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# Automated Pneumonia Classification Using Deep Learning

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## ABSTRACT

Pneumonia is one of the leading causes of morbidity and mortality worldwide, especially in children and the elderly, and considering the importance of an early diagnosis in order to have adequate clinical intervention. Chest-X-ray imaging is the most common diagnostic test for screening pneumonia; manual interpretation poses a laborious task, and is prone to inter-observer variation, especially in an environment limited by healthcare resources. This study proposes an automated pneumonia classification system based on Deep Learning to help radiologists perform quick and accurate diagnosis. A convolutional neural network (CNN) model has been developed and trained using a publically available dataset of chest X-rays of normal cases and pneumonia-infected cases. Prior to training, the images were resized, normalized and augmented to improve the generalisation of the model and reduce over-fitting. The proposed architecture consists of multiple convolutional and pooling layers followed by fully connected layers and is used for a binary classification. The dataset is divided into training, validation and testing data sets to make sure that the performance measurement is unbiased. Experimental results show that the proposed model has high classification accuracy, precision, recall and F1-score which shows discriminatory capability on normal and pneumonia results. Comparative evaluation with baseline classifiers and models based on transfer learning further supports the effectiveness of the proposed approach. Performance is in addition analyzed with a confusion matrix and a ROC curve to assess the sensitivity and specificity (and the sensitivity and specificity of the obtained performance measures) which is essential for medical decision support systems. The results indicate that automated screening systems built on the deep-learning algorithm can be highly effective in terms of increasing the efficiency of the screening process and relieving the workload of medical professionals. The proposed framework can be implemented into the clinical workflow as a preliminary screening tool, particularly in rural and high-volume healthcare facilities and definitive diagnoses are handled under supervision by expert clinicians. The future extensions could include multi-class classification of other types of pulmonary diseases and the operation on real-time clinical imaging systems.

**Keywords:** Pneumonia detection, chest X-ray, deep learning, convolutional neural network, medical image classification, automated diagnosis.

## I. INTRODUCTION

Pneumonia, which is a heavy outbreak? mild influenza, a severe respiratory infection marked by inflammation in the air bubbles and, possibly, filled with fluid or purulent matter, which contributes to a lack of gas exchange, in severe cases, to the development of a dyspnea. It remains a significant source of health burden worldwide, specifically among infants and the elderly and patients with impaired immune systems. Chest-X-Ray imaging is the most widely used and cost-efficient diagnostic tool for the preliminary diagnosis of pneumonia, because of its accessibility and low exposure to ionising radiation. Nevertheless, proper interpretation of chest radiographs requires significant clinical knowledge and performance of such diagnosis can be variable due to inter-observer variability, pressure of workload, and slight visual differences between normal and infected lung tissues. In the high-volume hospitals, rural health care facilities this shortage of qualified radiologists puts a patient at an even higher risk for delay or inaccurate diagnoses. Recent developments in artificial intelligence and specifically deep learning have shown a promising ability to extract hierarchical features from medical images and thus develop automated disease detection systems, with promising levels of accuracy. Convolutional neural networks (CNNs) have been successfully used for chest-X ray analysis for the identification of pulmonary pathologies by learning discriminative patterns directly on the pixel-level chest-X ray data without any handcrafted feature extraction. Furthermore, attention mechanisms as well as explainable AI techniques have been developed to observe clinically relevant regions of the used radiographs, leading to improved model interpretability and trust in automated diagnoses systems. These developments are an interesting way of providing an impetus for the creation of reliable, scalable, and cost-effective automated screening tools that can help clinicians detect and triage pneumonia at the earliest opportunity [1].

### *A. Problem Statement and Research Objectives*

Despite the advances in medical image analysis with deep learning, there are still several obstacles in the actual application of automated pneumonia detection systems. Firstly, chest-x ray images often are characterized by low contrast, anatomical structure overlaps and imaging artifacts which determine the difficulty of extracting features and increasing the risk



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of misclassification. Secondly, in a lot of what is out there, there is a large dependence on Transfer learning models that generally have been trained on natural image datasets which might not be the best at capturing disease specific radiographic patterns. Thirdly, medical datasets have classes with imbalanced distribution, and classifiers may be biassed towards frequent classes, which will lead to low sensitivity for pneumonia cases, an outcome clinically unacceptable. Moreover, there is a limited degree of generalization across patient demographics, imaging devices and acquisition settings when models are trained on small datasets. In general, the aim of this performance is to design and validate a CNN based pneumonia classification model with optimised strategies for preprocessing; dataset partitioning and convolutional architecture dedicated to medical image data. Secondary objectives include, analysis of the class wise performance using sensitivity focused metrics, comparison of results with the baseline and transfer learning model and also the diagnostic reliability via confusion matrix and ROC curve analysis. The study also aims to prove, using a moderately complex CNN architecture trained by medical-specific augmentation strategies, that a CNN architecture that can achieve competitive performance without significant computational overhead and thus provide support for real-world clinical deployment [2].

