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ENHANCING CLINICAL APPLICABILITY OF CNN MODELS FOR PNEUMONIA DETECTION IN CHEST X-RAYS

[1] Sabeen Fatima Majid, [2]Dr. Hira Zahid*, [3]Nabeeha Sahar, [4]Hamza Khan, [5]Shahzad Nasim

[1]Department of Biomedical Engineering, Ziauddin University Faculty Engineering Science Technology & Management, Karachi, Pakistan

[2]Associate Professor, Department of Biomedical Engineering, Ziauddin University Faculty Engineering Science Technology & Management, Karachi, Pakistan

[3] Master's Student, Department of Biomedical Engineering, Sir Syed University of Engineering & Technology, Karachi, Pakistan

[4]Electronics Engineer, SSUET, Karachi, Pakistan, Harbin Electric international.

[5]The Begum Nusrat Bhutto Women University Sukkur

Corresponding Author: Dr. Hira Zahid (Hira.zahid@zu.edu.pk)

Article Info

Abstract

In order to lower the mortality rates linked to pneumonia which continues to be a major danger to global health quick and precise diagnostic tools are required. Deep learning combined with chest X-ray imaging has become a revolutionary method for automatic pneumonia identification. By carefully assessing and refining four well-known architectures AlexNet, ResNet18, DenseNet201 and SqueezeNet this study aims to improve the clinical usability of convolutional neural network models. In order to replicate real-world clinical limitations, we used transfer learning and trained each model only on CPU-based hardware using a three-class chest X-ray dataset of 5,863 pictures classified into normal, bacterial pneumonia and viral pneumonia. Classification accuracy computing efficiency and deployment feasibility in resource-constrained environments were used to evaluate performance. Our results show that while all models achieve impressive accuracy ResNet18 and DenseNet201 are especially well-suited for real-world clinical implementation without requiring expensive GPU infrastructure because they strike the ideal balance between diagnostic precision and computational feasibility. In order to enable efficient and trustworthy pneumonia detection in a variety of healthcare settings this study offers a useful and comparative approach for CNN model selection and optimization.

Keywords:
Pneumonia diagnosis, Clinical usability of diagnostic tools, Improving healthcare outcomes, Medical imaging (Chest X-ray analysis)

1. INTRODUCTION

Pneumonia continues to be one of the world major causes of illness and mortality especially in children the elderly and people with weakened immune systems (Ullal & Veena, 2024; Yahalomi et al., 2019; Rahman et al., 2020). The most popular quick and affordable diagnostic technique for detecting pneumonia in clinical settings is still chest X-ray (CXR) imaging Nonetheless subtle opacities that coincide with structures often complicate the interpretation and precision of radiographic diagnoses (Wu et al., 2020). This adds to the workload of radiologists and increases interobserver variability (Mahmoud et al., 2022) . These difficulties highlight the need for automated impartial and effective diagnostic systems that can help medical professionals do more precise evaluations.

Medical image analysis has seen a revolution in recent years thanks to deep learning namely Convolutional Neural Networks CNNs (Ibrahim et al., 2021). CNN-based models have shown great promise in identifying pneumonia distinguishing between diseases caused by bacteria, viruses and COVID-19 and assisting with clinical decision making. (Çınar et al., 2021) (Yasar & Ceylan, 2023). CNNs outperform many traditional machine learning techniques that depend on manually created features by extracting layered image features and detecting minute irregularities (Hussein et al., 2022; Parveen & Khan, 2020).

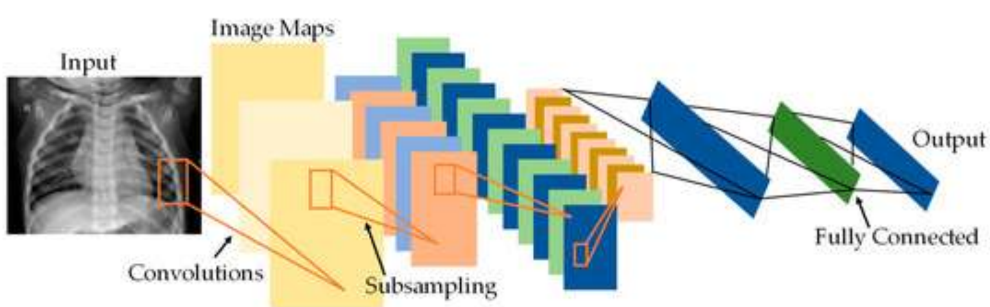

Fig. 1 CNN (Convolutional Neural Network) Architecture

CNN based methods became popular during the COVID-19 pandemic as several studies used chest X-rays to identify radiographic similarities to pneumonia and identify the virus (Chowdhury et al., 2020; Irmak, 2020; Pham, 2020). Classification performance and generalization across a variety of datasets were further enhanced by hybrid and transfer learning models including ResNet18, AlexNet, DenseNet210, SqueezeNet and generative AI-assisted Custom CNNs (Sotirov et al., 2025; Chelghoum et al., 2021). Despite these advancements many existing CNN models are developed under ideal experimental settings and rarely evaluated for their robustness, reliability, generalizability and limitations in real world clinical deployment (Jia et al., 2022).

