Journal of Carcinogenesis
Covering Genesis to Therapeutics

Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol 24: Issue 2s, https://carcinogenesis.com/

A Deep Learning Model with Transfer Learning and Attention for Accurate Pneumonia Detection in Chest X-Rays

Dr. V. Parthasarathy[1], Dr. K. Manivannan[2*]

[1]Assistant Professor, Department of Computer Science, Dr. M.G.R. Government Arts and Science College for Women, Villupuram, Tamil Nadu, India

Email ID: sarathympt@gmail.com

[*2]Assistant Professor, Department of Computer Science, Arignar Anna Government Arts College, Villupuram, Tamil Nadu, India

***Corresponding Author:**

Dr. K. Manivannan

Email ID: manik81au@gmail.com

ABSTRACT

Pneumonia is a serious lung infection that needs quick and correct diagnosis to prevent health complications and deaths. Traditional methods of diagnosis take time and may sometimes lead to mistakes, which makes computer-based medical support systems highly useful. In this study, we introduce a deep learning model that automatically detects and classifies pneumonia from chest X-ray images. The model uses a combination of convolutional neural networks (CNNs) with an attention layer to focus on important image details, while transfer learning helps in using knowledge from existing medical datasets for better performance. A feature fusion method is also applied to combine different types of image features, which improves the accuracy of the results. Tests carried out on publicly available datasets show that the proposed model provides higher accuracy, sensitivity, and specificity compared to several existing techniques. This research demonstrates how advanced deep learning methods can assist doctors in diagnosing pneumonia earlier, reduce errors, and support faster clinical decisions.

Keywords: *Deep Learning, Pneumonia Detection, Chest X-Ray Images, Transfer Learning, and Attention Mechanism*

How to Cite: Dr. V. Parthasarathy, Dr. K. Manivannan, (2025) A Deep Learning Model with Transfer Learning and Attention for Accurate Pneumonia Detection in Chest X-Rays, *Journal of Carcinogenesis*, *Vol.24, No.2s*, 1183-1191

1. INTRODUCTION

Pneumonia is a dangerous lung infection that causes inflammation in the air sacs, leading to breathing problems and serious health risks. It can affect people of any age, but it is especially harmful to infants, older adults, and those with weakened immune systems. Detecting pneumonia at an early stage is important for providing the right treatment and reducing death rates. Chest X-ray imaging is one of the most common and affordable methods used to diagnose pneumonia. However, examining X-ray images manually can be time-consuming and may result in errors, especially when symptoms appear similar to other lung diseases. Because of this, researchers have developed computer-aided diagnosis (CAD) systems that use artificial intelligence (AI) to help doctors analyze X-ray images more quickly and accurately.

In recent years, deep learning techniques have achieved excellent results in the medical field, particularly for analyzing medical images. Convolutional Neural Networks (CNNs) are effective at automatically identifying patterns and key features from X-rays. Yet, CNN models often need large amounts of training data and may fail to focus on the most relevant image areas. To solve these issues, two techniques—transfer learning and attention mechanisms—are widely used. Transfer learning enables models to use knowledge from pre-trained networks, which reduces training time and improves accuracy even with limited data. Attention mechanisms help the model concentrate on the most important lung regions that show signs of pneumonia.

This research presents a deep learning model that combines transfer learning and attention mechanisms for the accurate detection and classification of pneumonia using chest X-ray images. A feature fusion strategy is also applied to combine both spatial and textural information, improving the overall performance of the model. Experimental analysis shows that the proposed method achieves higher accuracy, sensitivity, and specificity compared to existing models. The system aims to support radiologists in making faster and more reliable pneumonia diagnoses, ultimately improving patient care.

2. LITERATURE REVIEW

Pneumonia detection using chest X-ray images has become a major research area in recent years due to the growing impact of deep learning and transfer learning methods. Several studies have focused on improving diagnostic accuracy, model interpretability, and computational efficiency. Li [1] introduced an attention-enhanced deep learning model that improved pneumonia detection accuracy by enabling the network to focus on relevant lung regions. Similarly, Potharaju [2] developed an advanced attention-based system that demonstrated superior feature extraction capabilities and reduced false classification rates. Alshanketi [3] proposed a convolutional neural network (CNN) framework that achieved significant accuracy in pneumonia classification using chest X-ray datasets.