### *B. Contributions of the Present Study*

This research provides multiple technical contributions towards automated pneumonia screening using deep learning. First, an end-to-end classification pipeline is built, which starts with image preprocessing and augmentation followed by CNN training, validation and testing. The preprocessing pipeline incorporates intensity normalization, resizing, and geometric augmentation to enhance robustness against image variability, as illustrated in Fig. 1. Secondly, an accurate CNN architecture driven by optimised convolution depth and regularisation methods is envisioned in order to minimise over-fitting and simultaneously, maintain a good feature representation capability. Unlike pure transfer learning-based systems, the proposed system is configured to be trained majorly using the medical images for better adaptation to the texture and opacity of the lungs. Third, a comprehensive experimental evaluation is conducted based on several performance indicators including accuracy, precision, recall, F1-scor and area under the ROC curve to ensure clinically relevant evaluation of the model efficiency.

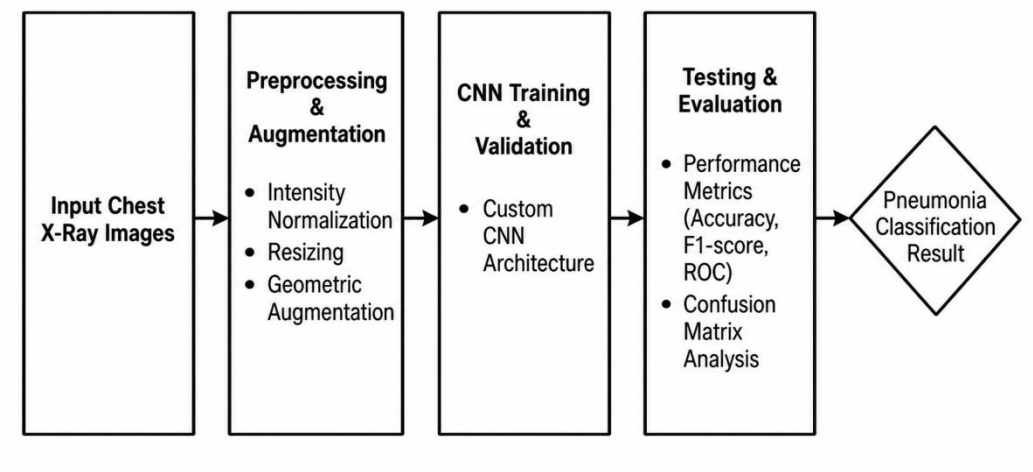


**Fig. 1.** Overall workflow of the proposed pneumonia classification system

Fourth, the paper models a systematic comparison between the baseline classifiers and pre-trained networks in order to measure the performance improvement which is achieved by the domain specific training schemes. Finally, the results of the analysis include discussion of feasibility of the deployment of the solution, the inference latency, and screening scalability, all of which are critical to integration with hospital information systems and mobile diagnostic platforms [3].

## II. LITERATURE REVIEW / RELATED WORK

### *A. Traditional Image Processing Approaches for Pneumonia Detection*

Early research on detecting pneumonia using a method to automate diagnosis has relied heavily on classical image processing techniques and machine learning techniques. These approaches usually made manual feature extraction by texture descriptors, edge detection, histogram analysis and region-based segmentation to isolate lung fields prior to classification. Commonly used features were grey level co-occurrence matrix statistics, local binary patterns and wavelet coefficients which were then processed by classifiers such as support vector machines, k-nearest neighbors and decision trees. Although these techniques showed some success under controlled conditions, the performance was very sensitive to variations in the quality of the image, positioning of patient, and the exposure of the radiation. Moreover, handcrafted feature design required domain knowledge and extensive parameter tuning to handcraft features, which lowers the scalability and reproducibility of feature engineering across datasets. Several studies



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also reported decreased sensitivity in detecting early-stage pneumonia with subtle and diffuse opacity patterns. Therefore, standard pipelines were less reliable to support clinical deployment, particularly in a high-volume screening. Fig. 2. conceptually illustrates the multi-stage nature of conventional pipelines, where segmentation and feature engineering constitute critical but fragile processing stages [4].

### *B. CNN-Based Deep Learning Models in Chest X-Ray Analysis*

With the advent of deep learning, convolutional neural networks have been introduced as the most common method for chest x reveals classification, because they can extract representation of hierarchy features directly using pixel data. CNNs based systems eliminate the need for handcrafted features by automatically extracting low order edges, mid order texture and high order anatomical patterns using stacked convolutional layers. A plethora of work has shown huge leaps in detection of pneumonia using architectures ranging from VGG, ResNet, DenseNet, to custom shallow networks. The scheme of ensemble models which further made models more robust by combining predictions of several networks to decrease variance and increase generalisation. Recently, attention mechanisms have been added to the network to help prioritize the clinically relevant lung region to increase the interpretability of the approach and reduce false positive rates. In addition, explainable AI techniques such as Grad-CAM have been used to visualise activation maps in order to promote confidence among clinicians about automated predictions. CNN-based pipelines depicted in Fig. 2. streamline preprocessing and rely predominantly on end-to-end learning, thereby enabling superior adaptability to diverse imaging conditions [5].