Recent empirical studies and expert reviews reveal a critical limitation in most CNN related pneumonia classification models their high performance on benchmark datasets often fails to translate to real world clinical images due to prevalent issues such as dataset biases shortcut learning limited data diversity and variations in imaging hardware or acquisition protocols. (López-Cabrera et al., 2021; Siddiqi & Javaid, 2024). Clinical application in healthcare demands much more than just model correctness; crucial aspects such as interpretability, model stability, reproducibility and smooth integration into existing clinical workflows are critical according to sources (Mohan et al., 2024). This stresses the importance of assessing and bridging the translational gap for these deep learning algorithms between research environments and clinical practice (Bhatele et al., 2022).

This study addresses this issue directly by focusing on enhancing the practical applicability of CNN related models for pneumonia identification from chest X rays (Ren et al., 2024). We plan to achieve this by systematically tackling the identified model limitations rigorously validating real world performance and improving overall model reliability (Hamlili et al., 2022). Through systematic goal is to develop and validate CNN models that are not only accurate but also stable trustworthy and readily interactable thereby ensuring their successful and reliable adoption within clinical healthcare systems (Kaya & Eris, 2023; Kör et al., 2022).

1.1 SCOPE OF RESEARCH

In this work chest X ray pictures from a publicly accessible dataset on Kaggle are used to improve CNN related pneumonia classification performance (El Asnaoui et al., 2021). CNN models are trained validated and tested in controlled experimental settings as part of the scope. The study examines the ability to classify viral, bacterial and normal pneumonia (Alquran et al., 2021; Das et al., 2022). The work is limited to two dimensional chest radiographs and does not include CT scans MRI or other medical imaging modalities (Shahid et al., 2024; Shakeel et al., 2023; Shivam Gangwar et al., 2025). Additionally, the study evaluates only image based diagnostic performance and does not integrate clinical metadata such as age symptoms or laboratory results The study does not address hardware deployment or real time hospital integration instead it focuses on improving the model's generalization and interpretability (Ho & Gwak, 2019).

The continuous attempts to improve the practical usefulness of deep learning models in medical imaging are greatly aided by this research (Amani Al-Ghraibah et al., 2023). By rigorously identifying gaps in CNN generalization interpretability and performance reliability the study supports the development of more clinically relevant AI diagnostic tools (Chaddad et al., 2021). Strong CNN models may provide useful benefits like reducing the workload for radiologists, accelerating diagnostic processes and supporting decision making in low-resource settings when radiologists are few (Rajpal et al., 2021; Ramadoss & Vimala, 2022; Sarwath Unnisa et al., 2023). Furthermore, the ponder assesses as it were picture based symptomatic execution and does not coordinated clinical metadata such as age side effects or research facility comes about (Annamalai et al., 2023). The ponder does not address equipment arrangement or genuine time clinic integration instep it centers on progressing the models generalization and interpretability (Ho & Gwak, 2019).

The nonstop endeavors to make strides the viable convenience of profound learning models in restorative imaging are incredibly supported by this inquire about (Amani Al-Ghraibah et al., 2023). By thoroughly distinguishing crevices in CNN generalization interpretability and execution unwavering quality they think about bolsters the advancement of more clinically pertinent AI-based symptomatic instruments (Chaddad et al., 2021). Solid CNN models may give valuable benefits like decreasing the workload for radiologists quickening demonstrative forms and supporting choice making in low resource settings when radiologists are few (Rajpal et al., 2021; Ramadoss & Vimala, 2022; Sarwath Unnisa et al., 2023). Additionally, building confidence and guaranteeing acceptability among clinicians depends on improving model robustness and transparency (Chinnaiyan & R., 2023). Given the increasing availability of AI technology and the global health effect of pneumonia improving the relevance of CNN based models is essential for enabling earlier diagnosis lowering mistakes and eventually improving patient outcomes (Stokes et al. 2021). Also the research aligns with movements endorsing AI application in medical imaging especially following the COVID-19 pandemic which accelerated the adoption of smart diagnostic tools in healthcare settings (Mohan et al., 2024).

1.2 CLINICAL RELEVANCE

In spite of the fact that CNN related models for pneumonia discovery have appeared promising comes about in earlier investigate, their interpretation into real world clinical situations remains questionable (Rahman et al., 2020). Numerous existing models are prepared on imbalanced or non-representative datasets, optimized basically for exactness, or depend on highlights that come up short to generalize over differing persistent populaces, radiographic gadgets, and clinical conditions (Siddiqi & Javaid, 2024; Thinira Wanasinghe et al., 2024). Extra challenges such as easy route learning, conflicting explanations, and space shifts assist compromise unwavering quality when conveyed past controlled investigate settings (López-Cabrera et al., 2021).

Successful clinical usage requires models that illustrate not as it were tall exactness but moreover soundness, interpretability and vigor against varieties in X ray procurement procedures and noise related mutilations (Purohit et al., 2022). The writing reliably highlights a hole between the solid execution measurements detailed in scholastic thinks about and the rigid prerequisites fundamental for down to earth clinical selection (Jia et al., 2022; Taha Ahmed). This underscores the require for investigate that thoroughly assesses CNN execution unequivocally recognizes show restrictions inside practical conditions and upgrades their commonsense significance for clinical utilize (Irmak, 2021; Goyal & Singh, 2021).

