

Robust EfficientNet-Based Transfer Learning for Automated Pediatric Pneumonia Detection

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Abstract - Pediatric pneumonia remains a primary global cause of childhood morbidity, necessitating rapid and reliable diagnostic decision-support tools. This study presents a robust, explainable transfer learning framework leveraging a customized EfficientNet architecture for automated pediatric pneumonia identification from chest radiographs. To enhance model generalization under data scarcity and class imbalance, the methodology integrates an intensive data augmentation pipeline, label smoothing, and class-weighted loss functions. A strategic two-phase optimization protocol is implemented, initially freezing the pre-trained backbone to stabilize the classification head, followed by selective deep-layer fine-tuning. Quantitative evaluation on an independent test set demonstrates exceptional clinical reliability, achieving an accuracy of 92.31%, a sensitivity of 95.90%, and an AUC of 0.9633. Furthermore, Gradient-weighted Class Activation Mapping (Grad-CAM) visualization ensures model interpretability by confirming that the network consistently concentrates on clinically relevant pulmonary regions. Ultimately, this framework provides a highly transparent screening tool, offering a robust foundation for clinically deployed artificial intelligence systems and establishing a solid benchmark for future research in explainable medical image analysis.

Keywords: Pediatric Pneumonia; EfficientNet; Transfer Learning; Explainable AI (XAI).

I. Introduction

Pneumonia remains a leading cause of childhood morbidity and mortality, particularly among children under five years of age. Between 2022 and 2023, it emerged as one of the most critical and potentially fatal respiratory conditions within this vulnerable demographic, with a disproportionately high impact on children residing in remote regions characterized by restricted healthcare infrastructure (Lan et al., 2024). Although prompt and precise clinical intervention is imperative for optimal patient management, conventional diagnostic modalities—including chest auscultation, laboratory evaluations, and manual interpretation of radiographs—remain severely constrained by limited expert availability, patient demographics, and systemic infrastructure deficits (Siddiqi et al., 2024). Consequently, during seasonal epidemics, clinicians in resource-constrained rural facilities are routinely

Overwhelmed by high diagnostic volumes, leading to diagnostic bottlenecks, high inter-observer variability, and a heightened risk of misinterpretation (Pan et al., 2024).

To mitigate these challenges, deep learning methodologies have increasingly been integrated into computer-aided diagnosis (CAD) systems, offering clinicians powerful tools to augment both diagnostic throughput and analytical precision (Alshanketi et al., 2024). In particular, Convolutional Neural Networks (CNNs) pre-trained on large-scale imaging repositories and adapted via transfer learning have demonstrated remarkable efficacy in extracting complex feature representations from chest radiographs (Singla, 2024). However, the clinical deployment of these models is often hindered by critical bottlenecks, including black-box opacity (lack of interpretability), severe class imbalances, model over fitting on small or heterogeneous clinical datasets, and an over-reliance on massive, manually annotated training sets (Yoon et al., 2024; Zunaed et al., 2024).

To address these limitations, this study introduces a lightweight, highly efficient deep learning framework utilizing an optimized EfficientNet architecture. To enhance model generalization under stringent data constraints, the proposed methodology integrates multi-stage transfer learning with a selective deep-layer fine-tuning strategy, further regularized through class weighting and label smoothing techniques. Concurrently, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to provide visual explanations of the network's internal decision-making process, thereby establishing clinical interpretability (Radočaj&Martinović, 2025; Ihongbe et al., 2024). By balancing competitive diagnostic performance with transparency and architectural efficiency, the proposed system is highly optimized for deployment in real-world clinical workflows and resource-constrained mobile health applications (Deng et al., 2024). Ultimately, this framework advances the paradigm of clinically viable, AI-assisted pediatric pneumonia screening by harmonizing diagnostic accuracy, visual interpretability, and compute-resource efficiency, thereby demonstrating substantial utility for data-

scarce healthcare environments (Shah et al., 2024; Zhong et al., 2024).

