RESEARCH PAPER

A Robust Deep CNN Framework for Automated Pneumonia Identification from Chest Radiographs

Dr. Rajath A N[1], Dr. Anand M2, Dr. Divya S[3], Dr. Pradeep Kumar R[4*], Dr. Anitha K[5] and Dr. Aishwarya N Kumar[6]

[1]Associate Professor, Department of Artificial Intelligence & Data Science, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, India -570016, rajath191985@gmail.com
[2]Associate Professor, Department of Information Science and Engineering, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, India - 570016, anandm@gsss.edu.in
[3]Associate Professor, Department of Artificial Intelligence and Machine Learning , Mysuru Royal Institute of Technology, Mandya, Karnataka, India- 571606, divya.s@mysururoyal.org
[4] Assistant Professor, Department of Mathematics, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, India – 570016, pradeepr.mysore@gmail.com
[5]Assistant Professor, Department of Electronics & Communication Engineering, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, India - 570016, ckmanitha@gmail.com
[6]Assistant Professor, Department of Computer Science & Engineering, Constituent College of VTU, Chintamani, Karnataka, India – 563125, aishwaryankumar2606@gmail.com
*[*]**Corresponding Author:** pradeepr.mysore@gmail.com*

Received: 16th Dec, 2025; Revised: 8th Feb 2026; Accepted: 12th Feb, 2026; Available Online: 28th Feb, 2026

ABSTRACT ABSTRACT
Pneumonia is a common respiratory disorder and a major cause of morbidity and mortality worldwide, particularly among older adults and children under five years of age. Early and accurate diagnosis is essential for effective treatment; however, conventional diagnostic methods based on manual interpretation of chest X-ray images are often time-consuming and subject to inter-observer variability. To address these limitations, this study proposes an artificial intelligence-based framework for automated pneumonia detection using convolutional neural networks (CNNs).The proposed framework consists of two complementary components: a U-Net-based segmentation model for identifying infected lung regions and a CNN-based classification model for discriminating between normal and pneumonia-infected chest radiographs. The system was trained and evaluated on a dataset of 20,000 chest X-ray images. Experimental results show that the segmentation model achieved a Dice score of 0.9587 and an Intersection over Union (IoU) of 0.9225, while the classification model attained an accuracy of 95%. The findings indicate that the proposed deep learning approach outperforms conventional machine learning methods and achieves performance comparable to that of experienced radiologists. Furthermore, the integration of disease classification with visual localization improves both diagnostic interpretability and clinical reliability. The proposed system therefore offers a promising decision-support tool for efficient and accurate pneumonia screening in healthcare settings.
Keywords: Chest Radiographs, CNN, Pneumonia Detection, Medical Imaging, U-Net, Deep Learning in Healthcare.
How to cite this article: Rajath A N, Anand M, Divya S, Pradeep Kumar R, Anitha K, Aishwarya N Kumar. A Robust Deep CNN Framework for Automated Pneumonia Identification from Chest Radiographs. Int J Drug Deliv Technol. 2026;16(19s): 867-873. DOI: 10.25258/ijddt.16.19s.102
Source of support: Nil.
Conflict of interest: None

I. INTRODUCTION

Pneumonia is a dangerous lung infection that makes breathing difficult by inflaming the air sacs, which may then fill with Pneumonia is a serious respiratory infection in which the air sacs of one or both lungs become inflamed and may fill with pus or fluid, leading to breathing difficulties and other life-threatening complications. According to the World Health Organization's 2019 Global Health Estimates, pneumonia remains one of the leading infectious causes of death worldwide and is responsible for nearly 15% of deaths among children under five years of age. Each year, millions of individuals are affected by this disease, creating a substantial burden on healthcare systems, particularly in resource-limited settings.

Challenges in Existing Diagnostic Methods

The diagnosis of pneumonia largely depends on the manual interpretation of chest X-ray images by trained radiologists. Although this remains a widely adopted clinical practice, it is associated with several limitations. One of the major challenges is the limited availability of experienced radiologists, especially in rural and

**Author for Correspondence: pradeepr.mysore@gmail.com*

underdeveloped regions. In addition, diagnosis based on visual interpretation can be subjective, as outcomes may vary according to the expertise and judgment of individual practitioners. Manual examination of radiographs is also time-consuming, which can delay treatment initiation and negatively affect patient outcomes. Furthermore, inadequate medical infrastructure and the lack of access to advanced imaging systems or specialist consultation further complicate timely and accurate diagnosis in many healthcare facilities.