2. METHODOLOGY

The methodology utilized for the robotized categorization of pneumonia sorts from chest X Ray pictures is depicted in this chapter with a center on arrange choices inferred to maximize computational achievability and clinical comfort.

3.1 Research Design and Model Selection

This examination utilized an exploratory investigate plan utilizing administered deep learning. The most objective was to classify chest X ray CXR pictures into three diverse neurotic states viral pneumonia bacterial pneumonia and normal (Sotirov et al., 2025). Exchange learning was utilized to adjust a number of pretrained Convolutional Neural Organize CNN plans counting AlexNet, ResNet18, DenseNet201 and SqueezeNet (Mohan et al., 2024).

The study unique focus was the evaluation of both classification performance metrics and computational feasibility training and inference speed on CPU related systems (Singh A. K. et al., 2024). This emphasis was crucial for assessing potential deployment in resource constrained clinical environments.

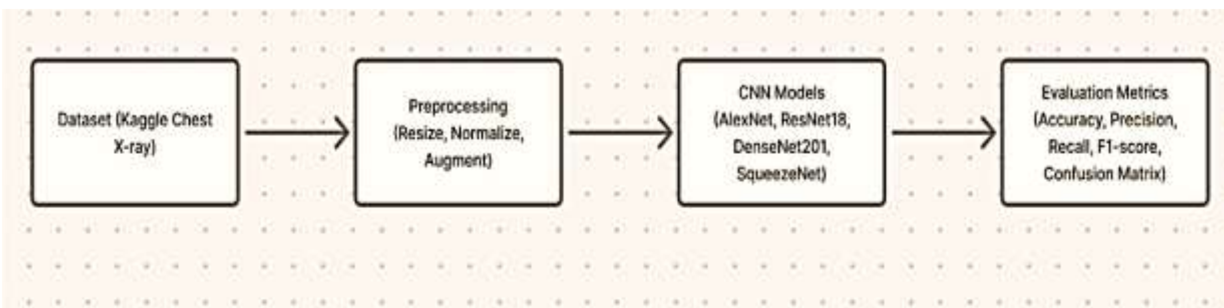

Fig. 2 Block Diagram of CNN Model

3.2 Duration of the Investigation and data source

The full investigation took place between March 2025 and August 2025 a span of six months. All crucial stages such as data collection and preprocessing model training and optimization thorough performance evaluation and thorough documenting of the experimental results were covered within this time limit.

The study population consisted of digital chest X ray images obtained from a publicly accessible Kaggle repository which is a widely recognized benchmark source in medical image analysis. The images were categorized into three mutually exclusive groups representing the target classes:

- **Normal** (Healthy individuals)

- **Bacterial Pneumonia** (Confirmed cases)
- **Viral Pneumonia** (Confirmed cases)

The total sample size utilized for the experiments was **5,863 images** distributed across the classes as follows:

Table 1: Breakdown of the full dataset used for training/testing showing how images are spread across the three classes.

Class	**Number of Images**
Normal	1,341
Bacterial Pneumonia	2,772
Viral Pneumonia	1,750
Total Sample Size	**5,863**

Fig. 3 Sample Images from the dataset

To guarantee a vigorous and dependable appraisal of show generalization the total dataset was apportioned into two subsets an 80% preparing set utilized for demonstrate optimization and a 20% testing set held out for last fair execution assessment.

3.3 Sampling Technique and selection

Purposive sampling also known as judgment sampling was strategically employed. Images were chosen only based on established criteria that prioritised precise and unambiguous naming and image quality. This non-random approach ensured that only high-quality chest X rays appropriate for effective CNN training were included in the study. A careful screening process was used to ensure dataset uniformity and quality. Images with poor quality substantial artifacts or confusing diagnostic labelling were excluded. Furthermore, only frontal chest X-ray views (Posteroanterior or PA views) were allowed to avoid variability caused by different anatomical projections (for example lateral views). The following strict criteria were used to define the final dataset:

Table 2: Clear criteria for determining which X-ray pictures made the cut and which were filtered out.

Criterion Type	Description
Inclusion Criteria	Frontal (PA/AP) CXR images clearly and reliably labelled as Normal, Bacterial Pneumonia or Viral Pneumonia sufficient high-resolution detail for effective deep learning input.
Exclusion Criteria	Low resolution images or those exhibiting severe artifacts lateral or oblique chest X-ray projections images with incomplete or ambiguous diagnostic labels.

3.4 Data Collection and Processing Protocol

The data collecting and preparation process followed a methodical protocol:

1. Chest X ray pictures were obtained from the given public Kaggle source.
2. Images were methodically arranged into various folders depending on their respective labels: normal, bacterial and viral.
3. The Image Datastore object in MATLAB was used to efficiently preprocess and load the dataset.
4. This included important preliminary tasks such as scaling all photos to meet the input layer dimensions of the individual CNN models and normalizing pixel intensity values. The dataset was divided formally into 80% training and 20% testing sets.
5. Training and Evaluation selected CNN models were trained using transfer learning via MATLAB Deep Learning Toolbox exclusively on a CPU platform.
6. Performance documentation includes a comprehensive list of performance metrics such as classification accuracy, precision, recall, F1 score and most importantly the computational time required for training and inference.