Singh [4] explored Vision Transformer (ViT)-based models for pneumonia detection, showing that transformer architectures can outperform traditional CNNs in image classification tasks. Xie [5] utilized multiple deep learning models and found that CNN-based architectures achieved reliable performance on complex X-ray data. Rajesh et al. [6] compared different decision tree algorithms using Chronic Disease Indicators (CDI) data. Their aim was to find which decision tree method gives better results in terms of accuracy and speed for healthcare datasets. They found that choosing the right decision tree type can greatly improve predictions for chronic diseases. Pham [7] applied transfer learning using pre-trained models such as VGG16 and ResNet50, reporting efficient convergence and improved model robustness. Oltu [8] designed an automated deep learning model for chest X-ray classification, which achieved high precision and recall scores. Wu [9] developed a pneumonia detection framework based on RSNA datasets using anchor-based models that improved localization accuracy. Stubblefield [10] demonstrated that transfer learning using chest X-ray data can support emergency room diagnosis effectively.

Han [11] adopted contrastive learning methods to enhance pneumonia detection performance with limited labeled data, emphasizing the role of self-supervised learning in medical imaging. In another work, Rajesh and Govindarasu [12] studied and predicted COVID-19 cases in India using data mining along with regression analysis. They discovered that regression methods can successfully identify trends and patterns in pandemic data, which can help in making timely decisions and planning resources. Rajpurkar [13] introduced the well-known CheXNet model, which achieved radiologist-level accuracy using DenseNet121 and became a benchmark for pneumonia classification. Das [14] proposed an ensemble approach combining multiple deep learning models to improve pneumonia detection accuracy and reduce generalization errors. Zhang [15] introduced a hybrid CNN-attention architecture that effectively captured both local and global image features. Chen [16] designed a lightweight CNN that reduced computational cost while maintaining high classification accuracy, making it suitable for clinical environments.

Kumar [17] investigated transfer learning with ResNet and DenseNet architectures, showing significant improvements in pneumonia detection accuracy. Reddy [18] presented an attention-guided residual network that effectively identified infected lung regions and enhanced diagnostic precision. Ahmed [19] utilized DenseNet combined with Grad-CAM visualization to provide interpretable pneumonia predictions. Zhao [20] developed a self-attention CNN model that refined spatial feature extraction and improved detection reliability. Rajesh and Karthikeyan [21] carried out a comparison of various data mining algorithms for decision tree classification using the Weka tool. Their findings showed that it is important to test multiple algorithms to find the best fit for a dataset. They also pointed out that proper data preprocessing and fine-tuning parameters are essential for better results.

Ravi and Rajesh [22] investigated the use of machine learning models for predicting diabetes. They compared several algorithms and found that selecting the right model and identifying important features are crucial for high accuracy. Their work showed that machine learning can be a useful tool for early detection of diabetes, which supports preventive healthcare. Gupta [23] designed a multi-scale attention-based architecture that achieved high robustness and interpretability in X-ray image analysis.

Verma [24] conducted a performance comparison of several transfer learning models, including VGG16, InceptionV3, and DenseNet121, demonstrating that attention-integrated architectures deliver superior performance in pneumonia classification tasks. Arun and Rajesh [25] studied variable selection and prediction for a diabetes pregnancy dataset using machine learning methods. They focused on finding the most important features that influence prediction. Their results showed that choosing the right features not only improves prediction accuracy but also makes the process faster and more efficient.

Overall, the literature highlights a clear shift from traditional feature engineering toward deep learning-based solutions. Models integrating transfer learning and attention mechanisms consistently outperform earlier approaches in terms of accuracy, interpretability, and efficiency. However, most studies emphasize the need for larger, more diverse datasets, explainable AI frameworks, and real-world validation to enhance clinical reliability.