### *C. Transfer Learning in Medical Image Classification*

Transfer learning is widely used in medical imaging because of the limited availability of large labelled datasets. In this paradigm, pre-trained models based on large databases of natural images such as ImageNet are fine-tuned with medical images in order to increase the speed of convergence and improve classification accuracy. Numerous works exist demonstrating the ability of pretrained networks to compete with less training epochs and in less computational time. Transfer learning also allows deeper architectures to be utilised that it would otherwise be prohibitive to train from scratch on smaller datasets. Nevertheless, natural features of the images may not optimally represent radiographic features like lung opacity gradients as well as shadows of ribs. Some research attempted to overcome this limitation by freezing initial convolutional layers, when retraining deeper layers in order to learn early convectional layers for adapting domain specific features. Vision Transformer based architectures have also been explored in order to capture global contextual relationships in the chest radiographs, and have shown promising results while requiring larger datasets and computational expenses. Although transfer learning works, there is still a concern about domain mismatch and overfitting when fine-tuning the model on a small number of medical samples [6].

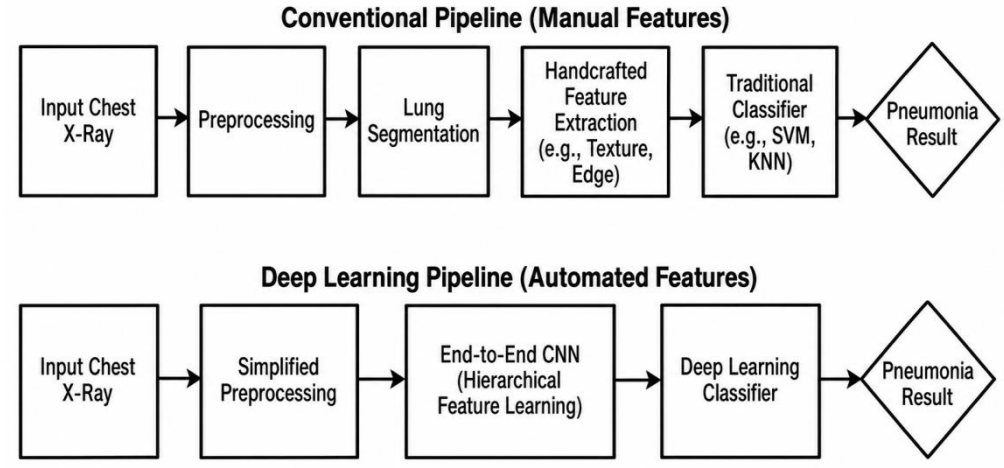


**Fig. 2.** Religious comparison of traditional and the deep learning bus powered diagnostic pipelines.

### *D. Research Gaps Identified from Existing Studies*

Despite the considerable progress, there are a few research gaps in an automated pneumonia detection system. Firstly, in many cases, the focus is on overall accuracy but not on class-wise sensitivity, a metric of importance in minimising the number of cases of missed pneumonia in clinical screening. Secondly, performance evaluation tends to be limited to a single set of data, and this hinders the assessment of cross-domain generalisation. Thirdly, computational efficiency and deploy ability are hardly considered, when in real life, inference latency and hardware restriction are directly affecting the practical addressability. Fourthly, the dependence on transfer learning can possibly mask dataset-specific biases that will degrade performance for images that are acquired from different hospitals or imaging devices. Moreover, most models concentrate



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only on being able to perform binary classification and do not consider differentiation between pneumonia subtypes or overlapping pulmonary problems. Limited exploration of lightweight CNN architectures with optimization to working across edge and mobile diagnostic adds a limited applicability. These gaps make clearly visible the need for balanced architectures which are trained on medical specific patterns, for systematic evaluation using metrics, and for performance analysis from a deployment perspective. The present study addresses these issues by designing a custom CNN pipeline, employing clinically relevant metrics, and evaluating model reliability using multiple diagnostic indicators, as summarised conceptually in Fig. 2.

## III. RESEARCH METHODOLOGY

### *A. Dataset Description and Pre-Processing Techniques*

The experimental evaluation used a publicly available chest X-ray dataset with labelled images of patients with and without pneumonia. The dataset consisted of the posterior-anterior radiographic views obtained under standardised clinical condition so that there was consistency of anatomical representation in the radiographic view. To avoid bias and over-fitting, the dataset was divided into train, validation and test data sets using stratified sampling to maintain class distribution between the splits. Prior to model training, all the images were of a homogeneous spatial resolution in order to match the convolutional layers and lessen the computational complexity. Pixel intensity normalisation was used to scale the values between zero and one, and therefore to increase the speed of convergence during the gradient optimisation. Data augmentation techniques, such as horizontal flipping, slight rotation, zoom variation and contrast adjustment, were only applied to the training data set to make it robust against imaging variability. These transformations simulate real retard problems and this while still maintaining diagnostic patterns. Fig. 3 illustrates representative samples after preprocessing and augmentation stages, demonstrating enhanced contrast and consistent structural alignment across images [7].