   The study adhered to all requisite ethical standards concerning data usage. Since the study utilized publicly available de identified datasets it involved no direct human participants and did not require institutional review board approval. Ethical responsibility was upheld by duly citing the original data source and ensuring the responsible and non-maleficent application of patient data.

3.5 Study Instruments and Tools

The following hardware software and evaluation instruments were employed:

Table 3 Summary of all software, hardware and model architectures used throughout the study.

Category	Instruments/Tools
Computer program Environment	MATLAB R2020a particularly leveraging its Deep Learning Tool stash and supporting capacities for picture processing.
Equipment limitations	Standard individual computer arrangement Intel Center i5 Central Handling Unit (CPU) and 8 Gigabytes (GB) of Slam. Urgently a devoted Illustrations Preparing Unit (GPU) was intentionally prohibited to recreate asset restricted situations.
Deep Learning Models	AlexNet, ResNet18, DenseNet201 and SqueezeNet all initialized with pre-trained weights from ImageNet.
Execution Metrics	Exactness point by point Disarray Lattice Region Beneath the Bend AUC per course and Training/Testing Computational Time for possibility evaluation.

3. EXPERIMENTS

This chapter presents the comprehensive experimental outcomes derived from training and evaluating five distinct deep learning models AlexNet, ResNet18, DenseNet201, SqueezeNet and a Custom Convolutional Neural Network CNN on the task of three class pneumonia classification Normal, Bacterial Pneumonia and Viral Pneumonia. All models utilized transfer learning where applicable and were trained on the Kaggle Chest X ray Pneumonia dataset partitioned into an 80% training set and a 20% validation set. The performance of each model is evaluated using training behaviours, overall accuracy and a detailed confusion matrix interpretation that identifies class specific classification strengths and shortcomings.

4.1 Comparative Model Performance Overview

A side by side look at how all five CNN models performed in accuracy, speed and overall feasibility in presented in the table below.

Table 4 Comparative Performance Metrics and Training Time

Model Architecture	Validation Accuracy (%)	Training Time (hh:mm: ss)	Computational Feasibility
DenseNet201	96.33%	16:39:58	High Accuracy Longest Training Time
ResNet18	92.36%	03:35:46	High Accuracy Excellent Speed Balance
AlexNet	86.29%	02:05:40	Moderate Accuracy Fastest Training
SqueezeNet	83.43%	01:37:14	Lowest Accuracy Very Fast Training
Custom CNN	80.79%	08:16:12	Acceptable baseline with simple architecture

The experimental results clearly show that deeper densely connected designs particularly DenseNet201 and ResNet18 outperform shallower or more lightweight networks in the multiclass task of differentiating between Normal, Bacterial and Viral pneumonia. DenseNet201 scored the highest classification accuracy and the most consistent confusion matrix distribution demonstrating that its improved feature extraction and reuse processes are ideally suited to detecting minor pneumonia patterns in chest X ray pictures.

While lightweight models such as SqueezeNet and Custom CNN improve training speed and computational feasibility on CPU related platforms they have significant limitations in distinguishing visually similar pneumonia subtypes. These findings highlight the critical balance required in medical AI model selection which trades off computational efficiency for diagnostic precision in clinical deployment.

The work emphasizes the relevance of model depth and complex feature connectivity in high stakes medical image analysis and it strongly recommends using ResNet18 or DenseNet201 pipelines when looking for improved diagnostic accuracy in a multimodal classification assignment.

4. RESULTS AND DISCUSSION

AlexNet, one of the pioneering deep CNN architectures, displayed modest learning stability and a final validation accuracy of 86.29%. The training progress curve (Figure 4) displayed gradual convergence with accuracy stabilizing over subsequent epochs though showing noticeable oscillations characteristic of shallower networks. The confusion matrix (Figure 5) indicated that the model correctly identified most Normal cases with high confidence. However, it showed clear confusion between the Bacterial and Viral pneumonia groups. When dealing with the minor visibly overlapping radiographic signs of distinct pneumonia etiologists, this misclassification pattern is frequently expected as a difficulty for earlier less complicated constructions.