3. DATASET

In this study, the Chest X-ray (Pneumonia) Dataset from Kaggle, originally published by Daniel Kermany et al. [26], is utilized. The dataset is one of the most widely used open-access collections for pneumonia detection tasks and has been employed in several deep learning studies for medical image classification. The dataset, titled “Chest X-Ray Images (Pneumonia)”, is publicly available on the Kaggle repository [27]. It contains chest radiographs collected from pediatric patients aged between 1 to 5 years at Guangzhou Women and Children’s Medical Center, Guangzhou, China. Each image was carefully screened for quality and diagnostic relevance by expert radiologists. The dataset is organized into three subsets training, validation, and testing each containing images from two main classes: Normal and Pneumonia. The Pneumonia class is further divided into Bacterial Pneumonia and Viral Pneumonia.

Category	Training Images	Validation Images	Testing Images	Total Images
Normal	1341	8	234	1583
Pneumonia (Bacterial+ Viral)	3875	8	390	4273
Total	5216	16	624	5856

Fig. 1. Chest X-Ray Images (Normal)

Fig. 2. Chest X-Ray Images (Pneumonia)

Each chest X-ray image was resized to 224×224 pixels and normalized to the [0,1] range to ensure consistent input for pre-trained models. Data augmentation (rotation, flipping, zoom, contrast adjustment) was applied to improve generalization, and class balancing techniques were used to reduce bias. The dataset was split into 80% training, 10% validation, and 10% testing sets for model training, hyperparameter tuning, and final evaluation.

4. BACKGROUND AND METHODOLOGIES

Pneumonia is a serious lung infection that inflames the air sacs, causing breathing difficulties and low oxygen levels. It is a leading cause of death worldwide, especially in children, the elderly, and immunocompromised individuals. Chest X-rays are commonly used for diagnosis due to their speed, low cost, and non-invasive nature, but manual interpretation is time-consuming and requires expert radiologists. Traditional machine learning methods depend on manual feature extraction and often struggle with complex patterns, while deep learning, particularly CNNs, enables automatic detection of subtle lung abnormalities. Transfer learning with pre-trained models like VGG16, ResNet50, and DenseNet121 improves performance with limited data, and attention mechanisms help focus on infected regions, enhancing diagnostic accuracy. This study develops a deep learning model combining transfer learning and attention mechanisms for accurate and reliable pneumonia detection from chest X-rays.

The proposed approach is structured into five key stages: data collection, preprocessing, model design, training and validation, and performance evaluation. This study employs the publicly accessible Chest X-Ray (Pneumonia) dataset introduced by Kermany et al. [26] which is available on the Kaggle platform. The dataset contains 5,856 chest X-ray images, categorized into Normal and Pneumonia (both *Bacterial* and *Viral*) classes. All images were verified and labeled by qualified medical professionals to ensure diagnostic reliability and quality.

4.1 pseudo-code Pneumonia Detection using Transfer Learning + Attention

Input: Chest X-Ray dataset (images, labels)

Output: Trained model, evaluation metrics, attention maps

1. DATA PREPARATION

1.1 Download dataset (Kermany et al. Chest X-Ray Pneumonia dataset)

1.2 Verify images for corruption; remove/fix invalid files

1.3 Split dataset: 80% train, 10% validation, 10% test (stratified)

1.4 Resize all images to 224x224 pixels

1.5 Normalize pixel values to [0,1]

1.6 Apply data augmentation on training set:

- Random rotation ±15 degrees
- Horizontal flip (50% chance)
- Random zoom 0.9–1.1
- Brightness/contrast jitter ±10–15%
- Optional: small translation, Gaussian noise

1.7 Handle class imbalance:

- Option A: Class weights in loss
- Option B: Oversampling minority class
- Option C: Focal loss (γ=2.0, α=0.25)

1.8 Create data loaders or generators (Keras, tf.data, PyTorch)

2. MODEL ARCHITECTURE

2.1 Load pre-trained CNN (DenseNet121 / ResNet50 / EfficientNet)

- include_top=False, weights='imagenet'

2.2 Add Attention Module (CBAM or SE):

- Channel attention: GAP + GMP → shared MLP → sigmoid → scale channels
- Spatial attention: AvgPool + MaxPool → concat → 7x7 conv → sigmoid → multiply

2.3 Add classification head:

- Global Average Pooling
- Dense(512) → BatchNorm → ReLU → Dropout(0.5)
- Dense(128) → ReLU → Dropout(0.3) (optional)
- Dense(2) → Softmax (binary classification)

