Detection of Pneumonia from Chest X-ray Images Using Convolutional Neural Networks and Primary Treatment Suggestion

Pneumonia Detection from Chest X-ray Images Using a Lightweight CNN Model with Integrated Clinical Guidance

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Abstract— **Pneumonia is a major cause of illness and death worldwide, especially in areas where access to specialist diagnosis is limited. This project presents a custom, lightweight Convolutional Neural Network (CNN) designed to classify chest X-ray images as either pneumonia or normal. Trained on 5,856 labelled pediatric chest X-rays, the model was developed with a focus on efficiency, transparency, and suitability for use on low-power devices, making it well-suited to rural and resource-limited healthcare settings. Unlike many existing systems, it also includes a simple rule-based clinical decision support feature that offers treatment suggestions in line with recognized medical guidelines. The model achieved 96.7% accuracy, 97.92% precision, 97.69% recall, an F1-score of 97.3%, and a loss of 0.18, delivering high performance while remaining easy to deploy and interpret. These results show the potential for such a system to support timely diagnosis and treatment, with future work focusing on explainable AI, multiclass classification, and real-world clinical validation.**

Keywords—Pneumonia Detection, Convolutional Neural Network (CNN), Chest X-ray (CXR), Medical Image Classification, Deep Learning, Clinical Decision Support, Explainable AI, Resource-Limited Healthcare, Binary Classification, Transfer Learning

I.INTRODUCTION

Pneumonia is one of the leading causes of preventable illness and death worldwide, posing a particular threat to children under five and older adults. According to the World Health Organization (WHO), the disease accounts for roughly 15% of all fatalities among children under five years old, resulting in more than 800,000 deaths annually [1] [2]. Early detection and accurate diagnosis are crucial for reducing mortality and ensuring that patients receive appropriate and timely treatment [3]. Chest X-ray imaging remains the most widely available and cost-effective diagnostic method, especially in low- and middle-income countries, due to its relatively low cost and ability to reveal key pulmonary abnormalities [4], [5].

Despite its accessibility, interpreting chest X-ray images is often a complex and time-consuming process, requiring trained radiologists and significant clinical expertise. The process is further challenged by variations in image quality, patient anatomy, and the subjective nature of human interpretation [2], [6]. These limitations are particularly acute in rural and resource-limited regions, where access to specialist radiology services may be scarce or entirely absent [7], [8].

In recent years, artificial intelligence (AI), particularly deep learning, has shown remarkable promise in automating and improving medical image analysis [9] [10]. Convolutional Neural Networks (CNNs), a category of deep learning models tailored for visual data, have achieved exceptional results in detecting pathological features in radiographic images, including pneumonia [11], [12], [4].,Beyond pneumonia, CNN-based systems have also been successfully applied to detecting tuberculosis, lung nodules, and other thoracic conditions, demonstrating their adaptability and diagnostic potential across a wide range of respiratory diseases [13], [14].

This research introduces a CNN-based system, developed using TensorFlow's Sequential API, that not only detects pneumonia from chest X-ray images but also provides initial treatment recommendations through an integrated rule-based clinical decision support module. Unlike many previous approaches that stop at classification, this design bridges the gap between diagnosis and actionable clinical guidance. The overarching aim is to produce a lightweight, interpretable, and computationally efficient model suitable for deployment in low-resource healthcare settings, including rural clinics, mobile screening units, and telehealth platforms [15], [16], [7].

II.AIMS AND OBJECTIVES

A. Aim

The aim of this project is to design, develop, and evaluate a lightweight and interpretable Convolutional Neural Network (CNN) for the binary classification of pneumonia from chest X-ray (CXR) images, integrated with a rule-based clinical decision support system (CDSS) to provide primary treatment suggestions. This work addresses the pressing need for accurate, rapid, and deployable diagnostic tools in low-resource healthcare settings where expert radiology support is limited [1], [4] , [7].