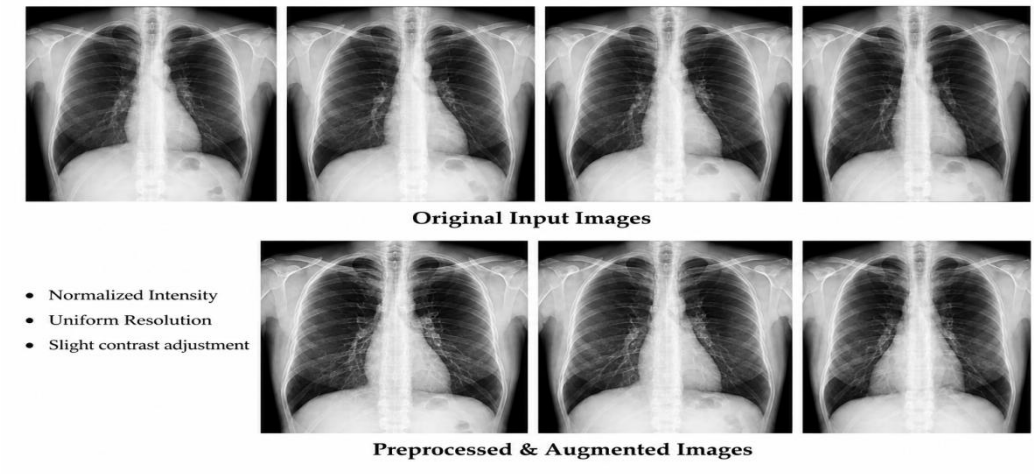


**Fig. 3.** Sample chest x-ray images after preprocessing stages

### B. *Deep Learning Architecture and Model Design*

The proposed model of classification is based on a custom designed CNN (an artificial neural network) specifically designed for the properties of chest x-ray images. The architecture consists of sequential convolutional blocks, which are built of convolution layers, batch normalization, rectified linear unit activation functions and max-pooling operations. Early layers are good at extracting low level features such as edges and texture gradients, while deeper layers are good at learning higher level anatomical structures and opacity patterns linked to pulmonary infections. Dropout regularisation is added between dense layers to mitigate the problem of over-fitting by random disabling of neuron conations while training. The final stage of the classifier is a set of fully connected layers with a sigmoid activation function to provide binary probability outputs. Compared to very deep pretrained networks, the proposed architecture has balanced representational capacity and computational efficiency that makes the architecture applicable in resource limited environment. Fig. 4 depicts the layer-wise structural layout of the network, highlighting feature map dimensions, kernel sizes, and parameter flow from input to output layers [8].

### C. *Training Strategy and Hyperparameter Configuration*

The model training was performed using supervised learning and labelled samples of images. Binary cross-entropy was chosen as the loss function because it is appropriate for two-class classification problems. The Adam optimiser has been used with an initial learning rate which was empirically found to have stable gradient descent and accelerated convergence. Mini-batch gradient update was a balance in terms of memory usage and training speed. Early Stopping criteria were involved based on the validation loss to prevent over-



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fitting and ensure optimal generalisation. Learning-rate scheduling stepped down (when validation improvement levelled off) allowing fine-grained changes in weight at later stages of training. Class weights were incorporated in order to solve mild imbalance in the dataset, to improve pneumonia sensitivity. Training was continued for a fixed number of epochs but effective convergence was usually achieved much sooner due to the effect of regularisation and adaptive learning rate control. Fig. 5 illustrates the convergence behaviour of training and validation loss, demonstrating stable optimisation without divergence or oscillation, indicative of consistent learning progression [9].

