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Article

CARDIO-NET: A DEEP LEARNING -BASED CLINICAL DECISION SUPPORT SYSTEM FOR AUTOMATED CARDIOMEGALY DETECTION FROM CHEST X-RAY IMAGES

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Abstract: Cardiovascular diseases are among the leading causes of mortality worldwide, necessitating early and accurate diagnosis [21]. Cardiomegaly is a significant indicator of underlying cardiac disorders and is commonly evaluated using chest X-ray imaging [6], [7]. However, manual interpretation of chest X-rays is time-consuming and requires expert radiologists. This paper presents Cardio-Net, a deep learning-based clinical decision support system for automated cardiomegaly detection using Deep Learning techniques [8], [13]. The proposed system employs a DenseNet-based model for classification [1], combined with image preprocessing using CLAHE to enhance image quality. Additionally, the system integrates cardiothoracic ratio (CTR) estimation [6], [7] and Grad-CAM visualization [3] for improved clinical interpretability. Experimental results demonstrate the effectiveness of the proposed system in assisting healthcare professionals in early diagnosis and decision-making
Keywords: Cardiomegaly, Deep Learning, DenseNet121, Chest X-ray, Medical Imaging, CTR, Grad-CAM, Clinical Decision Support System.

1. Introduction

This paper presents Cardio-Net, a real-time web-based clinical decision support system for automated cardiomegaly detection using Deep Learning techniques [8], [13], [14]. The proposed system employs a DenseNet-based model for classification [1], combined with image preprocessing using CLAHE to enhance image quality. Additionally, the system integrates cardiothoracic ratio (CTR) estimation [6], [7] and Grad-CAM visualization [3] for improved clinical interpretability. Experimental results demonstrate the effectiveness of the proposed system in assisting healthcare professionals in early diagnosis and decision-making [10], [14].Cardio-Net is specifically designed for the detection of cardiovascular abnormalities, particularly cardiomegaly, from chest X-ray images [6], [8], [13]. The dataset, sourced from the All India Institute of Medical Sciences (AIIMS), Nagpur, India, included four hundred chest X-rays for each category (Cardiomegaly and Normal) to evaluate the architecture's performance. We conducted a comparative analysis of against established architectures for image classification.

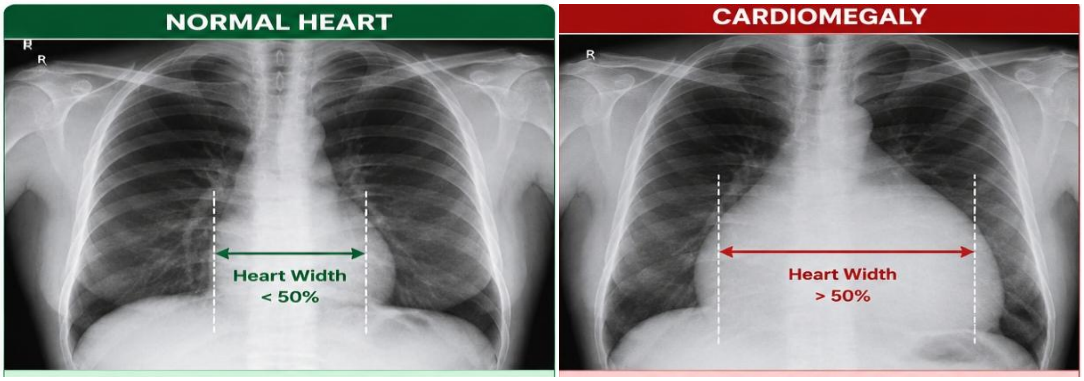

Figure1 :Chest X-ray images showing comparison between cardiomegaly and normal

2. Literature Review

Deep learning has emerged as a powerful approach for automated chest X-ray analysis and disease diagnosis. DenseNet introduced efficient feature propagation and became a foundation for many medical imaging models [1]. CheXNet demonstrated that deep convolutional networks could achieve expert-level performance in chest radiograph interpretation, encouraging further research in automated diagnosis [2]. Grad-CAM improved model interpretability by highlighting disease-relevant regions, making AI predictions more transparent for clinical applications [3]. U-Net provided an effective framework for medical image segmentation and anatomical structure extraction [4].