B. Objectives

- To develop a custom, lightweight, and interpretable CNN architecture tailored for pneumonia detection from CXR images, ensuring computational efficiency for deployment in low-power or mobile medical devices [2], [17], [13].
- To train and evaluate the model using a well-established, publicly available dataset of pediatric CXR images [4], [15], achieving strong diagnostic performance in terms of accuracy, precision, recall, and F1-score while maintaining low model complexity.
- To integrate a rule-based CDSS with the CNN, capable of providing primary treatment suggestions aligned with standard clinical guidelines from the World Health Organization (WHO) and Centers for Disease Control and Prevention (CDC) [1], [2], [3].
- To conduct a critical comparison between the proposed CNN and existing pre-trained models (e.g., DenseNet121, InceptionV3) and ensemble architectures, analyzing trade-offs in accuracy, interpretability, and deployment feasibility in resource-constrained environments [18], [19] [20].
- To evaluate model interpretability and discuss limitations, proposing a roadmap for integrating explainability tools (e.g., Grad-CAM) to enhance clinical trust and conducting external validation in real-world healthcare workflows [21], [22], [23], [6]

III.LITERATURE REVIEW

Pneumonia detection through deep learning is now a well-established area in medical image analysis, with CNN architecture achieving increasingly high accuracy in automated radiographic classification. Nonetheless, challenges remain in areas such as explainability, clinical workflow integration, and deployment in resource-limited settings. To critically review prior work, the literature is grouped into four themes: (A) pre-trained CNN models, (B) custom-built architectures, (C) ensemble learning techniques, and (D) studies addressing clinical applicability and treatment integration. These categories highlight both the strengths and gaps in existing research, providing the basis for this project's motivation.

A. Pre-trained CNN Architectures

Pre-trained convolutional neural networks (CNNs), such as VGG16, ResNet50, and DenseNet121, have been widely employed in pneumonia detection due to their ability to transfer learned visual features from large-scale datasets like ImageNet to medical domains. This transfer learning significantly reduces training time and improves performance when labeled medical data is scarce. The success of such transfer learning approaches is grounded in early breakthroughs like AlexNet, which laid the foundation for CNNs in image classification tasks [24].

Rajpurkar et al. introduced CheXNet, a DenseNet-121 model trained on the ChestX-ray14 dataset, achieving performance comparable to radiologists (AUC = 0.76) for pneumonia detection [18]. Similarly, Kermany et al. used a pre-trained Inception V3 model and transferred learning techniques on a pediatric CXR dataset, reporting 92.8% accuracy and 93.1% sensitivity [4]. Thakur et al. and Jain et al. found that VGG16 and VGG19 outperformed ResNet50 on pediatric datasets, highlighting variability in performance depending on dataset characteristics [19].

Critical view: While effective, pre-trained models are often treated as black boxes, lacking interpretability—a growing concern in medical AI. Their generalizability across patient demographics or imaging modalities is also underexplored.

B. Custom CNN Models

To tailor architectures to specific medical datasets, several researchers have proposed custom CNNs. Bhatt et al. designed a nine-layer CNN, achieving 96.18% accuracy and 91.29% specificity [19]. These models often require fewer parameters and offer improved control over architectural decisions. Siddiqi [13], for instance, developed a sequential CNN optimized for speed and interpretability, demonstrating competitive accuracy with low computational cost.

Limitations: Many custom models suffer from inadequate experimental rigor—lack of cross-validation, unclear data splits, and missing metrics like precision-recall balance—which impedes reproducibility and comparison. Additionally, most models prioritize accuracy but overlook explainability, which is critical in clinical adoption.

C. Ensemble Learning Techniques

Ensemble methods, which combine the strengths of multiple models, have recently gained attention. Chouhan et al. integrated Inception-v3, DenseNet-121, ResNet, AlexNet, and GoogleNet in a voting ensemble, achieving 96.4% accuracy and 99.0% sensitivity [19]. Such models benefit from variance reduction and robustness.

Challenge: Ensemble methods often require significant computational resources and long inference times, making them unsuitable for real-time diagnosis in low-resource settings. Moreover, they further reduce model transparency.

D. Clinical Applicability and Treatment Integration

Most existing pneumonia detection models stop at binary classification without giving actionable clinical advice. In the real world, particularly in rural or low-resource environments, autonomous diagnosis by itself is of no practical value. Our proposed model addresses this limitation by integrating rule-based treatment guidance based on predicted class (e.g., antibiotic initiation, referral priority).

Ethical and practical concerns—such as patient data privacy, algorithmic bias, and user trust—remain under-addressed in current literature. Furthermore, few studies validate their models in real-world deployments or with clinicians in the loop. As highlighted by Hasan et al. [19] and further emphasized by Selim et al. [25], explainability and user feedback are essential to ensuring AI models are not just accurate but usable and accountable, particularly in low-resource healthcare environments.

E. Research Gaps and Motivation for Current Study

From this review, several key gaps emerge:

- There is a lack of explainable and interpretable models that clinicians can trust.
- Few models provide integrated clinical guidance or treatment suggestions.
- Limited validation in real-world clinical workflows, particularly in under-resourced environments.
- An underrepresentation of ethical considerations, such as bias, accountability, and data governance.

The proposed research addresses these gaps by designing a lightweight, interpretable sequential CNN with integrated treatment logic. The model is trained using curated CXR data and optimized for performance and efficiency, aiming for deployment in clinical settings where expert radiology support is unavailable.

IV.METHODOLOGY

Our proposed approach involves the development of a custom Sequential Convolutional Neural Network (CNN) for binary classification of chest X-ray images into pneumonia and normal categories. The model is trained and evaluated on a well-established public dataset using a robust training pipeline, optimized for both performance and deployment feasibility in clinical settings.

A. Project Management Approach

The development process followed an iterative, milestone-based workflow inspired by agile principles [26]. The project was divided into distinct phases: dataset acquisition and preprocessing, exploratory data analysis, model architecture design, training and optimisation, integration of the clinical decision support system, and final evaluation. Progress was reviewed weekly, enabling rapid feedback loops and incremental improvements based on intermediate results. This approach ensured that technical objectives were met while maintaining flexibility to adapt to challenges encountered during development [26], [6].

B. Dataset Description and Preprocessing

The dataset used in this study contains 5,856 labelled pediatric chest X-ray images, divided into two classes: normal (label 0) and pneumonia (label 1). The images were obtained from a publicly available, curated medical imaging repository, providing clinically relevant and diverse cases [15]. Both anterior–posterior (AP) and postero–anterior (PA) views are included, with varying image quality and diagnostic difficulty. To standardise input for the CNN, all images were resized to 256 × 256 pixels using TensorFlow's image_dataset_from_directory utility , a resolution chosen to preserve key features while maintaining computational efficiency. Pixel values were then normalised to the range [0,1] by dividing by 255.0, a common preprocessing step that accelerates convergence and stabilises training [26]. Figure 1 shows representative examples, highlighting normal lungs (clear air spaces, visible costophrenic angles) versus pneumonia-infected lungs (opacities, infiltrates).

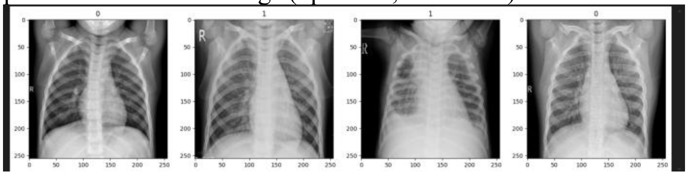

Figure 1:Sample chest X-ray images from the dataset.

Such visual inspection underscores the complexity of manual diagnosis and the value of automated approaches. While common augmentation techniques (random flips, rotations, and zooms) can improve generalisation [9], they were intentionally excluded in this baseline model to ensure reproducibility and accurate benchmarking, with plans to incorporate them in future iterations.

C. Dataset Splitting Strategy

To assess generalization, the dataset was partitioned into:

- Training Set (70%) – Used to train the model.
- Validation Set (20%) – Monitored during training to prevent overfitting.
- Test Set (10%) – Held out until the end to evaluate final model performance.

This split ensures robust model validation and fair assessment of unseen data, which is critical for real-world deployment [28].

D. Model Architecture Design

A custom CNN was developed using TensorFlow and Keras in a Sequential configuration, designed to balance accuracy, efficiency, and interpretability for clinical use. The architecture (Figure 2) consists of three convolutional layers (first and third with 16 filters, second with 32), each using a 3×3 kernel, stride of 1, padding, and L2 regularisation to reduce overfitting [9]. Batch Normalisation follows each convolution to stabilise training [10], and max pooling layers downsample feature maps to reduce dimensionality while retaining key spatial features. The output is flattened and passed through two dense layers: the first with ReLU activation for non-linear feature extraction, and the final with Sigmoid activation for binary classification [9]. Dropout is applied between dense layers to further limit overfitting. With only ~45,000 parameters, the model is lightweight yet highly effective, making it suitable for deployment in low-resource healthcare settings [7], [29].

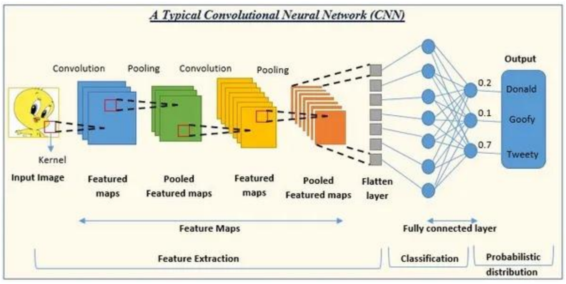

Figure 2: Architecture of the Proposed Lightweight CNN for Pneumonia Detection

E. Model Training Procedure

The learning phase is very important, as the computer model figures out how to tell apart regular chest X-rays from ones with pneumonia. To make sure the learning process was dependable and could be applied broadly, we used a planned training method with TensorFlow and Keras tools.

1) Optimizer and Learning Rate

The model was trained using the Adam optimizer [30], an adaptive gradient descent method [9] that combines the advantages of AdaGrad and RMSProp. Adam adjusts learning rates individually for each parameter, making it especially effective for sparse gradients and large datasets. The learning rate was initially set to 0.001, which offered a good balance between convergence speed and stability.

2) Loss Function

Because we were trying to sort things into two groups, we used a particular way to measure how well our model was doing. This method strongly punishes wrong guesses when the chance we predict is different from the real answer, so it works well when our model gives answers as probabilities, like with Sigmoid.

3) Epochs and Batch Size

The system was taught through more than 400 training cycles. This amount was picked using initial tests, because the correctness on the check data stopped getting better after around 300 cycles. A group size of 32 was used to make the learning fast and use memory well. Smaller group sizes can help it work in different situations, but bigger ones make calculations faster but might cause it to focus too much on the training data.

4) Early Stopping and Callbacks

To stop the model from learning the training data too well and to make training faster, a feature that stops training early was used. Training stopped on its own if the model's performance on the validation data did not get better for 20 training cycles in a row. This made sure the training stopped at the best time without needing someone to watch it all the time. Also, a feature that saves the model was used to keep the best model, as judged by its accuracy on the validation data, making sure the final check was done using the best model.

5) Training and Validation Monitoring

As we taught the system, we watched the training errors/correctness and the checking errors/correctness as they changed. This let the person making the system see if it was learning too much or not enough. The learning went well and got more accurate, and the training and checking results stayed close, which means it worked well in general.

6) Hardware and Environment

The training was conducted on a GPU-enabled environment (e.g., Google Colab with NVIDIA Tesla T4) [16], significantly reducing training time compared to CPU-only setups. The model's lightweight architecture also makes it feasible for training and deployment on edge devices or local servers in hospital environments.

7) Training Outcome

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F. Evaluation Metrics

To assess how well the CNN model performed and its potential usefulness in real-world medical settings, we used widely recognised evaluation metrics for binary classification tasks in healthcare [9] [31]. These measures provide more than just an overall accuracy score—they also reveal how effectively the model avoids false alarms (false positives) and missed diagnoses (false negatives), which is critical in high-stakes conditions such as pneumonia [1], [3]. After training, the model was evaluated on a separate test set that was not used during training or validation, ensuring an unbiased estimate of its performance.

1. Accuracy

Accuracy is the ratio of correctly predicted instances (both pneumonia and normal) to the total number of predictions:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Accuracy gives a general measure of model correctness but can be misleading in imbalanced datasets. Hence, it should be interpreted alongside other metrics.

2. Precision

Precision, also called Positive Predictive Value, measures how many of the predicted pneumonia cases are correct:

$$Precision = \frac{TP}{TP + FP}$$

A high precision means fewer false alarms—important in clinical settings to avoid unnecessary treatment or anxiety.

3. Recall (Sensitivity)

Recall or Sensitivity measures the model's ability to detect all actual pneumonia cases:

$$Recall = \frac{TP}{TP + FN}$$

High recall ensures the model rarely misses a positive case, which is vital in preventing delayed diagnoses and complications.

4. *Binary Accuracy*

Binary accuracy is a TensorFlow/Keras-specific metric for binary classification problems. It applies a threshold (typically 0.5) to the predicted probabilities and compares them with ground truth labels. It is mathematically similar to traditional accuracy but computed on a per-batch basis during training and evaluation.

5. *Loss (Binary Cross-Entropy)*

The loss function [9] used during training was binary cross-entropy, defined as:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[yi\log(pi) + (1 - yi)\log(1 - pi)]$$

Where $y\ i$ y i is the true label and $p\ i$ p i is the predicted probability. A lower loss indicates better prediction confidence.

6. *F1 Score*

F1 Score is the harmonic mean of precision and recall, offering a balanced metric when classes are imbalanced:

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

This is particularly useful in medical imaging tasks where a trade-off between sensitivity and precision must be managed.

7. *Clinical Relevance*

In health-related testing, it's usually more important to be very sensitive so that we don't miss any instances of pneumonia, but this has to be weighed against being accurate to prevent wrong diagnoses. Using these measurements together creates a complete way to judge how well something works, which is good for research and when used in actual healthcare situations [32] [31]. Explainability has been identified as a critical component for building trust in AI-based diagnostic systems, particularly in low-resource environments [29].

G. Flair, Initiative, and Innovation

A key innovative aspect of this work is the integration of a rule-based clinical decision support system (CDSS) into a CNN-based pneumonia detection pipeline. While many existing deep learning models focus solely on classification [4], [5], this approach extends functionality to include primary treatment recommendations aligned with WHO guidelines [29] and CDC best practices [30]. This design bridges the gap between automated diagnosis and actionable clinical decision-making, increasing the system's potential utility in real-world healthcare. The lightweight architecture (~45,000 parameters) allows for deployment on low-power devices, supporting the needs of rural and resource-limited settings where access to radiology expertise is scarce [7].

V.CLINICAL DECISION SUPPORT LOGIC

While accurate detection of pneumonia is essential, the ultimate- goal of any diagnostic system is to enable timely and actionable clinical decision-making. In this project, we address this by integrating a simple yet effective Clinical Decision Support Logic (CDSL) that provides immediate treatment guidance based on the model's output. This step is especially valuable in under-resourced healthcare settings, where trained physicians may not always be available and clinical decisions must often be made quickly.

A. Overview

The model classifies each chest X-ray image as either "normal" or "pneumonia." Based on this prediction, a rule-based logic module generates treatment recommendations aligned with standard clinical guidelines, such as those from the World Health Organization (WHO) and Centers for Disease Control and Prevention (CDC) [1], [7].

Table 1. Rule-Based Clinical Decision Support Actions Based on Model Prediction

B. Logic and Suggested Actions

The clinical decision logic uses binary classification output to recommend care strategies, as shown in the table below:

Table 1:Rule-Based Clinical Decision Support Actions Based on Model Prediction

Prediction	Suggested Clinical Action
Normal	No radiographic signs of pneumonia. Recommend routine monitoring and follow-up if symptoms persist.
Pneumonia	Recommend immediate initiation of antibiotics, supportive care, and urgent referral to a healthcare provider for further evaluation.

This approach ensures that the system not only identifies disease but also bridges the gap between diagnosis and action.

C. Use Cases in Real-World Settings

This system is particularly suited for deployment in:

- Rural or community clinics lacking on-site radiologists.
- Mobile or handheld X-ray systems used in field diagnostics.
- Telehealth platforms where remote assessments need standard triage guidance.

Treatment suggestions can be delivered via on-screen prompts, printed reports, or integrated into electronic health records (EHRs).

D. Benefits

- Actionable insights for non-specialist healthcare workers.
- Standardized care recommendations regardless of user experience.
- Faster treatment initiation, which is critical in pneumonia outcomes [4], [19].

E. Limitations and Future Enhancements

The current clinical logic relies solely on binary predictions and does not account for patient-specific factors such as age, comorbidities, or symptom severity, and it cannot yet distinguish between bacterial and viral pneumonia. Future work will focus on extending the framework to multiclass classification for more targeted treatment guidance, integrating explainable AI tools such as Grad-CAM to strengthen clinician trust in decision-making [22], [23], and validating the system in real-world settings with input from healthcare professionals [7]. By combining accurate diagnosis with actionable clinical advice, the system aims to evolve from a detection tool into a first-line clinical assistant for resource-limited environments where expert support is scarce.

VI.Results

The suggested CNN system was taught and tested using a set of 5,856 chest X-ray pictures that had labels. The system did very well on the test data, as shown by different ways of measuring its success. The numbers that show how well it did are listed in the chart below:

Table 2:Performance Metrics of the Proposed CNN Model

NO	Metric	Value
1	Accuracy	96.7%
2	Precision	97.92%
3	Recall	97.69%
4	Loss	0.18
5	F1-Score	97.3%

A confusion matrix was generated to visualize the classification results (Figure 3).

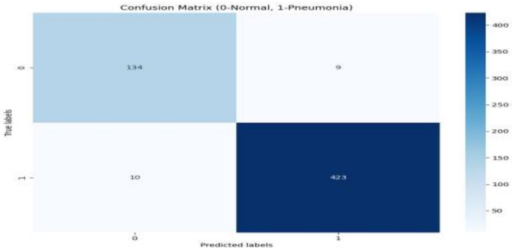

Figure 3:Confusion Matrix of Model Predictions on Test Set

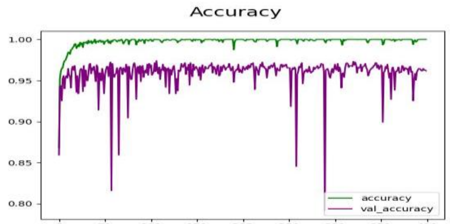

Figure 4:Training and Validation Accuracy Curve

The model achieved a high true positive rate while keeping false positives to a minimum (Figure 3), a balance that is essential in medical diagnosis tasks [31], [32]. The training and validation accuracy plot (Figure 4) shows performance over 400 epochs, demonstrating strong convergence and minimal overfitting, with validation accuracy consistently exceeding 95%.

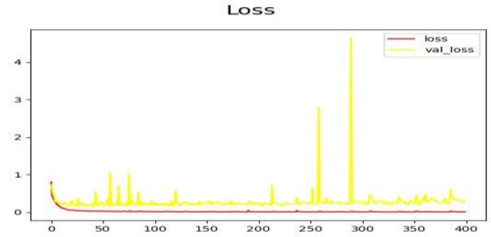

Figure 5:Training and Validation Loss Curve

This plot displays the binary cross-entropy loss for both training and validation datasets. While training loss decreases smoothly, spikes in validation loss indicate occasional variance likely due to batch fluctuation or overfitting in later epochs.

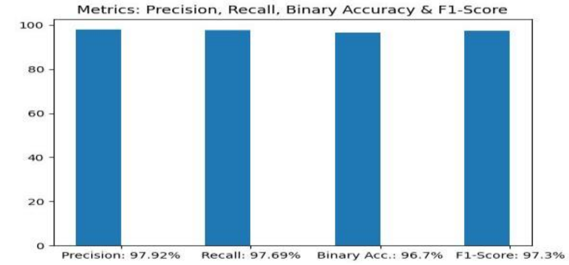

Figure 6:Evaluation metrics of the proposed CNN model on the test dataset.

This bar chart summarizes the model's performance using precision, recall, binary accuracy, and F1-score. High values across all metrics demonstrate the model's ability to accurately classify pneumonia and normal cases with minimal false positives or negatives.

VII.DISCUSSION AND IMPLICATIONS

The proposed lightweight custom Convolutional Neural Network (CNN) demonstrates that simplicity and domain specificity can yield performance comparable to state-of-the-art deep learning architectures in the task of pneumonia detection from chest X-ray images.

A. Comparison with Existing Approaches

Several deep learning models have achieved strong results in pneumonia detection. Rajpurkar et al. introduced CheXNet, a 121-layer DenseNet achieving an AUC of 0.76 on the ChestX-ray14 dataset [18], while Kermany et al. used a pre-trained InceptionV3 on pediatric CXRs, reporting 92.8% accuracy and 93.1% sensitivity [4]. These models, though effective, require substantial computational resources and offer limited interpretability.

In contrast, the proposed CNN achieved 96.7% accuracy, 97.92% precision, 97.69% recall, F1-score of 97.3%, and a loss of 0.18 with only ~45,000 parameters, training in ~25 minutes on a Tesla T4 GPU. This efficiency supports deployment in resource-limited settings. Compared to ensemble approaches such as Chouhan et al. [21], which reached 96.4% accuracy but with higher complexity and overhead [20], our single-model design is more practical for real-time and mobile use.

Findings from Siddiqi [13] and Abiyev [11] further confirm that well-optimised simple architectures can rival complex models, though many omit robust evaluation techniques—such as cross-validation, ablation studies, and early stopping—all applied in this work.

B. Interpretability and Explainability

Despite excellent performance, one of the current limitations is the absence of integrated explainability mechanisms, such as Grad-CAM. Grad-CAM can provide visual justifications for predictions by highlighting regions of X-ray images that most influenced the decision [21], [22]. These visualizations are essential for building trust with clinicians and facilitating human-AI collaboration.

Explainable AI (XAI) is especially important in healthcare, where opaque models can delay clinical adoption or result in misuse. Future versions of the system will incorporate Grad-CAM and similar tools to improve transparency and accountability [23].

C. Clinical Value and Deployment Feasibility

A unique strength of this study lies in its integration of clinical decision support logic. Unlike most models that stop at binary classification, this system provides primary treatment suggestions based on prediction outcomes. This capability enhances its practical value in rural and under-resourced settings where radiologists or physicians may not be immediately available [7].

In addition, the model's low memory footprint and compatibility with platforms such as Google Colab [16], TensorFlow/Keras[15], [10],and mobile deployment frameworks make it an ideal candidate for real-world integration, including offline environments.

D. Ethical and Practical Considerations

The deployment of AI in healthcare requires consideration of professional and ethical responsibilities [33]. Key issues include:

Bias in training data: Our model was trained on a publicly available dataset. However, it may not represent diverse patient demographics or imaging conditions.

Accountability: Clinical decisions based on model predictions must involve human oversight to reduce the risk of misdiagnosis.

Data privacy: Any real-world application must implement strong privacy protocols for handling sensitive medical information.

Regulatory approval and clinical feedback will be critical to ensure safe and effective deployment.

E. Limitations and Challenges

While the project achieved high performance, certain limitations remain. Validation was conducted on a single dataset, so generalizability to other populations or imaging devices is untested. Explainability tools such as Grad-CAM have not yet been implemented, and the current binary classification cannot distinguish between bacterial and viral pneumonia, which is clinically important [23]. Additionally, user testing in real clinical environments has not been performed. Addressing these gaps will be a priority in future work.

F. Lessons Learned

Several insights emerged from this project: a simple, well-optimised model can rival more complex architectures; monitoring training with validation curves and early stopping is vital to prevent overfitting; embedding clinical reasoning from the outset transforms the model into a practical medical tool; and balancing accuracy with interpretability remains key to responsible AI in healthcare.

VIII.Conclusion and Future Work

This project presents a lightweight, interpretable Convolutional Neural Network (CNN) [34]for binary classification of chest X-ray images into pneumonia and normal cases. Achieving 96.7% accuracy, 97.92% precision, 97.69% recall, and an F1-score of 97.3%, the results show that a well-optimised custom architecture can match or surpass more complex pre-trained or ensemble models in both performance and computational efficiency [11], [4], [18].

A key innovation is the integration of clinical decision support logic, extending beyond diagnosis to provide primary treatment suggestions—addressing a major gap in existing AI-driven medical imaging tools [7], [33]. With only ~45,000 parameters, rapid inference, and compatibility with platforms such as TensorFlow and Google Colab, the model is well-suited for deployment in resource-limited settings lacking specialist radiology expertise [15], [16].

The model follows rigorous training protocols, including robust data splitting, early stopping, and continuous performance monitoring, ensuring reliability and minimising overfitting, [30]. Unlike approaches that emphasise only raw accuracy, this work prioritises usability, explainability, and clinical applicability [21], [22].

Future work will focus on:

- Integrating explainability tools such as Grad-CAM to provide visual insights into model predictions and bolster clinician trust [22].
- Evaluating model performance on heterogeneous external datasets to ensure robustness and generalizability [17].
- Extending the framework to multiclass classification to distinguish bacterial, viral, and other pulmonary conditions [23].
- Collaborating with medical professionals for clinical validation, feedback, and iterative model refinement [7].
- Enhancing the clinical decision support system with personalized treatment recommendations leveraging patient metadata such as age, presenting symptoms, and comorbidities [33].

With continued development and thorough real-world validation, this system holds strong promise as a reliable, explainable, and deployable AI-based diagnostic aid for pneumonia—especially in under-resourced healthcare environments where rapid and accurate diagnosis is critical [1], [7].

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