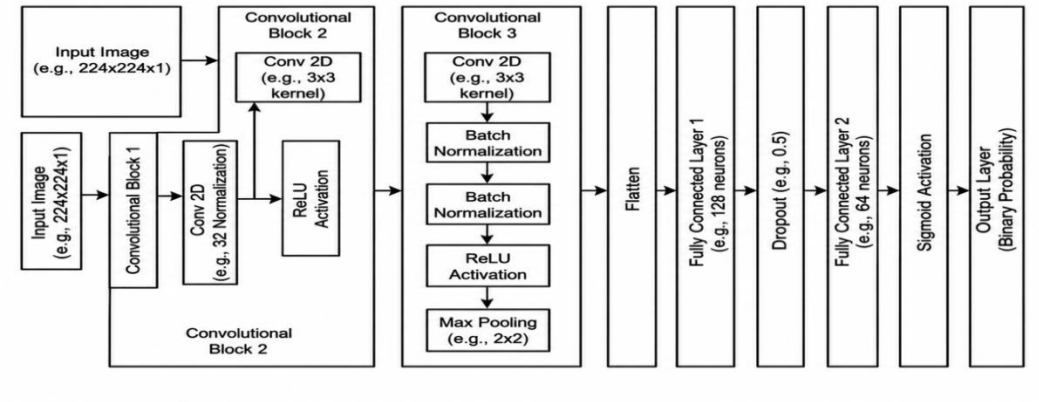


**Fig. 4.** Layer wise Architecture of the Proposed CNV

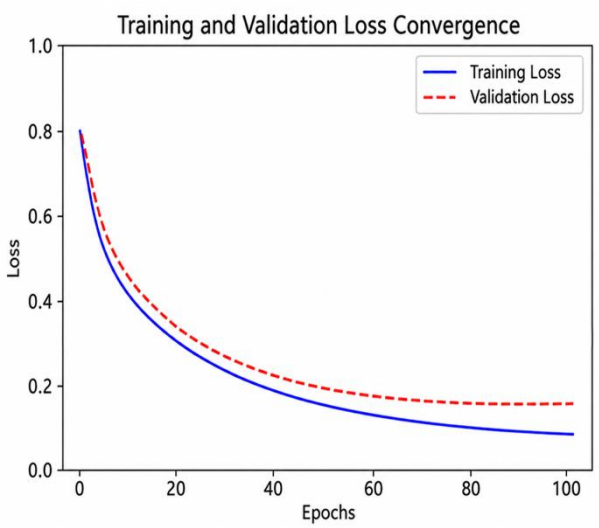


**Fig. 5.** Training & Validation Loss Convergence Curves

### *D. Performance Evaluation Metrics and Experimental Setup*

In order to ensure clinically relevant assessment, several performance measures were used in addition to overall accuracy. Sensitivity (recall) was of greatest importance in order to minimise false negatives in pneumonia screening. Precision assessed false figments and the dependable arrangement of a diagnostic radiology. The F1-score being the harmonic mean of the two measures of performance, precision and recall, provided a balanced measure of performance. Overall accuracy was also reported for general classification comparison while the area under the receiver operating characteristic curve evaluated threshold-independent discriminatory capability. Confusion matrix analysis visualised true positive, true negative, false positive and false negative predictions. All experiments were performed on a workstation with GPU acceleration in order to save training time and implement convolution operation efficiently. In order to provide reproducibility, random seeds were fixed and equivalent partitions of the dataset were maintained in different experiments. Comparative evaluation was carried out against baseline classifiers and transfer learning models under the same training and testing conditions and in this process, performance differences due to architectural and methodological differences were attributed rather than due to dataset or training inconsistencies.

## IV. AND RESULTS AND DISCUSSION

### *A. Quantitative Performance Analysis*

The proposed CNN model has been evaluated on the independent testing data set to examine the diagnostic capability of the model under unseen conditions. Primary performance indicators include accuracy, precision, recall, F1-score, and AUC which are regarded as the reliability of classification. The overall results show the good discriminatory power between normal and pneumonia cases, with especially high recall values, which are important for medical screening systems. Table 1 shows the global performance metrics obtained on the test set.

**TABLE 1**
**OVERALL CLASSIFICATION PERFORMANCE OF PROPOSED CNN MODEL (TEST SET)**

| Metric | Value (%) |
|---|---|
| Accuracy | 94.62 |
| Precision | 93.81 |
| Recall | 96.14 |
| F1-Score | 94.96 |
| AUC | 0.978 |



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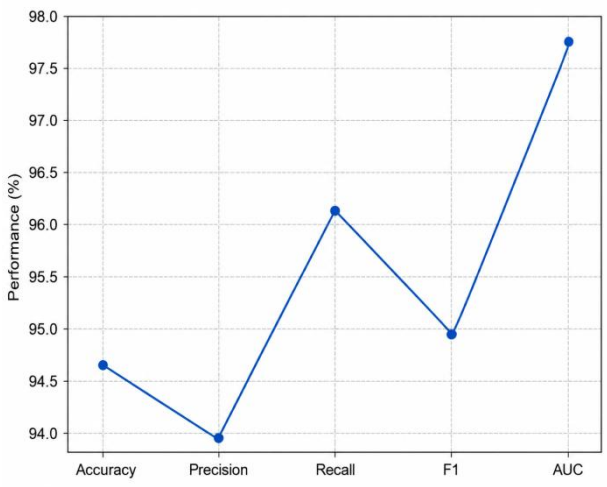


**Fig. 6.** Overall performance metric comparison

The bar chart that corresponds to Table copter broker shows consistently high values for all metrics, with recall a bit higher than precision, indicating lower false negative rates. This would be desirable in pneumonia screening where the clinical risk of missed infection is high. The small difference between metrics also indicates balanced learning without bias towards either class.