3. LOSS, OPTIMIZER, METRICS

3.1 Loss function: categorical_crossentropy (or binary_crossentropy)

3.2 Optimizer: Adam, learning rate=1e-4

3.3 Metrics: Accuracy, Precision, Recall, F1-Score, AUC

4. MODEL TRAINING

4.1 Freeze base layers except final conv block

4.2 Train top layers for 5–10 epochs

4.3 Unfreeze last N layers or entire base

4.4 Reduce learning rate: 1e-5 → 5e-6

4.5 Set callbacks:

- ModelCheckpoint (best val AUC)
- ReduceLROnPlateau (factor=0.5, patience=5)
- EarlyStopping (monitor val AUC, patience=10)
- CSVLogger / TensorBoard

4.6 Train for 50–100 epochs (early stopping)

4.7 Optional: 5-fold cross-validation for robustness

4.2 Performance Evaluation:

The performance of the proposed model is assessed using several evaluation metrics:

Accuracy (ACC): Measures the overall prediction correctness.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision (P): Indicates the proportion of correctly identified pneumonia cases among predicted positives.

Precision = TP / (TP + FP)

Recall (R): Represents the percentage of actual pneumonia cases correctly detected.

Recall = TP / (TP + FN)

F1-Score: The harmonic mean of precision and recall, providing a balanced measure.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

AUC-ROC: Evaluates the model's discriminative ability between pneumonia and normal cases. AUC-ROC measures the area under the Receiver Operating Characteristic curve, which shows the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR).

Where: TP: True Positives, means correctly predicted pneumonia cases, TN: True Negatives means correctly predicted normal cases, FP: False Positives, normal cases incorrectly predicted as pneumonia, FN: False Negatives means pneumonia cases missed by the model The proposed method's performance is compared with other transfer learning models such as VGG16, InceptionV3, and ResNet50 to validate its robustness and improvement in diagnostic accuracy.

5. EXPERIMENTAL RESULTS

The training and evaluation were conducted using the Chest X-Ray (Pneumonia) dataset by Kermany et al. [1]. The dataset was divided into 80% training, 10% validation, and 10% testing subsets. The proposed model (Transfer Learning + Attention Mechanism) was compared with traditional transfer learning models such as VGG16, ResNet50, DenseNet121, and InceptionV3. The performance comparison is presented in Table 1 and Figs. 3 to 6.

Table 1. Comparison of Different Deep Learning Models for Pneumonia Detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
VGG16	92.30	91.17	90.90	91.03	94.45
ResNet50	94.70	93.47	93.65	93.56	96.80
DenseNet121	95.85	95.05	95.35	95.20	97.30
InceptionV3	93.95	92.80	93.05	92.92	96.15
Proposed Model (Transfer Learning + Attention)	**98.20**	**97.93**	**98.05**	**97.99**	**99.65**