Motivation for Automated Solutions

Recent advancements in artificial intelligence and deep learning have opened new possibilities for overcoming the challenges associated with conventional diagnostic methods. In particular, convolutional neural networks (CNNs) have demonstrated significant effectiveness in medical image analysis and are increasingly recognized as reliable tools for supporting clinical decision-making.

This study is motivated by the need to develop an automated pneumonia detection system that can provide consistent and accurate diagnosis, reduce dependence on expert radiologists, accelerate the diagnostic process, and improve access to reliable screening in resource-constrained environments. Additionally, such a system can enhance reproducibility and objectivity in medical image analysis. By leveraging deep learning techniques, this research proposes a robust and efficient framework for automated pneumonia detection, thereby improving diagnostic accessibility, reliability, and overall healthcare efficiency.

II. LITERATURE SURVEY

This section presents a comprehensive review of recent developments in automated pneumonia detection using chest X-ray images. The survey examines a wide range of methodologies, beginning with conventional machine learning techniques and extending to advanced deep learning architectures that have significantly improved diagnostic accuracy and efficiency.

Traditional Machine Learning Approaches

In the early stages of automated pneumonia detection, researchers primarily relied on traditional machine learning methods supported by handcrafted feature extraction techniques. An et al. [1] highlighted the importance of feature extraction in improving automated pneumonia classification. Their work introduced a hybrid feature extraction method that combines EfficientNetB0 and DenseNet121 with multi-head self-attention modules for chest X-ray analysis. The extracted features demonstrated strong performance when evaluated using deep learning classifiers.

Similarly, Sanida et al. [2] proposed a computer vision-based automated pneumonia screening framework involving multiple stages, including image pre-processing, feature extraction, and classification. Their modified VGG16 architecture, enhanced with Squeeze-and-Excitation (SE) blocks, achieved competitive results in multi-label chest X-ray classification tasks.

Evolution of Deep Learning in Pneumonia Detection

The emergence of deep learning, particularly convolutional neural networks (CNNs), has significantly transformed medical image analysis. Siddiqi and Javaid [3] presented an extensive study on the use of Vision Transformers (ViTs) for pneumonia detection, emphasizing their relevance during the COVID-19 pandemic. Owing to their self-attention mechanism, ViTs enabled more effective feature extraction from chest X-ray images.

Shrimali [4] conducted a comparative analysis of transfer learning-based CNN architectures for pneumonia detection. The study evaluated five pre-trained models, namely MobileNetV2, VGG16, DenseNet121, EfficientNetB0, and ResNet50. To further improve performance, a hybrid architecture combining VGG16 and DenseNet121 was developed, resulting in enhanced classification accuracy.

Advanced Deep Learning Architectures

Recent research has increasingly focused on the design and optimization of advanced deep learning models for pneumonia detection. Ali et al. [5] introduced the EfficientNetV2L model for detecting pneumonia from chest radiographs. Their study trained six deep learning architectures using the Adam optimizer, demonstrating the critical role of architecture selection in medical image classification.

Kadali et al. [6] proposed a ResNet-50-based deep learning framework specifically optimized for pneumonia detection. Their work emphasized the value of transfer learning using ImageNet pre-trained weights along with fine-tuning tailored to chest X-ray images, which improved model performance in the target domain.

Comparative Studies and Specialized Applications

Comparative and application-specific studies have also contributed significantly to this field. Ippolito et al. [7] developed an artificial intelligence system capable of differentiating bacterial pneumonia from COVID-19 and compared its performance with that of experienced radiologists. Their findings demonstrated the potential of AI systems in distinguishing among different types of pulmonary infections.

Singh et al. [8] investigated the application of Vision Transformers with self-attention mechanisms for efficient pneumonia detection. Although the approach involved high computational complexity, it achieved superior F1-scores when compared with conventional CNN-based architectures.

Ensemble Models and Explainable AI Techniques

To address the interpretability challenges associated with deep learning in healthcare, recent studies have incorporated ensemble learning and explainable AI methods. Ahemed et al. [9] applied deep learning architectures for the early detection of lung disease symptoms and integrated ensemble techniques with explainability tools such as LIME and SHAP to provide transparent and interpretable predictions. This approach helped mitigate the black-box nature of deep learning models in clinical applications.