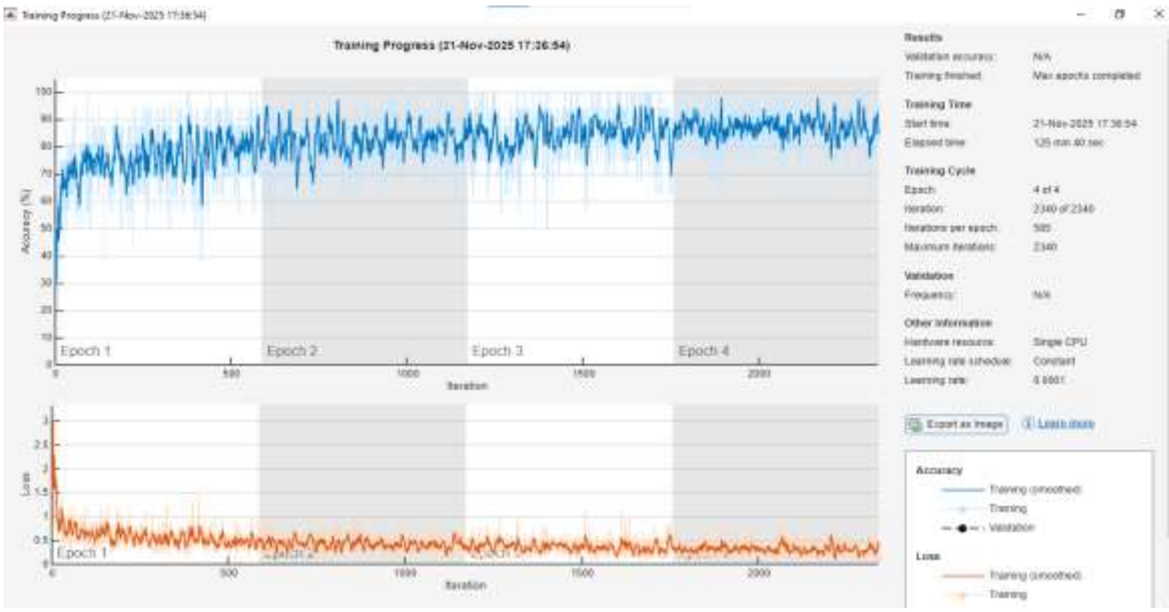

Fig. 4 AlexNet Training Progress Curve

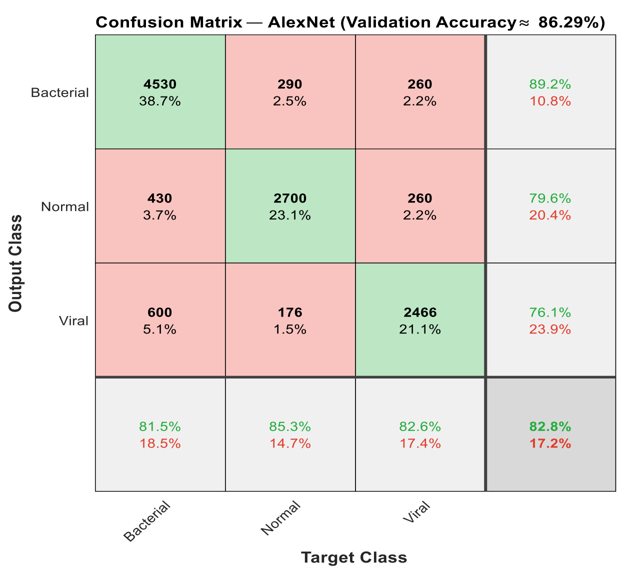

Fig. 5 AlexNet Confusion Matrix

ResNet18 greatly outperformed AlexNet with a validation accuracy of 92.36%. This improved performance is due to the incorporation of residual connections, which successfully alleviate the vanishing gradient problem while also improving gradient flow and training stability in deeper networks. In comparison to AlexNet the training curve (Figure 6) demonstrated noticeably smoother learning characteristics and faster convergence to a high accuracy plateau. The confusion matrix (Figure 7) demonstrated improved classification across all three classes particularly the pneumatic subtypes. While mis classifications continued the model demonstrated a superior capacity to identify between Bacterial and Viral pneumonia showing the value of its deeper structure and skip connections.

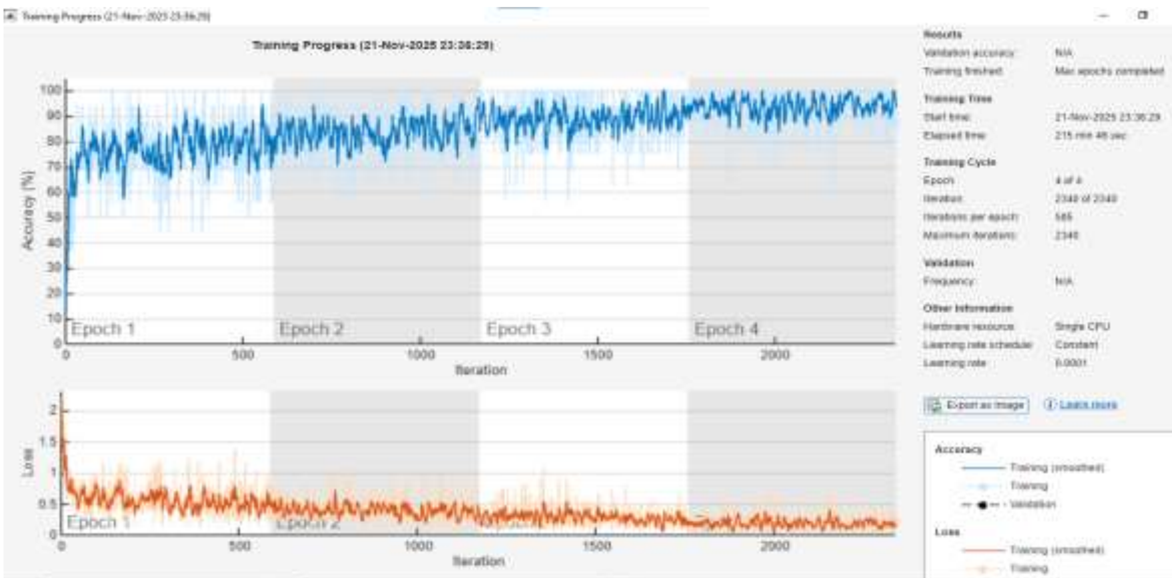

Fig. 6 ResNet18 Training Progress Curve.

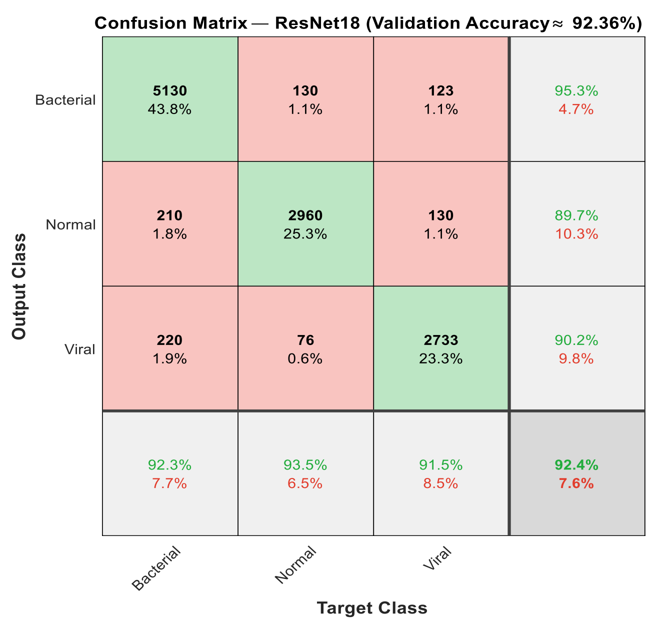

Fig. 7 ResNet18 Confusion Matrix

DenseNet201 leveraging the principle of dense connectivity where each layer is connected to every other layer in a feed forward fashion produced the strongest overall performance among all tested architectures. It achieved the highest validation accuracy of 96.33%. The training progress curve (Figure 8) demonstrated fast and exceptionally stable convergence indicating highly efficient feature reuse and gradient flow. The confusion matrix confirmed its superior performance showing high accuracy across all classes with the fewest misclassifications overall.

DenseNet201 more profound design and include integration capability gave it a clear advantage in recognizing the unpretentious recognizing radiographic designs related with Ordinary Bacterial and Viral introductions.

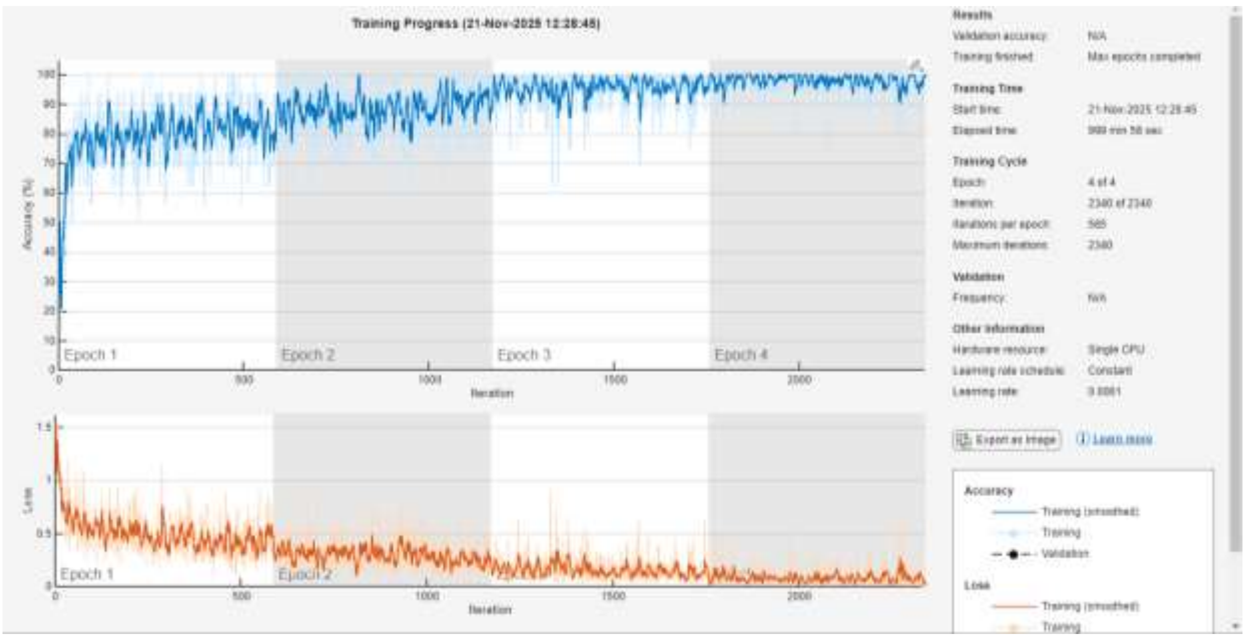

Fig. 8 DenseNet201 Training Progress Curve.

