyperparameter optimization across a broader range of values; and (3) exploring additional architectures such as EfficientNet or ResNet for comprehensive performance comparison.

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