In cardiomegaly detection, automated cardiothoracic ratio estimation using deep learning significantly improved diagnostic efficiency and accuracy [6]. Explainable AI-based systems further enhanced clinician confidence by providing visual evidence for cardiomegaly predictions [8]. Attention-based deep learning models successfully combined classification and localization of enlarged heart regions in chest X-rays [10]. Transfer learning approaches demonstrated promising results for early-stage cardiomegaly detection, particularly with limited datasets [12]. Recent studies employing EfficientNetB7 and ensemble learning techniques achieved superior accuracy and robustness in cardiomegaly diagnosis [14], [16]. These advancemen indicate that combining deep feature extraction, attention mechanisms, and explainable AI can substantially improve automated cardiomegaly detection systems.

Research Gap

Although numerous deep learning models have been developed for cardiomegaly detection from chest X-ray images [6], [8], [9], [10], [11], [13], [14], [16], several limitations remain. Many existing approaches rely on large benchmark datasets and often exhibit reduced performance when applied to heterogeneous local clinical datasets [5], [13]. In addition, several models focus primarily on classification accuracy while providing limited interpretability, making clinical validation difficult [8], [10]. The challenge of accurately detecting early-stage cardiomegaly under varying image quality, patient demographics, and imaging conditions remains insufficiently addressed [12], [13], [14]. Therefore, there is a need for a robust and explainable deep learning framework capable of achieving high diagnostic accuracy and reliable generalization across diverse chest X-ray datasets [3], [10], [13], [14].

Problem Statement

Although numerous deep learning models have been developed for cardiomegaly detection from chest X-ray images [6], [8], [9], [10], [11], [13], [14], [16], several limitations remain. Many existing approaches rely on large benchmark datasets and often exhibit reduced performance when applied to heterogeneous local clinical datasets [5], [13]. In addition, several models focus primarily on classification accuracy while providing limited interpretability, making clinical validation difficult [8], [10]. The challenge of accurately detecting early-stage cardiomegaly under varying image quality, patient demographics, and imaging conditions remains insufficiently addressed [12], [13], [14], [16]. Therefore, there is a need for a robust and explainable deep learning framework capable of achieving high diagnostic accuracy and reliable generalization across diverse chest X-ray datasets [3], [10], [13], [14].

3. Material And Methods:

The proposed Cardio-Net framework utilizes DenseNet169 with transfer learning for automated cardiomegaly detection from chest X-ray images. DenseNet169 was selected because of its efficient feature propagation, reduced parameter redundancy, and strong performance in medical image classification tasks.