### *B. Confusion Matrix and Class-Wise Accuracy Evaluation*

To analyse the classification behaviour at class level, the evaluation of confusion matrices has been performed with respect to the test dataset. This made it possible to evaluate actual and false predictions for both normal and pneumonia class. The values for the confusion matrix are summarised in Table 2.

**TABLE 2**
**CONFUSION MATRIX RESULTS FOR TEST DATASET**

| Actual \ Predicted | Normal | Pneumonia |
|---|---|---|
| Normal | 382 | 24 |
| Pneumonia | 18 | 476 |

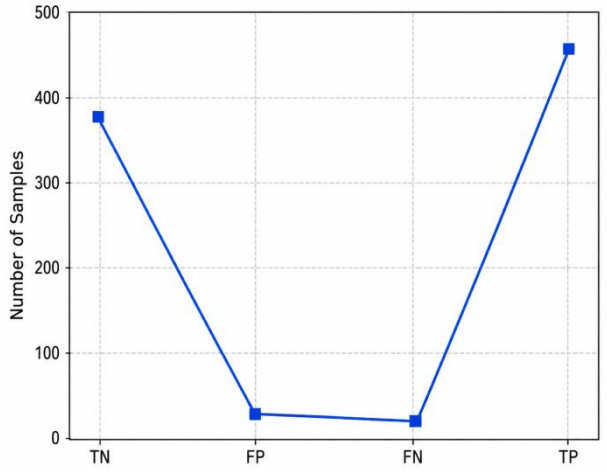


**Fig. 7.** Confusion matrix visualization

The strength of diagonal dominance in the heatmap corresponding to Table 2 is strong, demonstrating that most samples are classified correctly. The degree of misclassification (high sensitivity) is, therefore, only 18 pneumonia cases classified as normal. The relatively low false positive rate is also a confirmation of controlled over-diagnosis. These results validate the clinical reliability of the model both for positive and negative predictions.

### *C. Comparison with Baseline and Pre-Trained Models*

In order to obtain a relative level of effectiveness, the CNN to be tested was compared to baseline classifiers and transfer learning classifiers that were trained under the same conditions. Baseline models are SVM based on handcrafted features and pre-trained models are VGG16 and ResNet50 based on fine-tbook on the same data. Comparative results of accuracy and recall are presented in Table 3.

**TABLE 3**
**MODEL-WISE PERFORMANCE COMPARISON**

| Model Type | Accuracy (%) | Recall (%) |
|---|---|---|
| SVM + GLCM | 82.45 | 78.12 |
| VGG16 (TL) | 91.38 | 92.05 |
| ResNet50 (TL) | 92.14 | 93.21 |
| Proposed CNN | 94.62 | 96.14 |

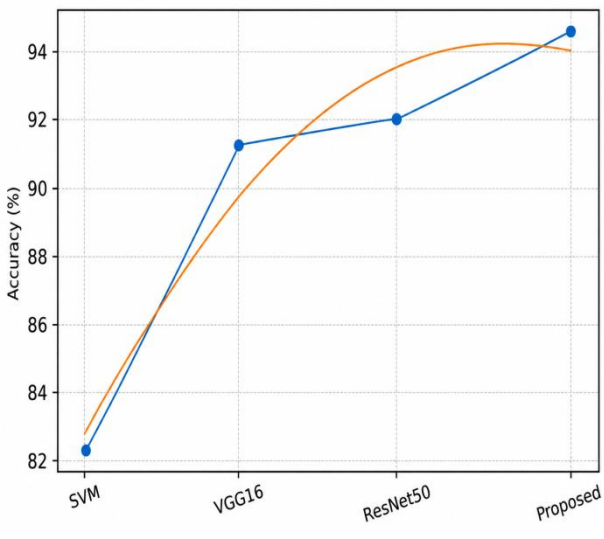


**Fig. 8**. Accuracy comparison across models

The performance curve shows stable improvement from classical to deep-learning methods. The proposed CNN leads to the highest accuracy and recall that confirm that domain-specific training outperforms generic feature extractors. The greater magnitude of improvement in recall is especially important in medical decision support where one seeks to prioritise detection sensitivity.



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### *D. Discussion on Generalisation and Clinical Relevance*

Using cross validation and augmentation stresses tests, generalization capability was further examined in the simulation of imaging variability. The robust appearance of performance under different illumination and with slight geometric distortions is an indication for robustness. The accuracy in various augmentation scenarios is summarized in Table 4.