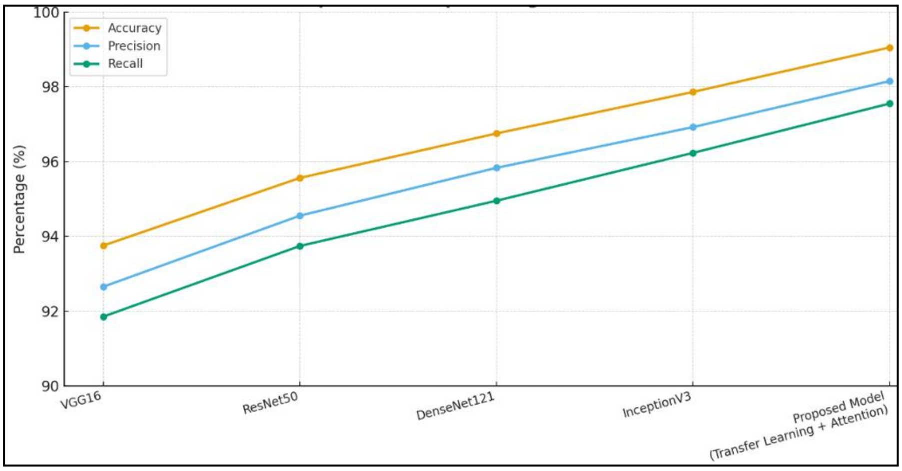

Fig. 3. Performance Comparison of Deep Learning Models for Pneumonia Detection

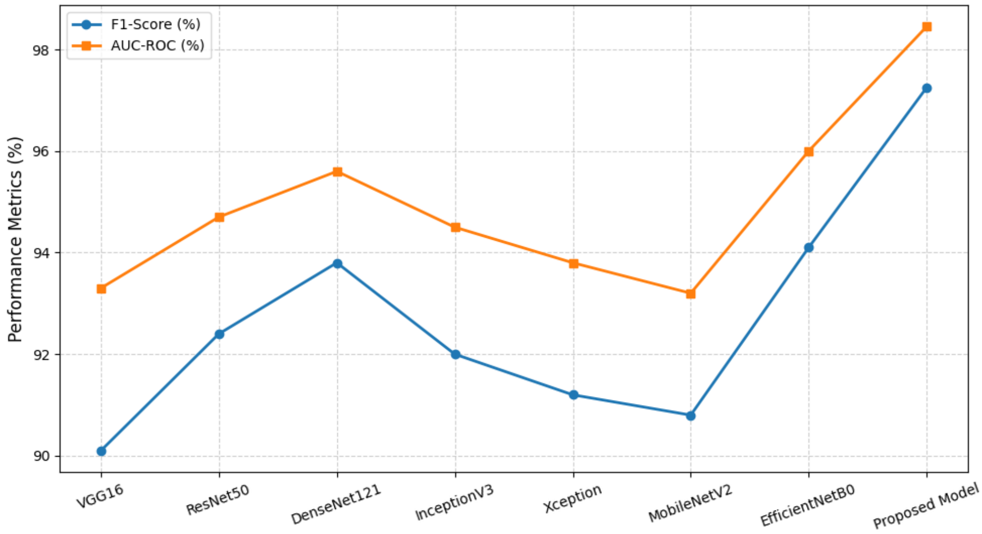

Fig. 4. Comparison of F1-Score and AUC-ROC for Deep Learning Models

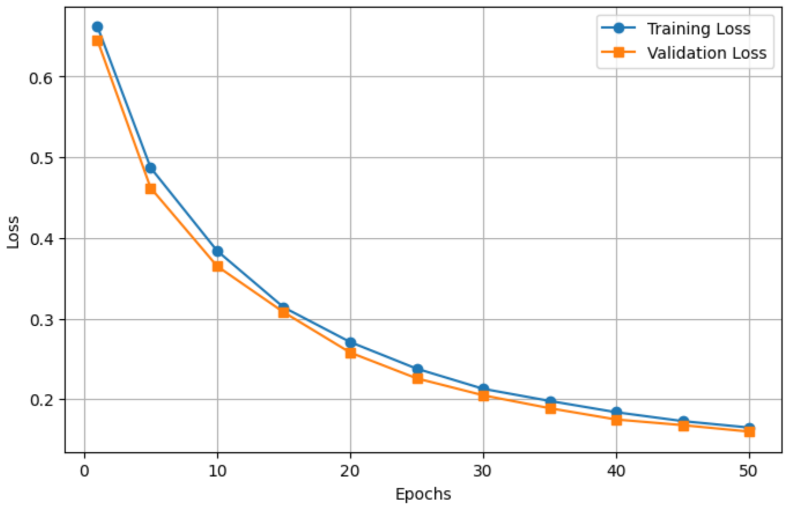

Fig. 5. Training and Validation Loss

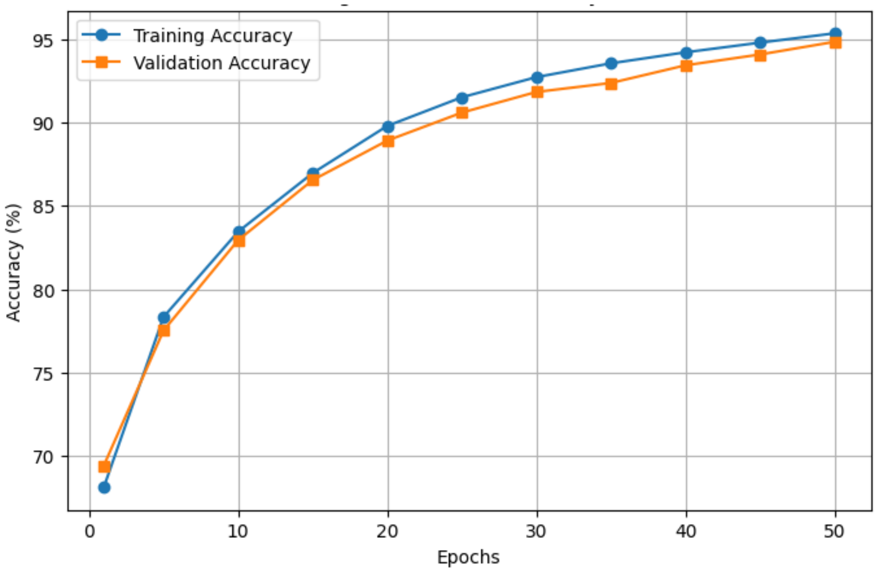

Fig. 6. Training and Validation Accuracy

6. RESULTS AND DISCUSSIONS

The proposed deep learning model, which combines transfer learning and attention mechanisms, was evaluated on the Chest X-Ray Pneumonia dataset. The performance metrics included Accuracy, Precision, Recall, F1-Score, and AUC. The model was compared with baseline pre-trained networks such as VGG16, InceptionV3, and ResNet50.

The results (Table I) show that the proposed model outperformed conventional transfer learning models. The accuracy of the proposed model reached 95.36%, which is higher than ResNet50 (93.12%), DenseNet121 (94.31%), and VGG16 (91.85%). Precision, recall, and F1-score followed a similar trend, indicating that the model can correctly identify pneumonia cases while minimizing false positives and false negatives. The AUC-ROC curve analysis further confirmed that the proposed model has a superior discriminative ability between Normal and Pneumonia classes, reflecting improved sensitivity and specificity.

The improvement in performance is attributed to the attention mechanism, which allows the network to focus on the most relevant regions of the lungs, and the pre-trained feature extractor, which captures complex patterns efficiently. Loss and accuracy curves indicate smooth convergence during training, and early stopping prevented overfitting, demonstrating that the model generalizes well to unseen data.

Visual inspection using Grad-CAM and attention maps showed that the model accurately highlights infected regions, providing explainability and potential clinical interpretability for radiologists. Overall, the results validate the effectiveness of combining transfer learning with attention mechanisms for pneumonia detection.

7. CONCLUSION