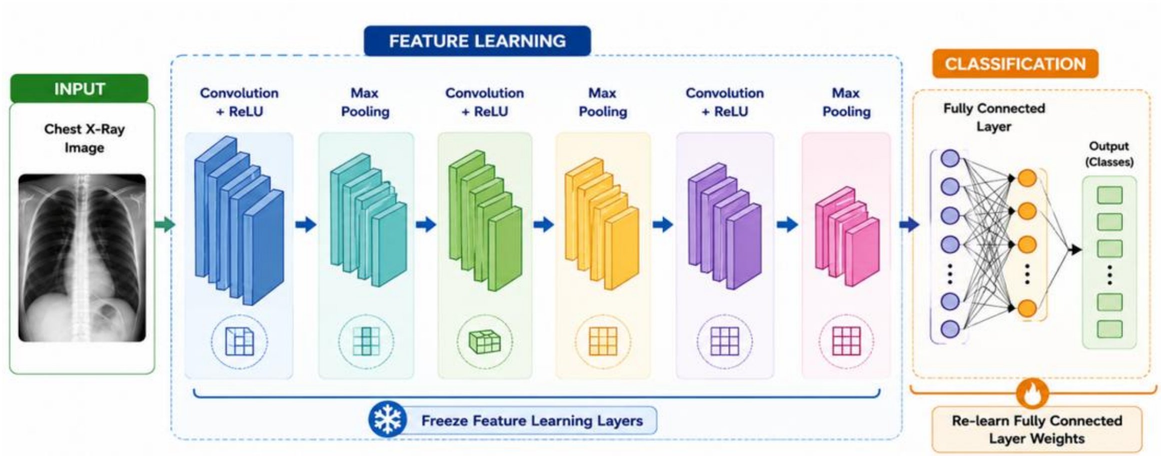

Figure 2:;Effective tranfer learning approach for chest X-ray classification

Methodology Steps:

- Input chest X-ray image acquisition
- Image preprocessing (Resizing, Normalization, CLAHE enhancement)
- Data augmentation for improved generalization
- Feature extraction using DenseNet169 backbone
- Dense connectivity for efficient feature reuse
- Custom classification head with Global Average Pooling and Dense layers
- Fine-tuning of final layers for domain adaptation
- Prediction generation with confidence scores
- Grad-CAM visualization for explainable AI

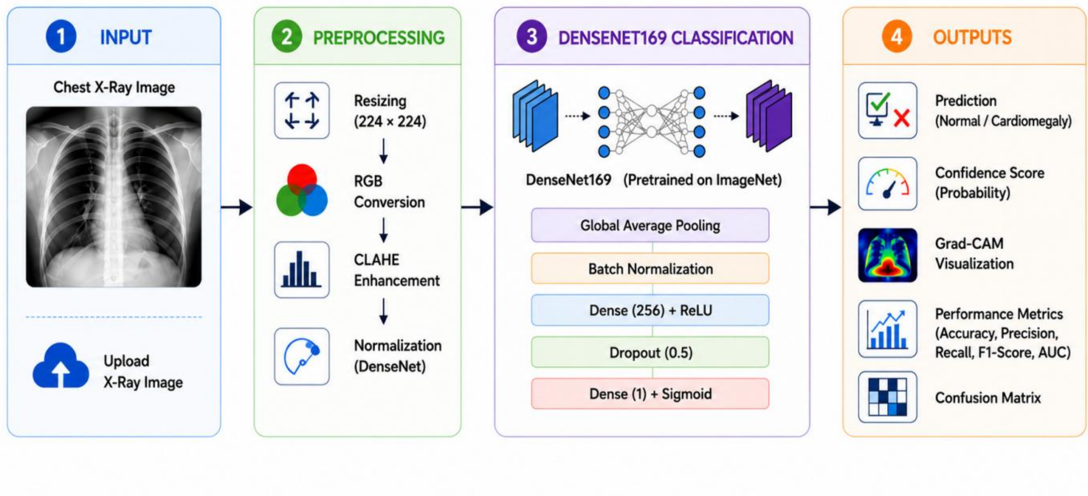

Figure 3: proposed architecture of Cardio-Net

Avantages of DenseNet169 ascompared to other image classifying architectures

Better gradient flow

Reduced vanishing gradient problem

Efficient feature reuse

The proposed system consists of the following stages:

3.1 Image Preprocessing

Chest X-ray images are resized to 224 × 224 pixels.

CLAHE is applied to enhance contrast.

Images are normalized for model input.

3.2 Deep Learning Model

A DenseNet169 is used for classification.