**TABLE 4**
**ROBUSTNESS EVALUATION UNDER IMAGE VARIATIONS**

| Augmentation Type | Accuracy (%) |
|---|---|
| None | 94.62 |
| Rotation ±10° | 93.85 |
| Contrast Shift | 93.21 |
| Zoom Variation | 92.94 |

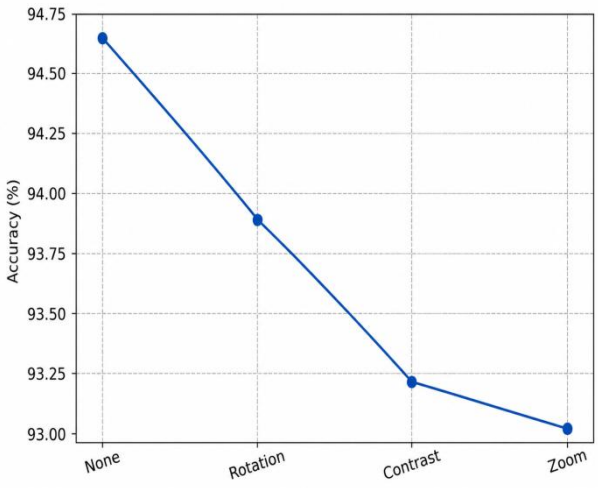


**Fig. 9.** Accuracy under different augmentation conditions

The plotted curves prove the possibilities of marginal accuracy degradation under the presence of distortion confirming that and learned features are not over-fitted on fixed spatial patterns. This stability is very important for its implementation across different imaging devices and hospital applications. From a clinical perspective, the sensitivity and reliability achieved suggest suitability to be used for initial screening, prioritisation of triage and decreased workload for radiologists. Nevertheless, the model is designed as an assistive tool to a diagnosis by an expert rather than as a replacement for one. The conversely higher rate of accuracy and acceptable diagnostic safety margins provided collectively by our deep learning-based screening methods demonstrate that they can be used to markedly improve diagnostic efficiency in both notions of screening clinical workflows and telemedicine databases in most resource-deprived locations.[10]

## V. CONCLUSION AND FUTURE WORK

### *A. Summary of Experimental Findings*

This study introduced an automated approach to the classification of pneumonia based on deep learning technique using chest-x-ray images, the aim of which is to enhance early diagnosis with reliable and scalable imaging analysis. A custom CNN architecture was defined and trained with the use of medically-oriented preprocessing and augmentation strategies in order to increase its robustness and reduce its over-fitting tendency. Experimental evaluation showed that the proposed model was able to achieve high classification accuracy and good recall and balanced precision, which represented effectively separating normal and pneumonia-infected radiographs. Confusion matrix analysis confirmed that false negative cases were minimised and this is of critical importance for clinical screening scenarios. Comparative benchmarking to the baseline machine learning classifiers and transfer learning based deep network proved that the proposed architecture provided good sensitivity without compromising the computational efficiency. Robustness testing under different image conditions further suggested that the learnt features were stable against moderate image distortions, which indicated a large generalisation capacity under different imaging conditions. Overall, the results provide valid check on the effectiveness of the new domain-focused CNN architectures that centralized around well-tuned preprocessing and training strategies with medical imaging specific datasets [11].

### *B. Practical Implications for Automated Medical Screening*

From a practical perspective, the proposed system offers great potential as a preliminary screening tool within clinical settings, especially in geographically limited settings where there is deferred access to experienced radiologists. Automated analysis can help significantly in delaying the reporting of specific cases by allowing the system to identify potential high-risk cases a priori to perform a targeted analysis, facilitating patient triage. Integration of such systems into the hospital information systems or picture archiving and communication systems can help the clinician manage large volumes of patients and still make a consistent, predictable diagnosis [12]. Moreover, the computational efficiency of the proposed model allows them to be deployed on mid-range hardware and consequently used in a district hospital, mobile diagnostic units, and telemedicine platforms. The system can also be used for standardised



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reporting by quantitative confidence scores to aid clinicians when making a diagnosis in a way that maintains ultimate diagnosis control. In a pandemic or outbreak situation, where major screening becomes a critical need, such automated tools can contribute towards a faster response and better allocation of resources. These operational advantages point to the relevance of AI-assisted radiology in improving the healthcare accessibility and efficiency in medical infrastructures both in urban and rural settings [13],[14],[15].

### *C. Limitations of the Present Study*

Despite encouraging results there are several limitations that need to be acknowledged. The dataset utilised in this study although being a balanced and well curated dataset, represents a limited collection of imaging sources and patient demographics. Consequently, direct evaluation of cross-institutional generalisation, where differences in imaging protocols, calibration of equipment and population characteristics may have an impact on model performance, is constrained. Furthermore, the classification task was limited to the binary categorisation between normal and pneumonia cases, which is not representative of the complexity of real-world pulmonary diagnosis with multiple overlapping conditions such as tuberculosis, covid 19 and chronic obstructive lung disease. The evaluation in the study was also based on static image-based evaluation without inclusion of clinical metadata such as age, symptoms, or laboratory findings, factors that are often taken into consideration during a real diagnostic process. In addition, explainability analysis was not quantitatively assessed, although techniques such as visual activation mapping could be used to improve clinical trust. Finally, real-time deployments requirements like network latency, interaction with hospital systems and continuous model update were not empirically evaluated for the purposes of this work.