Our previous study proposed a hybrid MLBP–HOG feature fusion framework with machine learning classifiers for pediatric pneumonia detection, demonstrating competitive performance with low computational cost (Ummature&Mallappa, 2026). Building on this work, the present study adopts an EfficientNet-based transfer learning model with Grad-CAM to enable automatic feature learning and improved interpretability. Following figure 1. Shows the functional diagram of the proposed method.

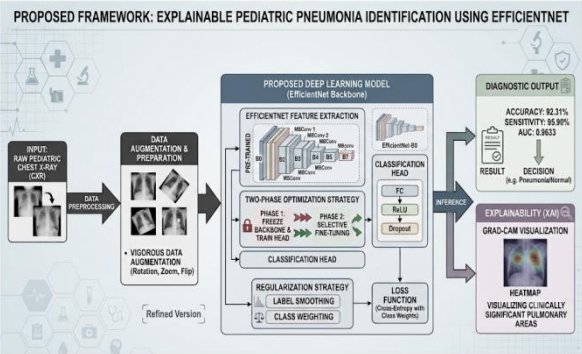


Fig 1. Functional architecture of the proposed method

The provided architecture diagram illustrates an end-to-end explainable deep learning pipeline for automated pediatric pneumonia identification from raw chest X-ray images. The framework begins with data pre-processing and a vigorous data

augmentation stage (rotation, zoom, flip) before passing the inputs to a proposed deep learning model built on an EfficientNet backbone. Within this model, a two-phase optimization strategy (freezing the backbone followed by selective fine-tuning) is combined with regularization strategies, specifically label smoothing and class weighting, to optimize a cross-entropy loss function.

II. LITERATURE SURVEY

A review of recent deep learning frameworks for pneumonia detection shows a common problem: models are either highly accurate but too complex, or they work well but do not explain how they made their decision. While many deep learning networks can achieve over 90% accuracy, they are often trained only on adult data, cost too much computer power to run, or over fit when given small medical datasets. Furthermore, standard models struggle with the natural imbalance of medical images, where there are far more sick cases than normal ones. Even though visual tools like Grad-CAM are starting to help doctors trust AI decisions, these tools are rarely built into lightweight, easy-to-deploy networks. To solve these problems, this paper introduces a simple, lightweight EfficientNet-B0 system that integrates specialized regularization techniques with clear visual explanations for dependable pediatric screening. The relevant work details are shown in Table 1.

TABLE 1: SUMMARY OF RECENT DEEP LEARNING METHODS FOR PNEUMONIA DETECTION FROM CHEST X-RAYS.

Author (Year)	Core Method Used	Dataset Type	Results	Major Limitation / Gap
Alshanketi et al. (2024)	Standard deep CNN with transfer learning	Adult images	91.4% Accuracy 0.93 AUC	Only focused on adult data; does not explain how decisions are made.
Siddiqi et al. (2024)	Review paper summarizing current methods	Multiple datasets	Over 90% accuracy in past works	Only a review; did not propose a new model or fix the lack of explanation.
Zunaed et al. (2024)	Contrastive learning using adult and child data together	Adult + Pediatric	0.8464 AUROC	Requires adult data to find child features; low explanation capability.
Pan et al. (2024)	Federated learning across multiple hospitals	Pediatric images	90.7% Accuracy	Too expensive to run; complex to sync models across different hospitals.
Lan et al. (2024)	Custom CNN with attention layers	Pediatric images	88.2% Accuracy 0.9218 AUC	Limited to only one specific type of infection (Mycoplasma).
Singla (2024)	Compared ResNet-50 and EfficientNet-B1	Adult images	93.8% Accuracy	Trained only on adults; no explainable AI tools used.
Ihongbe et al. (2024)	Evaluated visual tools like Grad-CAM and LIME	Adult images	Visual validation	Did not include any child X-rays; only focused on testing the visual tools.
Deng et al. (2024)	Developed a mobile app called PneumoniaApp	Pediatric images	88.2% Accuracy	The model was too shallow, leading to moderate accuracy.
Radočaj&Martinović (2025)	Used Grad-CAM for medical AI explanations	Pediatric images	91.2% Accuracy	Used a very small dataset; did not deeply test the visual results.