This study presents a deep learning approach for pneumonia detection that integrates transfer learning with an attention mechanism. The proposed model achieved high accuracy, precision, recall, F1-score, and AUC on chest X-ray images, outperforming conventional transfer learning models. The attention module improves the model's ability to focus on infected regions, enhancing feature extraction and diagnostic performance. The results indicate that the model is reliable, efficient, and has potential applications in computer-aided diagnosis for early detection of pneumonia.

8. FURTHER RESEARCH

Future research can focus on extending the proposed model to support multi-class classification. This would enable it to distinguish not only between normal and pneumonia cases but also between bacterial and viral pneumonia, allowing for more precise diagnosis and treatment planning. Another promising direction is the integration of multiple imaging modalities, such as combining chest X-rays with CT or MRI scans, which could further improve the accuracy and reliability of pneumonia detection.

Developing lightweight versions of the model suitable for deployment on mobile devices or in low-resource clinical environments is another important area, as it would allow broader accessibility and faster diagnosis in remote or under-equipped healthcare facilities. Enhancing explainable AI techniques is also crucial, as advanced attention modules or transformer-based architectures could provide better interpretability, helping clinicians understand the reasoning behind the model's predictions. Additionally, large-scale clinical validation across multiple centers is necessary to ensure the robustness and generalization of the model across diverse patient populations and imaging devices. Finally, implementing real-time inference pipelines could enable automated pneumonia detection in hospital systems or telemedicine applications, facilitating early intervention and improved patient outcomes.

REFERENCES

[1] D. Li, "Attention-enhanced architecture for improved pneumonia detection in chest X-ray images," BMC Medical Imaging, vol. 24, no. 6, 2024.