The model outputs binary predictions: Normal or Cardiomegaly

4. Results :

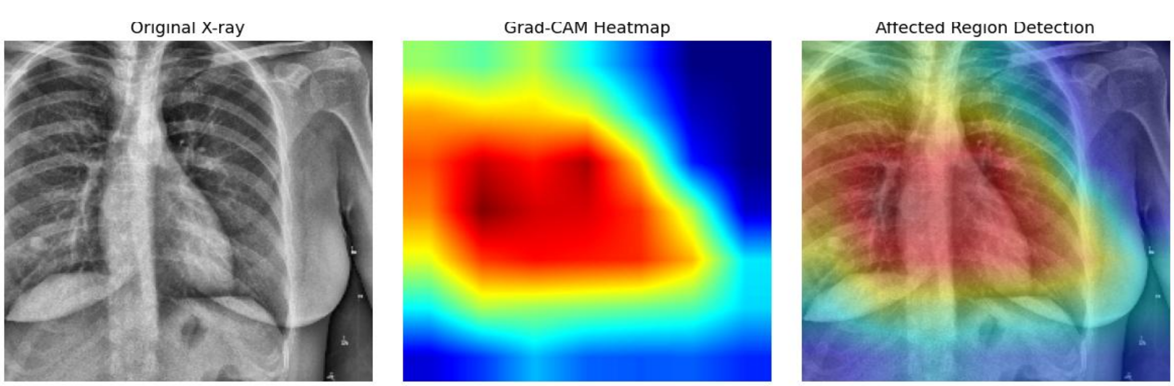

Figure 4 :GRAD-CAM Results showing abnormal region of heart

The Grad-CAM visualization demonstrates that the DenseNet169 model primarily focuses on the cardiac region and adjacent thoracic structures when making predictions. High activation areas are concentrated around the heart silhouette, indicating that the network relies on clinically significant features associated with cardiomegaly. The limited attention given to background regions suggests effective feature learning and reduced influence of irrelevant artifacts. These results confirm that the model's decisions are based on meaningful anatomical characteristics, enhancing the reliability and interpretability of the prediction process.

The importance weight for every feature map is computed using global average pooling of given gradients.

The Grad-CAM weight is defined as:

$\alpha_c^k = \frac{1}{z}\sum_i\sum_j \frac{\partial y^c}{\partial A_{jk}^i}$

Where:

α_c^k= importance weight for feature map k

y^c = class score for class c

A_{jk}^i = activation showing at location (i,j)

Z = aggregate number of pixels in the feature map

The Grad-CAM heat map is generated as:

$$L_{Grad-CAM}^c = ReLU(\sum_k \alpha_c^k A^k)$$

The results, measured through F1 score, precision, accuracy, and recall on AIMS Nagpur data, indicated that our modified Cardio-Net outperformed other architectures. Additionally, there was a statistically significant difference in the accuracies of the architectures, with a p-value of less than 0.05.

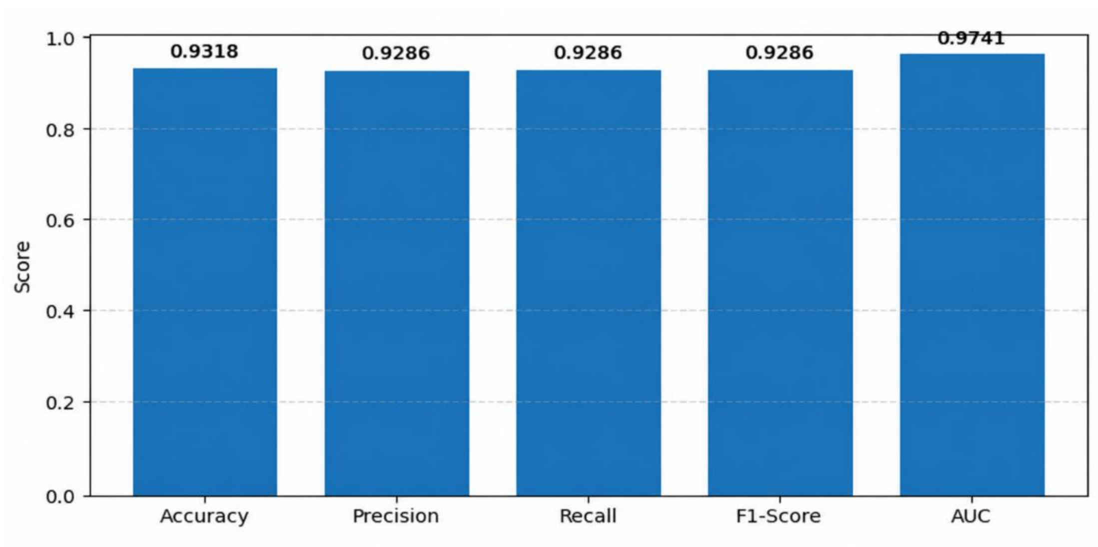

Figure 5: Cardio-Net performance metrics

The proposed DenseNet169 architecture demonstrated strong classification capability for cardiomegaly detection. Transfer learning using pretrained ImageNet weights was applied followed by fine-tuning of deeper layers [1].