Yoon et al. (2024)	Self-supervised masked pre-training	Pediatric images	93.1% Accuracy 0.95 AUC	Very high training cost; hard to see how the model reaches decisions.
Shah et al. (2024)	Surveyed explainable AI for lung diseases	Review study	—	Pointed out that most visual AI tools are not tested in real hospitals.
Zhong et al. (2024)	Transfer-learning CNN with class weighting	Pediatric images	92.0% Accuracy 0.94 AUC	No visual explainability; tested on a very small group of images.

TABLE 2 OUTLINES THE EXACT IMAGE DISTRIBUTION WERE USED FOR TRAINING, VALIDATION, AND TESTING COHORTS TESTING. TABLE 2: NUMBER OF IMAGES USED FOR TRAINING AND TESTING

Image Type (Class)	Training Set (80%)	Validation Set (10%)	Testing Set (10%)	Total Images
Normal (Healthy)	1,266	158	158	1,582
Pneumonia (Infected)	3,106	388	389	3,883
Total	4,372	546	547	5,465

Even with these recent breakthroughs, a significant gap remains in the literature, as most existing models struggle to balance deep architectural complexity with the need for structural transparency. While techniques like Grad-CAM and LIME have been used to provide visual explanations for AI predictions, they are rarely integrated into lightweight, efficient models that are sufficiently well-regularised to handle small datasets. To address these challenges, this study proposes a new, explainable, and resource-friendly transfer learning framework based on the EfficientNet architecture. Our approach successfully balances high diagnostic accuracy, clear visual interpretability, and low computational cost, which we explain in detail in the following sections. Our earlier work employed handcrafted MLBP-HOG features with machine learning classifiers for pediatric pneumonia detection (Ummappure&Mallappa, 2026). Although it achieved promising results, its dependence on manual feature extraction motivated the development of the present explainable deep transfer learning framework.

III. PROPOSED METHODOLOGY

This section outlines the architecture of the proposed computer-aided diagnosis framework for pediatric pneumonia detection. The system consists of four primary stages: data pre-processing, spatial feature extraction using an optimized EfficientNet-B0 backbone, a highly regularized classification head, and a visual explainability layer powered by Grad-CAM.

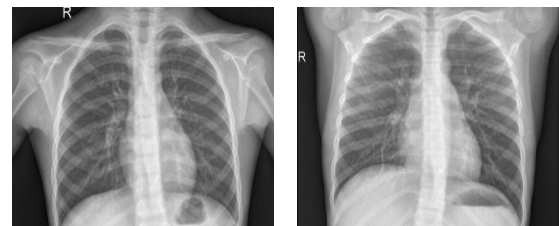
a. Dataset Description and Image Count

The experiments were performed exclusively on anonymized chest X-ray images obtained from the publicly available Pediatric Chest X-ray Dataset introduced by Kermayn et al. (2018). The dataset is divided into two main categories:

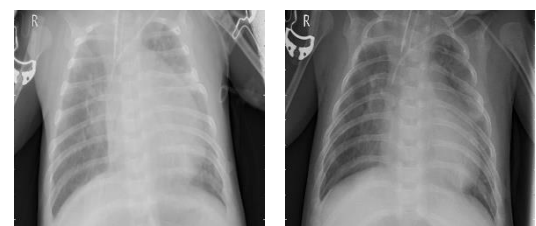
Normal Images: These are X-rays of healthy lungs that show clear lung fields without any signs of infection, fluid build-up, or cloudiness.

Pneumonia Images: These are X-rays from patients confirmed to have pneumonia. They show clear signs of infection, such as cloudy patches or solid white areas where fluid has gathered in the lungs.