[2] S. Potharaju, "Enhanced X-ray image classification for pneumonia detection using advanced attention mechanisms," Computer Methods and Programs in Biomedicine, vol. 145, 2025.

[3] F. Alshanketi, "Pneumonia detection from chest X-ray images using deep learning models," Journal of Medical Systems, vol. 48, no. 3, 2024.

[4] S. Singh, "Efficient pneumonia detection using Vision Transformers on chest X-ray images," Scientific Reports, vol. 14, no. 5, 2024.

[5] Y. Xie, "Diagnosis of pneumonia from chest X-ray images using deep learning approaches," Frontiers in Neurorobotics, vol. 19, 2025.

[6]

[7] T. A. Pham, "Chest X-ray image classification using transfer learning with deep convolutional neural networks," Journal of Medical Imaging and Health Informatics, vol. 14, no. 2, pp. 231–239, 2024.

[8] B. Oltu, "Automated classification of chest X-rays: a deep learning approach," BMC Medical Imaging, vol. 25, no. 16, 2025.

[9] L. Wu, "Pneumonia detection based on RSNA dataset and anchor-based deep learning models," Scientific Reports, vol. 14, no. 9, 2024.

[10] J. Stubblefield, "Transfer learning with chest X-rays for ER patient diagnosis," Scientific Reports, vol. 10, no. 12345, 2020.

[11] Y. Han, "Pneumonia detection on chest X-ray using contrastive learning," PLoS ONE, vol. 16, no. 5, 2021.

[12] P. Rajesh and V. Govindarasu, "Analyzing and predicting COVID-19 dataset in India using data mining with regression analysis," International Research Journal on Advanced Science Hub, vol. 3, pp. 91–95, 2021.

[13] N. Rajpurkar, "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," Proceedings of the Conference on Neural Information Processing Systems (NeurIPS), 2017.

[14] A. Das, "An ensemble-based approach for pneumonia detection using deep transfer learning," Biomedical Signal Processing and Control, vol. 86, 2024.

[15] M. Zhang, "Hybrid CNN and attention model for pneumonia classification," Computers in Biology and Medicine, vol. 162, 2024.

[16] H. Chen, "Lightweight CNN model for pneumonia detection using X-ray images," IEEE Access, vol. 12, pp. 44520–44531, 2024.

[17] R. Kumar, "Transfer learning-based deep convolutional neural network for pneumonia detection," International Journal of Imaging Systems and Technology, vol. 35, no. 1, pp. 87–95, 2025.

[18] P. Reddy, "Attention-guided residual network for pneumonia classification in chest X-rays," Pattern Recognition Letters, vol. 179, pp. 95–102, 2025.

[19] L. Ahmed, "Deep learning-based pneumonia detection using DenseNet and Grad-CAM visualization," Expert Systems with Applications, vol. 238, 2024.

[20] C. Zhao, "Self-attention CNN for accurate pneumonia detection in chest radiographs," Artificial Intelligence in Medicine, vol. 156, 2024.

[21] P. Rajesh and M. Karthikeyan, "A comparative study of data mining algorithms for decision tree approaches using Weka tool," Advances in Natural and Applied Sciences, vol. 11, no. 9, pp. 230–243, 2017.

[22] N. Ravi and P. Rajesh, "A study on data analysis and prediction of diabetes using machine learning models," Journal of Chemical Health Risks, vol. 13, no. 4, pp. 2034–2042, 2023.

[23] J. Gupta, "Multi-scale feature extraction with attention for pneumonia detection," IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 2, pp. 175–182, 2025.

[24] R. Verma, "Performance analysis of transfer learning models for chest X-ray pneumonia detection," International Journal of Computer Applications in Technology, vol. 71, no. 4, pp. 321–330, 2024.

[25] G. K. Arun and P. Rajesh, "A study on variable selections and prediction for diabetes pregnancy dataset using data mining with machine learning approaches," Journal of Advanced Zoology, vol. 44, no. 3, pp. 949–957, 2023.

[26] D. Kermany, K. Zhang, and M. Goldbaum, "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification," Cell, vol. 172, no. 5, pp. 1122–1131, 2018.

[27] P. Mooney, "Chest X-Ray Images (Pneumonia)," Kaggle, 2018. [Online]. Available: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia