Transfer Learning Based Pneumonia Diagnosis using Resnet50

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https://doi.org/10.55041/ijsmt.v2i3.349

Cite this Article: C.USHARANI, & THOUFIQ, M. (2026). Transfer Learning Based Pneumonia Diagnosis using Resnet50. International Journal of Science, Strategic Management and Technology, *02*(03). https://doi.org/10.55041/ijsmt.v2i3.349

ABSTRACT:

Early and precise diagnosis is essential to preventing complications and saving lives from pneumonia, a dangerous respiratory infection. Although chest X-rays are frequently used for detection, their interpretation is highly dependent on a physician's skill and may be impacted by human factors such as fatigue, workload, and subjective judgment. Our study presents a deep learning and transfer learning-powered intelligent pneumonia diagnosis system to address this. The system classifies chest X-ray images as either normal or pneumonia using the ResNet50 architecture. Grad-CAM technology then makes the logic of the system clear and reliable by highlighting the precise lung regions that underlie each diagnosis. Additionally, the system uses activation map analysis to classify infection severity as low, medium, or high. Each prediction is further assessed by an integrated confidence mechanism, which highlights ambiguous cases for human review. Strong classification accuracy and easily comprehensible results were confirmed by testing on a dataset of chest X-rays.

I. INTRODUCTION

Modern medical diagnostic tools have been significantly impacted by the advancement of artificial intelligence and computational intelligence techniques, particularly in the field of radiological image analysis. The development of automated tools to assist medical professionals in effectively and efficiently analyzing complex medical images is becoming more and more popular. Pneumonia is a serious worldwide health issue that has led to high death rates among vulnerable groups, including children, the elderly, and patients with compromised immune systems. Due to the subtle differences between normal and infected lung tissues, manual analysis of chest X-ray images can be challenging. However, early and accurate diagnosis is essential to prevent serious complications.Radiographic analysis in conventional clinical settings heavily relies on the knowledge and experience of qualified radiologists. Although expert analysis is thought to be accurate, it takes a lot of time and is subject to observer variability. Fatigue and workload pressures can also lead to inconsistent diagnoses in busy clinical settings. Furthermore, radiographic images frequently include complex pathological patterns that are challenging to visually interpret, overlapping anatomical features, and lighting variations. These difficulties highlight the necessity of creating automated diagnostic instruments that support clinical judgment.

Strong methods for classifying medical images have been made possible by recent advances in deep learning. While transfer learning enables pre-trained models to be optimized for particular clinical tasks, convolutional neural networks (CNNs) are particularly good at extracting intricate visual features from medical scans. Deeper, more dependable networks can be trained without sacrificing performance thanks to ResNet50's residual learning architecture. Nevertheless, despite their high accuracy, the majority of these models operate as "black boxes," generating results without providing a justification. In order to address that issue, this paper presents a pneumonia detection system that combines decision support, interpretability, and classification accuracy into a single framework. The system classifies chest X-ray images as either normal or pneumonia using ResNet50 with transfer learning. After that, Grad-CAM creates heatmap overlays that show the precise lung regions affecting each diagnosis. Additionally, the system determines a severity level of low, medium, or high and estimates lung involvement. Uncertain predictions are flagged for manual clinical review by a confidence-based module. The model advances standard deep learning classification into a more comprehensive and clinically useful decision support system by achieving strong diagnostic accuracy while maintaining transparency and interpretability, according to experimental results.

II. LITERATURE SURVEY

Rajpurkar et al. (2017). The model, which was based on the DenseNet architecture, showed how far deep learning had advanced in medical image classification and matched radiologist-level performance.By using pre-trained CNN models on chest X-ray datasets, Shin et al. (2016) investigated transfer learning in medical imaging. Their results demonstrated that transfer learning significantly enhanced classification performance, especially when there was a shortage of labeled training data.In order to identify pneumonia from chest radiographs, Gupta et al. (2022) developed a CNN model improved with data augmentation techniques. Even though the method improved the model's ability to generalize on smaller datasets, it was still not as accurate overall as deeper, pre-trained architectures. In order to strike a balance between solid accuracy and computational efficiency, Chen et al. (2023) created a lightweight CNN with transfer learning. Although the model lacked any significant interpretability features to explain its predictions, it demonstrated promise for deployment in low-resource environments.

Shakeel et al. (2024) used deep CNN architectures, highlighting the increasing importance of artificial intelligence in automated radiographic analysis. Although the model performed well in classification, it was essentially a black box that provided no visual cues as to how it made its decisions. To improve the transparency of pneumonia diagnosis, Colin and Surantha (2025) created an interpretable deep learning model that incorporates Grad-CAM. Although the disease region localisation was not completely accurate at the pixel level, their study demonstrated that visual explanations can increase clinical confidence in AI predictions. Rahman et al. (2021) looked into how preprocessing and image enhancement methods affect the results of pneumonia classification. Their results demonstrated that improving model accuracy requires the use of suitable normalisation and augmentation techniques. A multi-task learning framework that combined the classification and localisation of thoracic diseases was proposed by Wang et al. in 2024. Although the method improved feature learning, it also demanded

Li et al. in 2025. The significance of striking the correct balance between computational efficiency and prediction accuracy in healthcare settings was highlighted by their work. The necessity of transparency in medical AI systems has been reaffirmed by expanding research in Explainable Artificial Intelligence. AI diagnoses are now more comprehensible and clinically acceptable thanks to the widespread use of Grad-CAM-based visualisation techniques for determining the lung regions most important in influencing model predictions. Despite these developments, the majority of pneumonia detection models currently in use are only concerned with increasing classification accuracy. When it comes to quantifying infection severity, integrating confidence-based decision-making, and integrating these capabilities

International Journal of Science, Strategic Management and Technology
Volume **02** Issue **03** March-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

into a single explainable framework, there is a glaring research gap. By combining transfer learning, Grad-CAM interpretability, infection ratio-based severity estimation, and confidence-driven decision support into a single, cohesive system, the suggested model closes this gap by improving on traditional CNN-based classification.

III. PROPOSED METHODOLOGY:

The suggested framework is intended to assist medical practitioners in more precisely and effectively analysing chest X-ray images by serving as an intelligent and comprehensible pneumonia diagnosis system. To provide useful diagnostic support, it combines transfer learning, deep convolutional neural networks, visual interpretability, and severity estimation. This system prioritises transparency, clinical reliability, and minimising reliance on human interpretation, in contrast to traditional classification models that merely produce a category label.

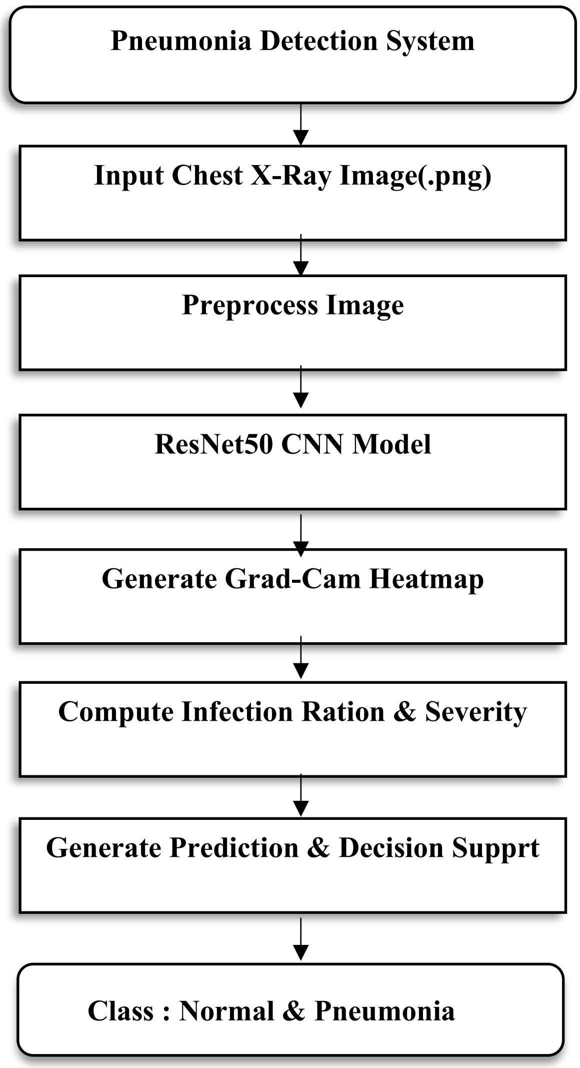

Figure 1: Architecture of Proposed Methodology

ResNet50 is the primary feature extractor used by the framework. It uses transfer learning to apply knowledge derived from large-scale image datasets directly to the analysis of chest radiographs. The model has been trained to differentiate between cases of pneumonia and normal.
Grad-CAM is used to create visual heatmaps that identify the lung regions most accountable for each prediction, making the system's decisions transparent. This provides a clear window for clinicians to understand how the model arrived at its conclusion. These activation maps are then used to calculate an infection ratio that provides clinically meaningful information beyond a simple classification result. The severity of lung involvement is then classified as low, medium,

or high based on predetermined thresholds.Additionally, the system uses softmax probability scores in a confidence-based decision-making process. Cases that fall below a predetermined confidence level are marked for manual medical review, while predictions that exceed it are deemed reliable. Preprocessing, classification, visualisation, severity analysis, and decision-making are the steps that make up the entire pipeline. The system achieves strong diagnostic accuracy and interpretability, according to experimental results, which supports the creation of reliable AI-driven healthcare tools.

i) Data Collection and Image Preprocessing Module

Gathering chest X-ray pictures and getting them ready for deep learning analysis is the first stage in the suggested system. Before the model can accurately analyze raw X-ray images, issues with resolution, brightness, contrast, and noise levels must be resolved. This module makes sure that each image is prepared for precise classification by entering the pipeline in a uniform, standardized format.

This module's primary responsibilities are:

• Image Acquisition: Gathers PNG or JPG chest X-ray pictures from organized datasets.

• Resizing: To satisfy ResNet50's input requirements, all images are scaled to a consistent size of 224 × 224 pixels.In order to ensure stable model training and testing, normalization modifies pixel intensity values to a standard range.

• Noise Removal: Eliminates image noise that might impair the performance of the model.

• Data Organization: For structured processing, images are sorted into clearly labeled categories, such as Normal and Pneumonia.

ii) Feature Extraction and Deep Learning Module (ResNet50)

ResNet50, a deep convolutional neural network that employs transfer learning to extract layered features from chest radiographs, receives the preprocessed images.

This module's primary responsibilities are:

• Transfer Learning: Enhances the model's capacity to learn pertinent features by utilizing preexisting knowledge from ImageNet.

• Deep feature extraction finds both high-level and low-level patterns in the pictures, such as abnormal lung opacities, edges, and textures.

• Fine-tuning: Modifies model parameters to more accurately depict the distinct visual traits linked to pneumonia.

• Classification: Generates predictions for the Normal and Pneumonia categories based on probability.

This module makes sure the model ignores superfluous surface-level visual cues and instead concentrates on clinically significant medical patterns.

iii) Explainable AI Module (Grad-CAM Visualization)

The framework incorporates an Explainable AI module based on Gradient-weighted Class Activation Mapping (Grad-CAM) to make the system's decisions easier to comprehend. This module opens up the prediction process and makes it visually understandable for clinicians instead of operating as a black-box classifier.

This module's primary functions are:

• Activation Mapping: Determines which areas of the chest X-ray image are most important for diagnosis.

• Heatmap Generation: Produces color-coded visual maps that show the model's focus.

• Overlay Visualization: For a more accurate side-by-side comparison, the generated heatmaps are superimposed onto the original X-ray image.

• Region Localization: Identifies the particular lung regions that were most important in predicting pneumonia.

When combined, these functions provide the system with a clear, visual layer of explanation that promotes trust and clinical comprehension.

iv) Severity Estimation Module

In addition to binary classification, the system analyzes activation values from Grad-CAM heatmaps to determine the degree of lung damage.

This module's primary functions are:
• Infection Ratio Calculation: This method quantifies involvement by calculating the percentage of activated lung area in relation to the overall image size.
• Threshold-Based Categorization: Assigns a severity level of Low, Medium, or High based on predetermined thresholds.
• Lung Region Identification: Identifies the upper, middle, or lower lung regions that exhibit abnormalities.
• Support for Clinical Interpretation: Provides organized severity data that can directly influence clinical judgment.

This module transforms the system into a complete diagnostic support tool, going far beyond simple detection.

v) Confidence-Aware Decision Support Module

A confidence-driven assessment mechanism is incorporated into the pipeline to guarantee that the system can be used safely in actual clinical settings. The system produces a probability score for each prediction, which expresses the model's level of confidence in its choice.

This module manages the following crucial tasks:
• Confidence Score Extraction: Takes softmax probability scores straight out of the output layer of the model.
• Threshold Evaluation: Assesses each prediction's degree of confidence in relation to a predetermined reliability threshold.
• Decision Recommendation: The prediction is either automatically approved or marked for radiologist review.
• Risk Reduction: By identifying low-confidence predictions prior to their clinical application, it reduces the possibility of misclassification.

vi) Automated Report Generation and Output Module

The last step puts the classification result, visual explanation, and severity assessment all together in one neat, organized diagnostic report.

This module's main jobs are:
• Result Compilation: Shows the predicted class, confidence score, and severity rating all in one place.
The visualization display shows the original chest X-ray, the Grad-CAM heatmap, and the overlay image all at once so you can easily compare them.
• Clinical Explanation Generation: Creates a written explanation of the diagnosis in simple language to help doctors understand it.
• Output Presentation: Prepares the final report for PDF export or digital storage.
The system gives a full and clinically useful AI-assisted pneumonia diagnosis by combining prediction, explanation, and decision support into one output.

IV. RESULT AND DISCUSSION

The AI-Based Pneumonia Detection and Severity Analysis Framework was tested on a chest X-ray dataset that had two groups: Normal and Pneumonia. To make sure that performance results were measured fairly and reliably, the dataset was split into training, validation, and testing subsets. The system was built on top of a deep convolutional neural network using transfer learning. We used a number of standard evaluation metrics to see how well it worked, such as accuracy curves, loss curves, confusion matrix analysis, ROC–AUC evaluation, and explainable AI visualization.

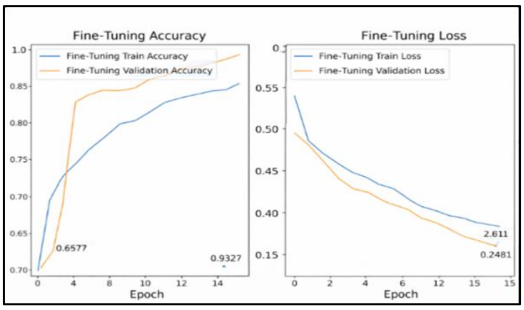

Figure 2 : Accuracy vs Loss

The accuracy curves show that the model kept learning during training. Training accuracy rose steadily over time until it reached a stable value. The accuracy of the validation also stayed high during the fine-tuning phase, going above 94–95%. A small difference between training and validation accuracy is a good sign. It means that the model works well with new data that it hasn't seen before and doesn't fit too closely to the training set.

The loss curves show a pattern that is similar. As the model was improved, the training loss went down, which showed that the learning process was working as planned. Validation loss went down in a similar way over epochs, which showed that the model kept getting better on data that it had not seen before.

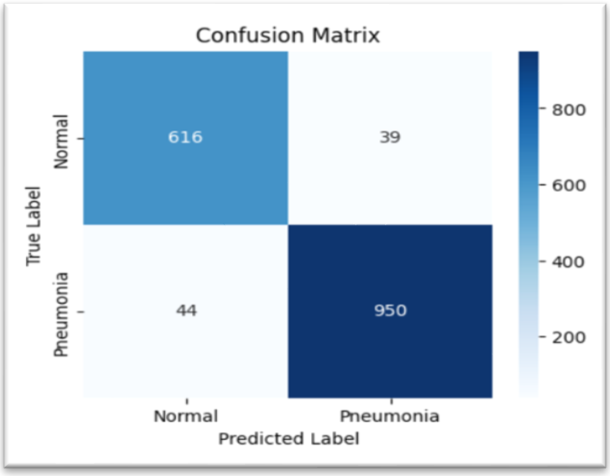

Figure 3: Confusion Matrix

To gauge how well the model separates the two classes, the Receiver Operating Characteristic (ROC) curve was analyzed. The plot's upper left corner, which is linked to strong classification performance, is where the curve is located. The exceptional separability between normal and pneumonia cases was demonstrated by the Area Under the Curve (AUC), which reached roughly 0.99. This outcome demonstrates that the model consistently distinguishes between the two classes and produces accurate, well-calibrated prediction probabilities.

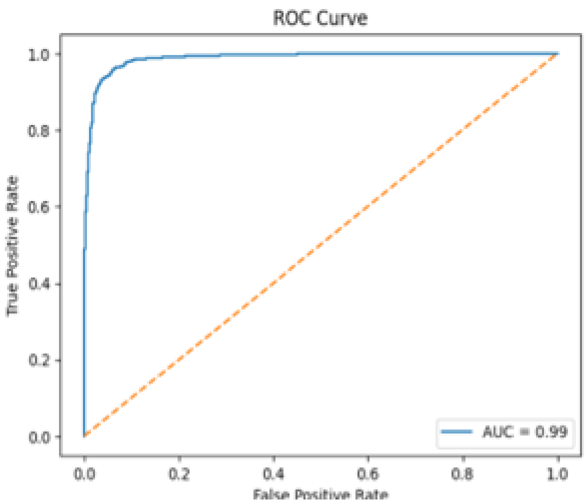

Figure 4 : ROC Curve

When combined, the experimental results confirm the suggested framework's overall efficacy. The system maintains an AUC of about 0.99, continuously achieves validation accuracy above 94%, and maintains low rates of false positives and false negatives. In addition to precise classification, the framework provides comprehensible Grad-CAM visualizations, assesses the severity of infection, and identifies lung regions that are impacted. This system is a far more useful and educational tool for real-world clinical decision support than traditional CNN-based detection models because it integrates disease classification, severity estimation, confidence scoring, regional localization, and explainable AI into a single, cohesive pipeline.

V. CONCLUSION

An intelligent AI-based pneumonia detection system that attempts to automatically categorize chest X-ray images and forecast the severity of pneumonia has been covered in this paper. With the use of explainable AI methods like Grad-CAM, deep learning algorithms, and transfer learning with CNNs, the system is able to accurately diagnose both normal and pneumonia samples. The system is further enhanced by the addition of severity analysis using the infection ratio, which measures the severity of lung infection and provides useful clinical information beyond simple classification. In contrast to traditional black-box models, the suggested system has visualization-based interpretability, which enables medical professionals to determine which lung components influenced the classification outcome. By recommending manual analysis for uncertain predictions, confidence-aware decision support systems enhance the system even more. The efficacy and generalizability of the suggested system are confirmed by the experimental results, which unmistakably demonstrate high classification accuracy, high AUC values, and low misclassification rates.In conclusion, the suggested system is a practical, effective, and scalable method for automated pneumonia detection, particularly for developing nations where prompt initial diagnosis is essential. To further enhance AI-assisted medical imaging systems, future research may incorporate lung segmentation models, multi-class disease detection, real-time clinical systems, and enhanced uncertainty estimation.

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