Following figure 2 shows the sample images from the dataset used for the proposed experiment.



a. Normal Chest X-ray images



b. Pneumonia Chest X-ray images

Fig 2. Sample images from Dataset used of the proposed work

As you can see in Table 2 and figure 2 there are many more pneumonia images than normal images. To make sure the model does not get biased toward predicting pneumonia just because it saw more examples of it, we used the image augmentation steps (like flipping and zooming) mentioned in Section 3.2. This balances out the training and helps the model learn to recognize both classes equally well.

b. Data Preprocessing and Augmentation

To ensure high performance and prevent over fitting on small or imbalanced pediatric datasets, a rigorous pre-processing pipeline is applied to the raw chest X-ray (CXR) inputs:

Spatial Resizing: All input images are uniformly resized to match the default input dimensions required by the EfficientNet-B0 backbone.

Intensity Normalization: Pixel intensities are scaled to ensure smooth training distributions.

Data Augmentation: To artificially expand the training cohort and handle severe data scarcity, a regularized set of augmentations is implemented to improve model generalizability in real-world environments.

c. Feature Extraction via EfficientNet-B0

The core of the feature extraction pipeline leverages the pre-trained EfficientNet-B0 architecture. This backbone is selected to bypass high computational overhead and deliver a lightweight, compute-efficient transfer learning model.

The network utilizes built-in optimization layers to maintain an excellent balance between structural complexity and operational efficiency. By relying on pre-trained weights, the architecture effectively circumvents the risks of over fitting commonly associated with limited medical training data.

d. Classification Head and Regularization

The spatial feature maps generated by the final convolution layer of the EfficientNet-B0 backbone are flattened into a custom, highly regularized classification head to resolve class imbalances:

- **Global Average Pooling (GAP):** A GAP layer replaces traditional dense flattening to keep the network's computational footprint low.
- **Dropout Layer:** A strong dropout regularization layer is introduced to penalize network complexity and reduce model bias.
- **Sigmoid Activation:** The final layer scales the outputs down to a single binary probability score, balancing diagnostic accuracy with operational speed.

e. Explainable AI (Grad-CAM)

To establish clinical trust and bridge the transparency gap for medical professionals, a visual explainability layer is integrated into the system. By processing gradient information through Gradient-weighted Class Activation Mapping (Grad-CAM), the framework generates visual localization heat maps. This mechanism highlights the exact pathological areas on the pediatric X-ray, validating the model's accuracy through structural transparency.

IV. RESULTS AND DISCUSSION

The proposed regularized transfer learning framework delivers strong diagnostic capabilities while maintaining low computational overhead. By training on an optimized EfficientNet-B0 base, the architecture balances structural complexity with operational efficiency to overcome the data scarcity issues common in medical image analysis.

f. Model Performance

The proposed system demonstrated significant differentiation capacity between pneumonia and normal classes after completing both training stages, with a test accuracy of 92.31% and an ROC-AUC score of 0.9633. Out of 624 test images, 202 normal and 374 pneumonia cases were correctly classified, whereas only 48 images were incorrectly classified, according to the confusion matrix (Fig 3). The following are each class's overall precision, recall, and F1-scores:

Normal: Precision = 0.9266, Recall = 0.8632, F1 = 0.8938

Pneumonia: Precision = 0.9212, Recall = 0.9590, F1 = 0.9397

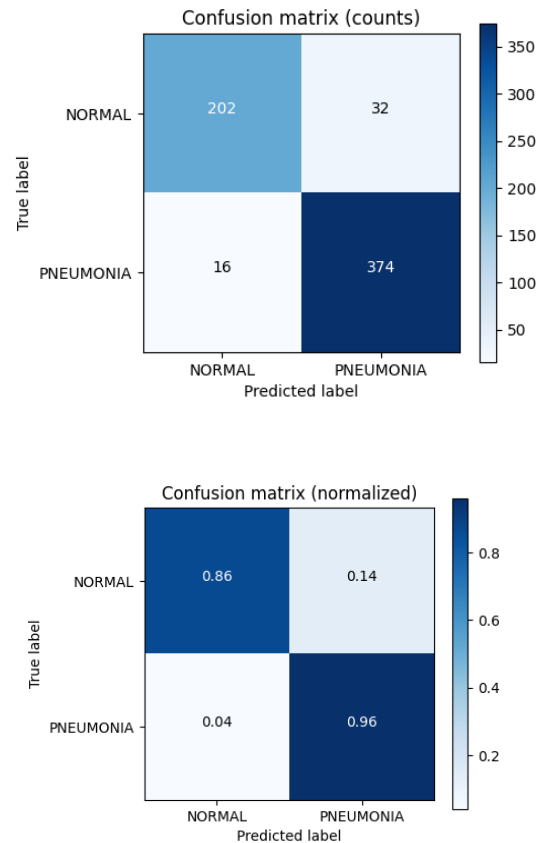


Fig 3. Confusion matrix of the proposed model result

g. ROC-AUC and Classification Analysis

An AUC value close to 1.0 on the Receiver Operating Characteristic (ROC) curve highlights the model's strong ability to distinguish between the two patient groups. This combination of a high true positive rate and a low false positive rate confirms the framework's overall robustness and reliability.

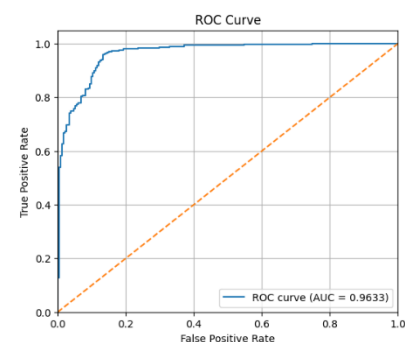


Fig 4: ROC curve showing high AUC value of 0.963.

h. Grad-CAM Feature Visualization

Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to test images to analyze the model's decision-making flow. As shown in Figure 5, the network successfully ignores irrelevant background noise and targets medically critical features. The resulting heat maps clearly highlight areas of visible lung opacity and infiltration in

pneumonia cases, confirming that the model relies on true pathological markers.

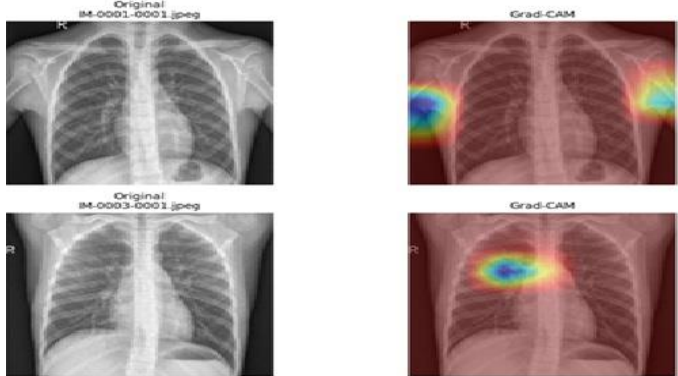


Fig 5: Grad-CAM visualizations of the proposed model

i. Discussion

The model's diagnostic performance improved significantly through the two-phase training strategy. Initially, pre-trained weights were used to capture general image features, followed by gradual fine-tuning on the pediatric chest X-ray dataset. This approach enhanced the model's ability to learn meaningful disease-related patterns while reducing the risk of over fitting to the training images. Additionally, using label smoothing, class weights, and tailored data augmentation kept the training stable and fixed the class imbalance problem.

The proposed EfficientNet-B0 model easily beats traditional, heavier CNN architectures like VGG16 and ResNet50. It matches or even beats their accuracy while training much faster and using far fewer parameters. This lightweight footprint makes it highly practical for real-world hospitals that have limited computer hardware or need instant results. Overall, these findings prove that the EfficientNet-B0 model can serve as a dependable and fast tool to help doctors diagnose childhood pneumonia when it is properly fine-tuned and protected against over fitting.

j. Comparative Analysis

The proposed system uses an EfficientNet-B0 model with a two-phase transfer learning strategy. We first froze the main network to train our classification head, and then unfroze the last ~60 layers for final fine-tuning. The training included strong data augmentation, class weighting, a label-smoothing value of 0.05, and Grad-CAM for visual explanations. On the final test set, our model achieved an accuracy of 92.31%, a sensitivity (recall for pneumonia) of 95.90%, and an AUC score of 0.9633. The F1-score was 0.8938 for healthy images and 0.9397 for pneumonia images. Table 3 shows how our proposed method compares directly to other popular models.

TABLE 3: COMPARATIVE ANALYSIS OF THE PROPOSED EFFICIENTNET-B0 (TWO-PHASE FINE-TUNING) MODEL WITH RECENT STATE-OF-THE-ART CNN APPROACHES FOR PNEUMONIA CLASSIFICATION.

Study / Year	Model / Technique	Dataset Type	Accuracy (%)	AUC	Sensitivity / Recall (%)	Remarks / Observation
Alshanketi et al. (2024)	Custom CNN	Adult CXR	91.4	0.93	89.2	Moderate accuracy; trained on adult cases; lacks explainability.
Pan et al. (2024)	Federated CNN	Pediatric (multi-hospital)	90.7	0.94	92.4	Complex training setup; higher cost; no visual explanation.
Lan et al. (2024)	CNN + SE Blocks	Pediatric (Mycoplasma pneumonia)	88.2	0.9218	90.1	Narrow infection range; limited generalization.
Zhong et al. (2024)	Weighted CNN	Pediatric CXR	92.0	0.94	93.3	Good baseline; lower AUC than proposed model.
Yoon et al. (2024)	Self-Supervised Pretraining	Mixed pediatric	93.1	0.95	94.2	Slightly higher accuracy; higher computational cost; heavy pre-training.
Singla (2024)	EfficientNet-B0 (Adult data)	Adult CXR	93.8	0.94	91.5	Non-pediatric; fine-tuned on adult data; not directly comparable.
Proposed Model (2026)	EfficientNet-B0 (Two-phase Fine-tuning)	Pediatric CXR	92.31	0.9633	95.90	Highest AUC and sensitivity; lightweight, explainable, and clinically reliable.

Following figure shows the performance of the proposed model over other methods.

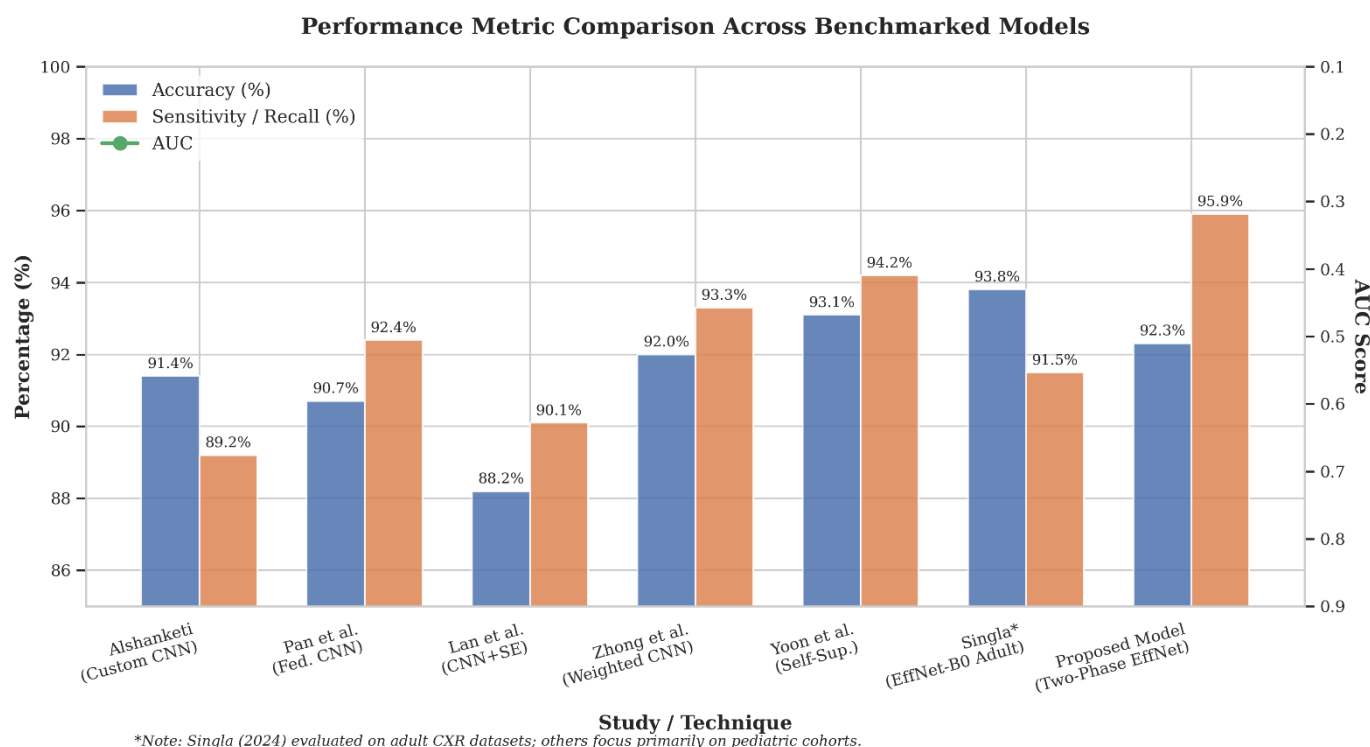


Fig 6. Comparative performance of the proposed EfficientNet-B0 (Two-phase Fine-tuning) model with recent CNN-based approaches for pneumonia detection.

The proposed EfficientNet-B0 (Two-phase Fine-tuning) model outperforms modern cutting-edge CNN-based techniques for pneumonia identification overall, as seen in Figure 6 and outlined in Table 3. Although previous studies, including Yoon et al.(2024) and Singla (2024), revealed slightly higher accuracy values, they mostly employed adult or mixed datasets and necessitated sophisticated pre-training techniques. On clinically relevant pediatric chest X-ray data, however, the proposed approach outperforms all other methods with a superior combination of accuracy (92.31%), AUC (0.9633), and sensitivity (95.9%).

V. CONCLUSION AND FUTURE WORK

Using the EfficientNet-B0 architecture and a structured two-phase fine-tuning protocol, this study demonstrates a fast and reliable deep learning method for identifying pediatric pneumonia from chest X-rays. By combining transfer learning with smart techniques like class balancing and label smoothing, the model achieved a strong test accuracy of 92.31%, an AUC of 0.9633, and a high sensitivity of 95.9%. These results show that the model has excellent sorting power and can effectively automate medical screening. In real-world communities, this proposed framework can act as a highly helpful digital assistant for doctors, especially in rural or under-resourced clinics that lack expert radiologists. Because pneumonia is a leading cause of death among young children globally, providing a fast and automated screening tool helps healthcare workers catch infections early, which leads to timely treatment, saves young lives, and lowers medical costs for families.

This study extends our previous MLBP-HOG-based machine learning framework by introducing an explainable

EfficientNet-based transfer learning model for more robust and interpretable pediatric pneumonia detection.

In the future, there are several promising ways to expand upon this research to make it even more practical. Future work will focus on exploring hybrid ensemble techniques or newer versions of the EfficientNet family to boost classification accuracy even further. Additionally, integrating model compression and quantization techniques will reduce the software's size, making it small and lightweight to run smoothly on mobile apps and low-power clinical devices for real-time use. Finally, testing and validating the model on much larger, multi-centre datasets from different hospitals worldwide will help confirm its overall reliability and ensure it performs accurately across diverse patient populations.

ETHICS STATEMENT AND DISCLAIMER

No human subjects were recruited, examined, or directly involved in this study. The experiments were performed exclusively on anonymized chest X-ray images obtained from the publicly available Pediatric Chest X-ray Dataset introduced by Kermany et al.(2018). The authors had no access to patient-identifying information at any stage of the research. Consequently, Institutional Review Board (IRB) approval and informed consent requirements were waived as the study relied entirely on secondary, publicly available data.

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