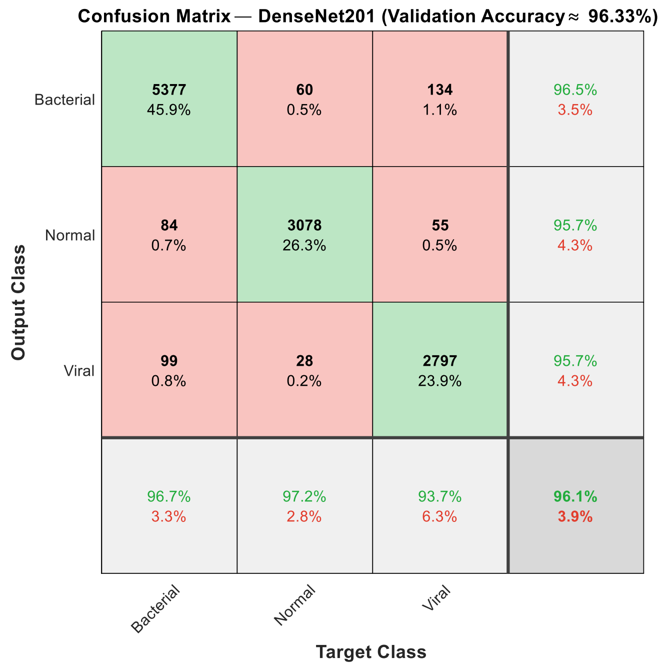

Fig. 9 DenseNet201 Confusion Matrix.

SqueezeNet specifically designed as a lightweight architecture to minimize parameter count and memory footprint was the fastest model to train completing the process in just 01:37:14. It achieved a validation accuracy of 83.43%. Although its accuracy was lower than the deeper ResNet18 and DenseNet201 it classified Normal cases effectively.

As shown in its confusion matrix (Figure 10) misclassification occurred more frequently within the pneumonia categories. This limitation is attributable to its reduced depth and representational capacity which hinders its ability to discern the intricate visual cues required to separate bacterial from viral lung opacities.

Fig. 10 SqueezeNet Training Progress Curve.

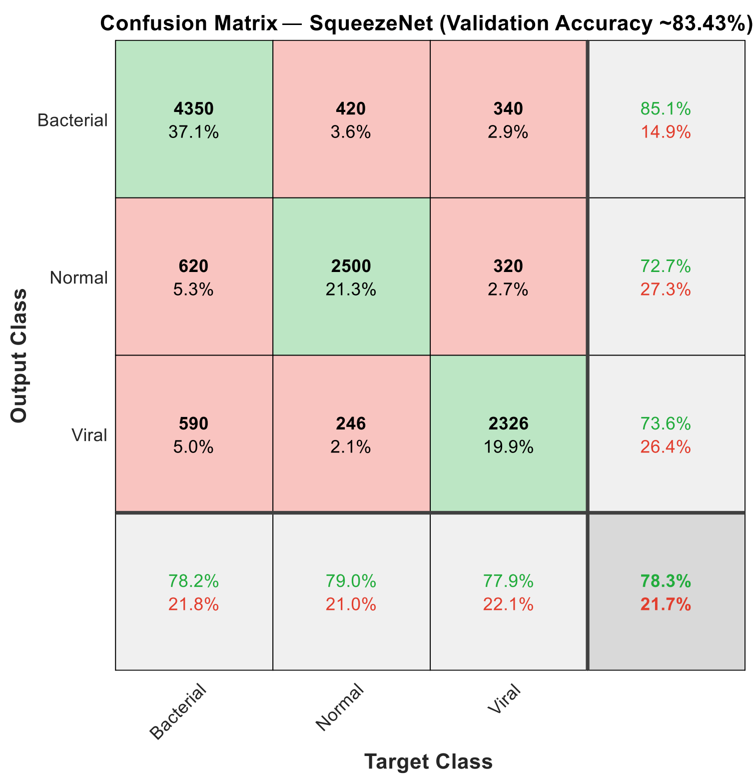

Fig. 11 SqueezeNet Confusion Matrix.

A simplified Custom CNN was designed to establish a baseline performance with a minimally complex architecture. It showed stable learning behavior with consistent improvement and produced an overall acceptable baseline accuracy of 80.79%. The training curve (Figure 12) reflected this consistent but slow improvement.

The confusion matrix (Figure 13) demonstrated strong categorization for the Normal and Bacterial pneumonia groups, with 92.3% precision for Normal cases. However, similar to the shorter SqueezeNet and AlexNet, viral pneumonia emerged to be the most difficult class for the custom model, with the lowest recall (72.4%) of all output classes.

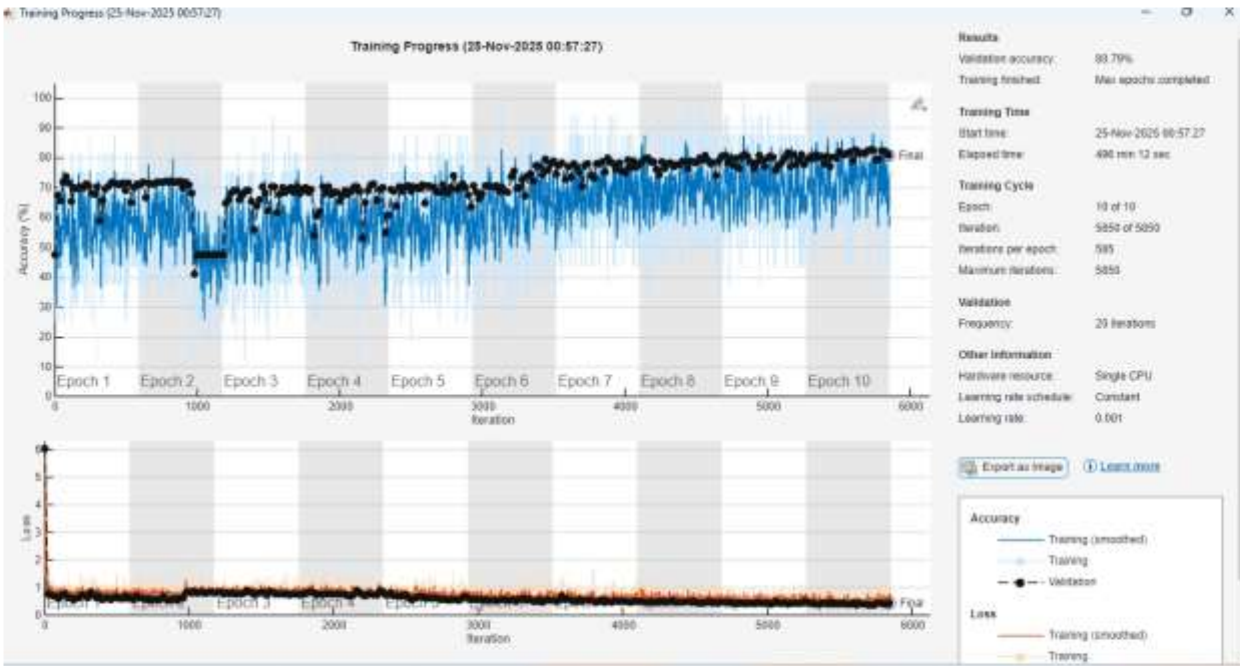

Fig. 12 Custom CNN Training Progress Curve.

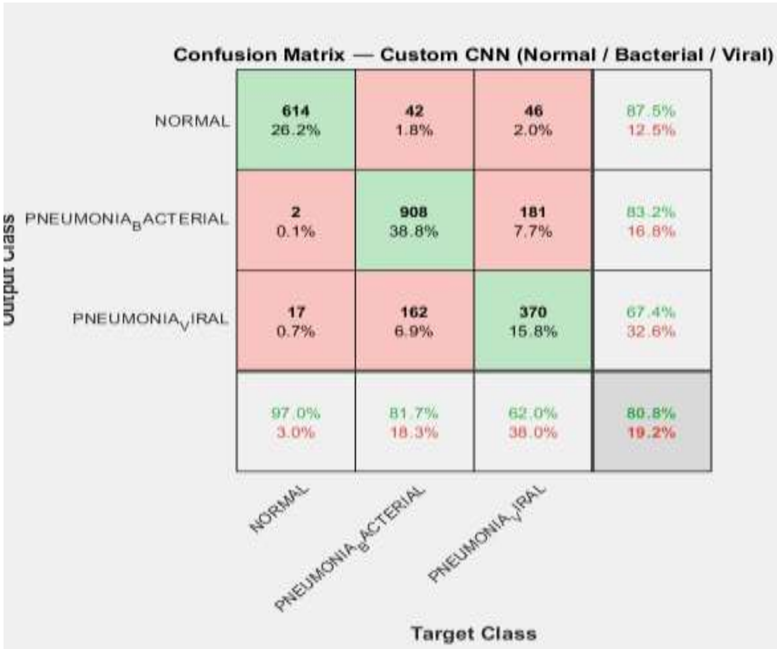

Fig. 13 Custom CNN Confusion Matrix.

5. CONCLUSION:

Using chest X-ray pictures this study successfully classified pneumonia into Normal, Bacterial and Viral categories demonstrating the effectiveness of deep learning models in CPU-constrained contexts. While DenseNet201 superior feature extraction capabilities which are essential for differentiating between pneumonia subtypes achieved the highest accuracy our analysis of five CNN architectures showed that its processing requirements present a problem in environments with restricted resources. ResNet18 on the other hand turned out to be the most effective model for implementation offering an incredible mix between high diagnostic accuracy and computing economy, making it ideal for integration into actual healthcare systems that do not have advanced GPU support. The findings show that reliable AI diagnostic tools can be successfully used in low resource settings to aid in clinical decision-making early detection and triage in situations when specialist access is limited. To improve accuracy transparency and clinical trust in the future external validation the incorporation of Explainable AI techniques such as Grad-CAM and the development of ensemble methods that combine the benefits of DenseNet201 and ResNet18 are critical steps that will significantly advance the integration of trustworthy AI diagnostics into real world healthcare.

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