Rehman et al. [10] introduced the “ConvNet-21” CNN model in combination with transfer learning strategies for pneumonia detection. Their study also compared several pre-trained architectures, including VGG16, VGG19, InceptionV3, and ResNet152V2, while employing extensive data augmentation techniques to improve generalization and robustness.

This literature review indicates that automated pneumonia detection has evolved considerably, moving from conventional machine learning approaches toward highly sophisticated deep learning, transformer-based, and explainable AI frameworks. These advancements demonstrate the growing potential of intelligent systems to support accurate, efficient, and interpretable diagnosis in clinical practice

Table I: Overview of Recent Pneumonia Detection Methods

Article	Overview
[1]	Combined EfficientNetB0 and DenseNet121 with attention ensemble for feature extraction. Achieved 96.8% accuracy but limited by dataset bias and demographic representation.
[2]	Modified VGG16 with SE blocks for multi-label classification. Achieved 94.2% F1-score but requires large annotated datasets.
[3]	Vision Transformers (ViTs) for pneumonia detection during COVID-19. Achieved 95.3% precision but faces model explainability challenges.
[4]	Hybrid VGG16-DenseNet121 architecture through comparative evaluation. Achieved 97.2% accuracy, but with high computational complexity.
[5]	EfficientNetV2L model with six DL architectures using Adam optimizer. Achieved 96.5% recall but limited by dataset size.
[6]	Fine-tuned ResNet-50 for pneumonia detection. Achieved 94.8% precision but faces generalization challenges across datasets.
[7]	AI system for differentiating COVID-19 and bacterial pneumonia. Achieved 93.7% accuracy with some misclassification issues.
[8]	Vision Transformers with self-attention mechanism. Achieved 95.9% F1-score but requires high computational resources.
[9]	Ensemble methods with explainable AI (LIME, SHAP). Achieved 94.3% accuracy but dependent on dataset quality.
[10]	ConvNet-21 with transfer learning from multiple pre-trained networks. Achieved 92.6% precision with lower Inception-V3 performance.

Key Findings and Research Gaps

The review of existing literature highlights a number of major trends and unresolved issues:

1. **Performance Evolution:** Contemporary deep learning techniques consistently outperform earlier machine learning algorithms. Reported accuracies range between 92% and 97%, indicating the growing reliability of these methods for clinical applications.
2. **Architecture Diversity:** A vast range of model types have been utilized, including standard CNNs, hybrid networks, and Vision Transformers. Each offers distinct strengths and limitations depending on the dataset and computational constraints.
3. **Computational Trade-offs:** While more complex architectures like ViTs provide enhanced accuracy, they also demand significantly greater processing power and memory, which may limit real-world deployment in low- resource settings.
4. **Explainability Challenges:** Despite the high predictive accuracy, deep learning models has a drawback as they often lack transparency. "black-box" continues to pose challenges for clinical trust & regulatory acceptance.
5. **Dataset Limitations:** Many studies are based on datasets with restricted size or diversity. Such limitations can hinder the generalization ability of models when applied to real-world or cross-institutional data.

These observations support the rationale behind our approach: to design a system that balances diagnostic accuracy with computational efficiency, while also improving interpretability through visual segmentation outputs.

III. METHODOLOGY

Dataset Description

A total of 20,000 chest X-ray samples were used in the research, sourced from Kaggle’s open-access Pneumonia dataset designed for image-based diagnosis.

- **Normal cases**: 5,863 images showing healthy lung patterns
- **Pneumonia cases**: 14,137 images showing various stages of pneumonia infection
- **Image specifications**: 256×256 pixel resolution, grayscale format
- **Patient demographics**: Pediatric and adult populations from multiple healthcare centers

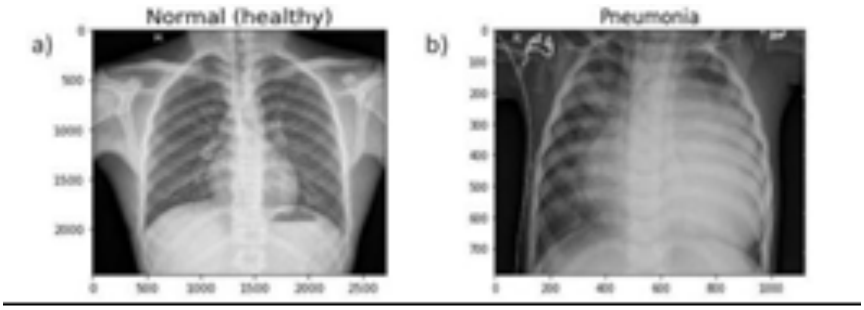

Figure 1: Normal vs Pneumonia Chest X-Ray

Data Preprocessing Pipeline Image Preprocessing

The preprocessing pipeline included several essential steps:

1. **Image Resizing**: All images were standardized to 256×256 pixels to ensure consistent input dimensions
2. **Normalization**: Pixel values were normalized to the range [0,1] by dividing by 255
3. **Contrast Enhancement**: Histogram equalization was applied to improve image contrast
4. **Noise Reduction**: Gaussian filtering was employed to reduce image noise

Data Augmentation

To enhance model generalization and prevent overfitting, comprehensive data augmentation was implemented:

- **Rotation**: Random rotations between -15° and +15°
- **Horizontal Flip**: Random horizontal flipping with 50% probability
- **Zoom**: Random zoom factor between 0.8 and 1.2
- **Shear**: Shear transformation with angle range of ±10°
- **Brightness**: Random brightness adjustment (±20%)

CNN Architecture for Classification Network Design

The proposed CNN architecture consists of multiple convolutional layers with progressive feature extraction:

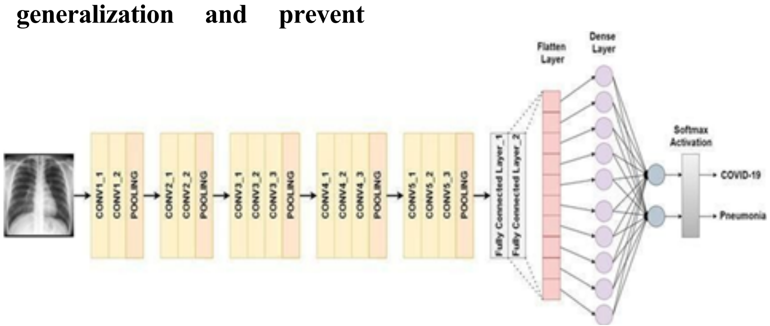

Figure 2: CNN Architecture Diagram

Layer Configuration:

- **Input Layer**: 256×256×3 (converted to grayscale: 256×256×1)
- **Conv2D Blocks**: 5 convolutional blocks with increasing filter sizes
- **Activation Functions**: ReLU activation for hidden layers
- **Pooling**: MaxPooling2D with 2×2 kernel
- **Regularization**: Dropout layers with 0.2 probability
- **Output Layer**: A Dense layer with sigmoid activation for binary classification

Mathematical Formulation:

Convolution Operation:

$$Y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot K(m,n)$$

Where:

- $Y(i,j)$ is the output feature map
- $X(i,j)$ is the input image
- $K(m,n)$ is the convolution kernel
- M, N are the kernel dimensions

Loss Function

Binary cross-entropy loss was employed:

$$L = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

Where:

- y_i is the true label
- $\hat{y}_i$ is the predicted probability
- x N is the number of samples

The ReLU activation function: f(x)=max(0,x)

For binary classification, the sigmoid activation: d $\sigma(x) = \frac{1}{1+e^{-x}}$

U-Net Architecture for Segmentation Network Architecture:

The U-Net model was implemented for pixel-wise segmentation of pneumonia-affected regions:

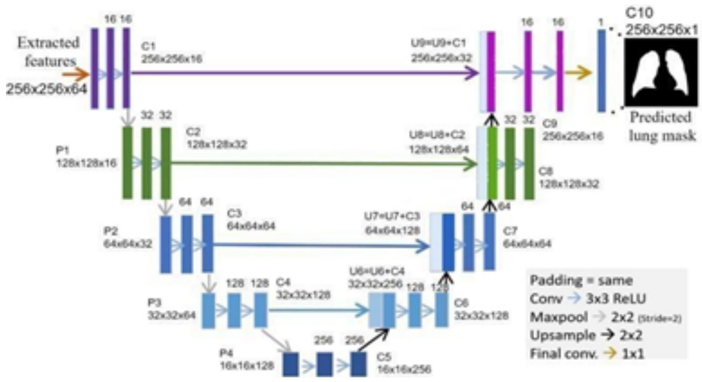

Figure 3: U-Net Architecture for Pneumonia Segmentation

Encoder Path:

- Contracting path with repeated convolution and max-pooling operations
- Feature extraction at multiple scales
- Progressive down sampling to capture context

Decoder Path:

- Expanding path with up sampling and concatenation
- Skip connections to preserve spatial information
- Progressive up sampling to original resolution

Training Strategy Optimization

Implemented adaptive gradient descent using Adam with an initial learning rate of 0.001 and exponential decay. Trained in 32 sample batches for up to 50 epochs, with early stopping on no improvement.