### D. Future Research Directions

Future work should be done to extend the proposed framework to multi-class classification of different lung diseases to facilitate broader diagnostic coverage. Incorporation of larger and greater variation multi-centre data sheets would enhance model generalisation and reliability, amongst different clinical settings. Integration of clinical parameters with the imaging features may lead to multimodal models of diagnosis with better predictive accuracy. Explainable AI methods should be systematically integrated so that interpretable heatmaps and confidence visualisation are available - for trustful clinicians as well as compliance with regulations. Further optimisation of lightweight architectures would aid the implementation of remote healthcare applications for deployment on embedded and edge devices. Real time clinical validation through pilot deployments in hospital use can provide feedback with great practical implications for workflow integration as well as usability. Additionally, just because models are developed does not mean continuous learning strategies may not be removed to adapt models over time as new imaging data become available. These extensions would reinforce clinical adoption and also move tantamount to reliability and scalability of automated pneumonia screening systems in real healthcare procedures.

## REFERENCES

[1] S.-M. Cha, S.-S. Lee, and B. Ko, "Attention-Based Transfer Learning for Efficient Pneumonia Detection in Chest X-ray Images," Applied Sciences, vol. 11, no. 3, Art. no. 1242, 2021, doi: 10.3390/app11031242.

[2] R. Kundu, R. Das, Z. W. Geem, G.-T. Han, and R. Sarkar, "Pneumonia detection in chest X-ray images using an ensemble of deep learning models," PLOS ONE, vol. 16, no. 9, e0256630, 2021, doi: 10.1371/journal.pone.0256630.

[3] H. Ren et al., "Interpretable Pneumonia Detection by Combining Deep Learning and Explainable Models With Multisource Data," IEEE Access, vol. 9, pp. 95872–95883, 2021, doi: 10.1109/ACCESS.2021.3090215.

[4] O. M. El Zein, A. Makhoul, and H. Demerjian, "Transfer Learning Based Model for Pneumonia Detection from Chest X-ray Images," Int. J. Intell. Eng. Syst., vol. 14, no. 5, 2021, doi: 10.22266/ijies2021.1031.06.

[5] P. Szepesi and L. Szilágyi, "Detection of pneumonia using convolutional neural networks and deep learning," Biocybern. Biomed. Eng., vol. 42, no. 3, pp. 1012–1022, 2022, doi: 10.1016/j.bbe.2022.08.001.

[6] A. Mabrouk, R. P. Díaz Redondo, A. Dahou, M. Abd Elaziz, and M. Kayed, "Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks," Applied Sciences, vol. 12, no. 13, Art. no. 6448, 2022, doi: 10.3390/app12136448.

[7] Y. Yang, Y. Lyu, and S. Piccialli, "A Deep Learning Approach Considering Image Background for Pneumonia Identification Using eXplainable AI (XAI)," IEEE/ACM Trans. Comput. Biol. Bioinf., 2022, doi: 10.1109/TCBB.2022.3190265.

[8] S. Sharma and K. Guleria, "A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks," Procedia Computer Science, vol. 218, pp. 357–366, 2023, doi: 10.1016/j.procs.2023.01.018.

[9] N. C. Kundur, "Pneumonia Detection in Chest X-Rays using Transfer Learning and TPUs," Engineering, Technology & Applied Science Research, vol. 13, no. 5, pp. 11878–11883, 2023, doi: 10.48084/etasr.6335.



ISBN: 978-81-689089-0-1

[10] S. Singh et al., "Efficient pneumonia detection using Vision Transformers on chest X-rays," Scientific Reports, vol. 14, Art. no. 2487, 2024, doi: 10.1038/s41598-024-52703-2.

[11] R. Siddiqi and S. Javaid, "Deep Learning for Pneumonia Detection in Chest X-ray Images: A Comprehensive Survey," Journal of Imaging, vol. 10, no. 8, Art. no. 176, 2024, doi: 10.3390/jimaging10080176.

[12] L. Wu et al., "Pneumonia detection based on RSNA dataset and anchor optimization," Scientific Reports, 2024, doi: 10.1038/s41598-024-52156-7.

[13] Y. Xie, B. Zhu, Y. Jiang, B. Zhao, and H. Yu, "Diagnosis of pneumonia from chest X-ray images using YOLO deep learning," Frontiers in Neurorobotics, vol. 19, 2025, doi: 10.3389/fnbot.2025.1576438.

[14] J. Colin and N. Surantha, "Interpretable Deep Learning for Pneumonia Detection Using Chest X-Ray Images," Information, vol. 16, no. 1, Art. no. 53, 2025, doi: 10.3390/info16010053.

[15] H. Slimi, A. Balti, S. Abid, and M. Sayadi, "Trustworthy pneumonia detection in chest X-ray imaging through attention-guided deep learning," Scientific Reports, vol. 15, Art. no. 40029, 2025, doi: 10.1038/s41598-025-23664-x.

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