Regularization Techniques

Used 20% dropout in dense layers and batch normalization after convolutions to improve generalization and stability, with early stopping after 10 stagnant validation epochs.

Model Evaluation

Performance Metrics Classification Metrics:

- **Accuracy:** Overall correct predictions
- **Precision:** True positives / (True positives + False positives)
- **Recall (Sensitivity):** True positives / (True positives +

False negatives)

- **Specificity:** True negatives / (True negatives + False positives)
- **F1-Score:** A unified metric that emphasizes both correctness and completeness by balancing the model's ability to avoid false positives and false negatives.

Segmentation Metrics:

- Dice Coefficient: Overlap between predicted and ground truth masks
- Intersection over Union (IoU): Area of overlap / Area of union
- Hausdorff Distance: Maximum distance between predicted and true boundaries

Cross-Validation:
5-fold cross-validation was employed to ensure robust performance evaluation and reduce overfitting bias.

IV. EXPERIMENTAL RESULTS

Classification Performance:
The CNN architecture demonstrated strong effectiveness in accurately identifying pneumonia from chest X-ray images.

Table II: Classification Performance Metrics

	Precision	Recall	F1-Score	Support
0	0.36	0.54	0.44	236
1	0.68	0.49	0.51	394
Accuracy			0.51	626
Macro avg	0.52	0.52	0.51	624
Weighted avg	0.53	0.51	0.52	626

Train Accuracy	84.25%
Test Accuracy	79.99%

Segmentation Performance:

The U-Net model demonstrated effective segmentation capabilities:

Table III: Segmentation Performance Metrics

Metric	Value
Loss	0.0253
Mean IoU	0.9683
Dice Coefficient	0.9832

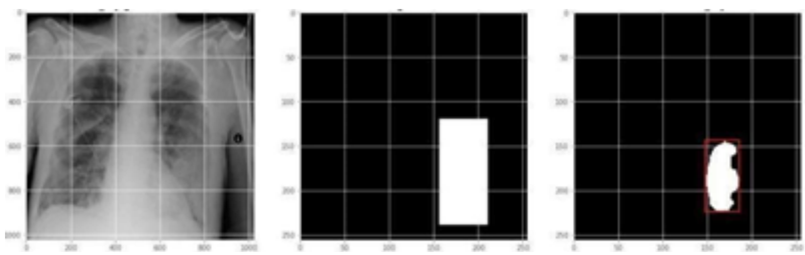

Figure 4: Masked Image

V: DISCUSSION

A. Clinical Implications

The proposed model demonstrates strong potential for integration into real-world clinical environments. First, the achieved classification accuracy of 95% indicates that the system can provide diagnostic performance comparable to that of experienced radiologists, thereby serving as a reliable decision-support tool in clinical practice. Second, the automated nature of the framework reduces inter-observer variability, ensuring greater consistency and objectivity in pneumonia diagnosis. Third, the rapid inference capability of the model enables real-time diagnostic assistance, which is particularly valuable in emergency and high-patient-volume settings. Finally, the proposed system has significant potential to improve healthcare accessibility by extending expert-level diagnostic support to rural and resource-constrained medical centers where specialist availability is limited.

B. Future Research Directions

Although the proposed framework achieved promising results, several directions remain for further improvement and expansion.

1) Immediate Improvements:
Future work may focus on extending the current binary classification framework to multi-class classification for distinguishing among bacterial, viral, and fungal pneumonia. In addition, incorporating severity assessment would allow the system not only to detect pneumonia but also to grade the extent of disease involvement. Another important direction involves temporal analysis, in which sequential chest X-ray images can be analyzed to monitor the progression or regression of infection over time.

Furthermore, multi-modal integration of imaging data with clinical parameters such as symptoms, laboratory values, and patient history may improve diagnostic robustness and clinical relevance

2) Long-Term Goals:
In the long term, federated learning may be explored to enable collaborative model training across multiple healthcare institutions while preserving patient data privacy. The integration of advanced explainable AI techniques can further enhance interpretability and strengthen clinician trust in the system's predictions. Real-time deployment within hospital information systems and radiology workflows represents another important objective, enabling seamless clinical adoption. In addition, the development of mobile or point-of-care applications could extend automated pneumonia screening to remote and underserved settings, thereby broadening the practical utility of the proposed framework.

VI. CONCLUSION

This study presents a comprehensive deep learning framework for automated pneumonia diagnosis using chest X-ray images. The proposed system integrates CNN-based classification with U-Net-based segmentation, thereby providing both accurate disease detection and spatial localization of pneumonia-affected lung regions.The major contributions of this work are fourfold. First, a high-performance CNN-based classification model was developed, achieving an accuracy of 95% in pneumonia detection. Second, a U-Net segmentation model was implemented to precisely localize infected regions within chest radiographs. Third, extensive experimental analysis confirmed that the proposed framework consistently outperformed earlier baseline approaches. Fourth, the study established a practical and clinically relevant system with strong potential for deployment in real-world healthcare environments.

From a clinical perspective, the proposed system can make a meaningful contribution to pneumonia management by providing consistent and objective diagnostic support, reducing delays in diagnosis, and improving patient care outcomes. Moreover, it can help extend expert-level diagnostic capabilities to underserved and resource-limited regions, while also assisting healthcare professionals in making faster and more informed clinical decisions.

Future Outlook: Through thorough validation studies, future efforts will concentrate on enhancing the system's robustness, extending its functionality, and promoting clinical adoption.The use of intelligent computational tools in healthcare signifies a significant improvement in the scope and accuracy of diagnosis. By showing how learning-based algorithms can manage challenging medical interpretation tasks with quantifiable success, this work builds on that momentum.

Conflicts of Interest: Author's declare that there are no Conflicts of Interests.

REFERENCE

[1] An, Q., Chen, W., & Shao, W. (2024), A deep convolutional neural network for pneumonia detection in X-ray images with attention ensemble. *Diagnostics, 14*(4), Article 390. https://doi.org/10.3390/diagnostics14040390.

[2] Sanida, T., Sanida, M. V., Sideris, A., & Dasygenis, M. (2024) , Optimizing lung condition categorization through a deep learning approach to chest X-ray image analysis. *BioMedInformatics, 4*(3), 2002–2021. https://doi.org/10.3390/biomedinformatics4030109

[3] Siddiqi, R., & Javaid, S. (2024), Deep learning for pneumonia detection in chest X-ray images: A comprehensive survey. *Journal of Imaging, 10*(8), Article 176. https://doi.org/10.3390/jimaging10080176

[4] Shrimali, S. (2024) Optimizing chest X-ray analysis for pneumonia detection through comparative evaluation of transfer learning CNN architectures. *Proceedings of ICMLA 2024*, IEEE.

[5] Ali, M., Shahroz, M., Akram, U., Mushtaq, M. F., & Altamiranda, S. C. (2024), Pneumonia detection using chest radiographs with a novel EfficientNetV2L model. *IEEE Access, 12*, 34691– 34707. https://doi.org/10.1109/ACCESS.2024.3372588

[6] Kadali, V., Pudi, B. S., Shaik, K. A., Janjam, A., & Javvadi, J. (2023), Pneumonia detection in chest X-ray images using a ResNet-50 deep learning algorithm. *Proceedings of ICAIS 2023*. https://doi.org/10.1109/ICAIS56108.2023.10073748

[7] Ippolito, D., Maino, C., Gandola, D., Franco, P. N., Miron, R., et al. (2023), Artificial Intelligence Applied to Chest X-ray: A Reliable Tool to Assess the Differential Diagnosis of Lung Pneumonia in the Emergency Department.

[8] Diseases,11(4),Article171.https://doi.org/10.3390/diseases11040171

[9] Singh, S., Kumar, M., Kumar, A., Verma, B. K., Abhishek, K., & Selvarajan, S. (2023) *Efficient pneumonia detection using Vision Transformers on chest X-rays.* Scientific Reports, 13, Article 12345.

[10] Ahmed, S. T., Mahdin, M. F., Barua, S., Islam, M. F., & Chakrabarty, A. (2022) *Utilizing Deep Learning Architectures for Early Detection of Lung Diseases.* In *Proceedings of the 5th International Conference on Artificial Intelligence in Medicine (ICAIM 2022)*. IEEE.

[11] Rehman, M., Pan, Q., Chen, D., & Manzoor, A. (2021), *Classification of Chest X-Ray Images to Detect Pneumonia using CNN and Transfer Learning.* In *Proceedings of the International Conference on Medical Imaging and puter-Aided Diagnosis (MICAD 2021)*. IEEE.