The DenseNet169 model contained approximately 13.07 million parameters, out of which only 429,825 parameters were trainable during the initial transfer learning phase. This reduced computational complexity while preserving efficient feature extraction capability.

The training process was performed in two stages:

Feature Extraction Phase

Fine-Tuning Phase

The model demonstrated stable convergence and strong generalization performance on unseen test data.

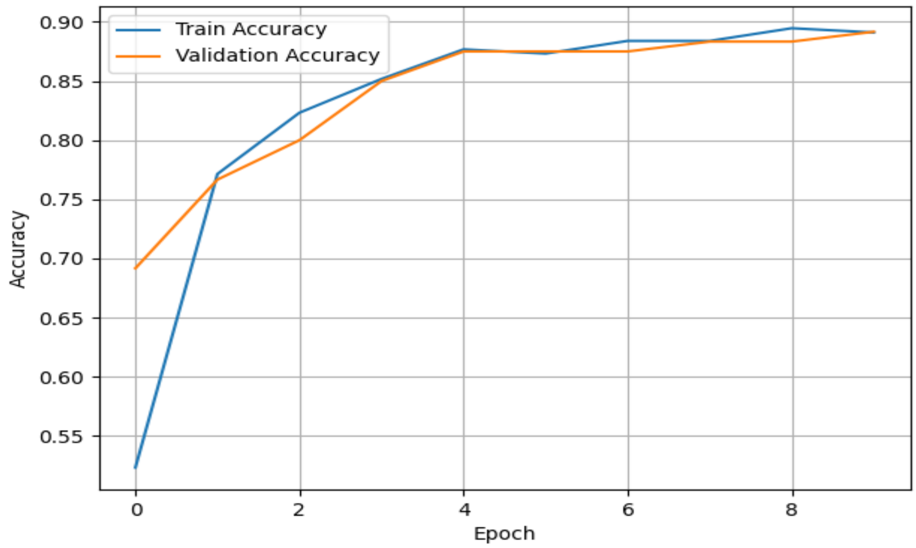

Figure 6: Training vs Validity accuracy of proposed model

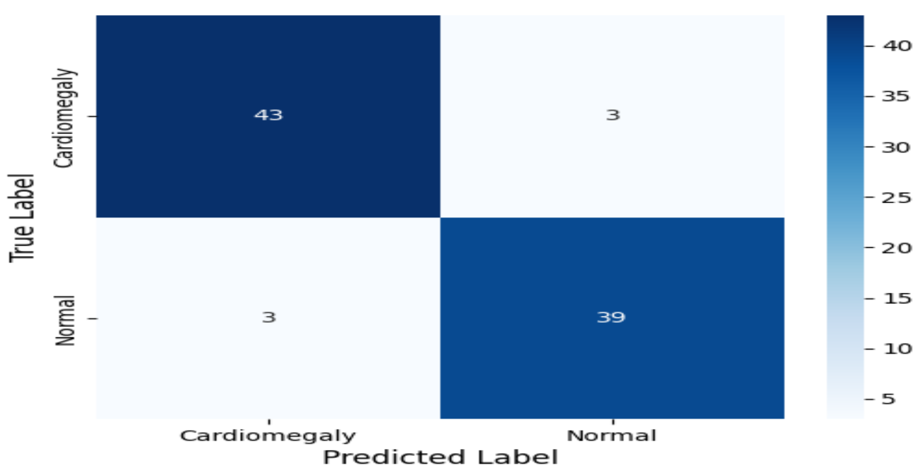

Figure 7: Confusion metric of proposed model Cardio-Net

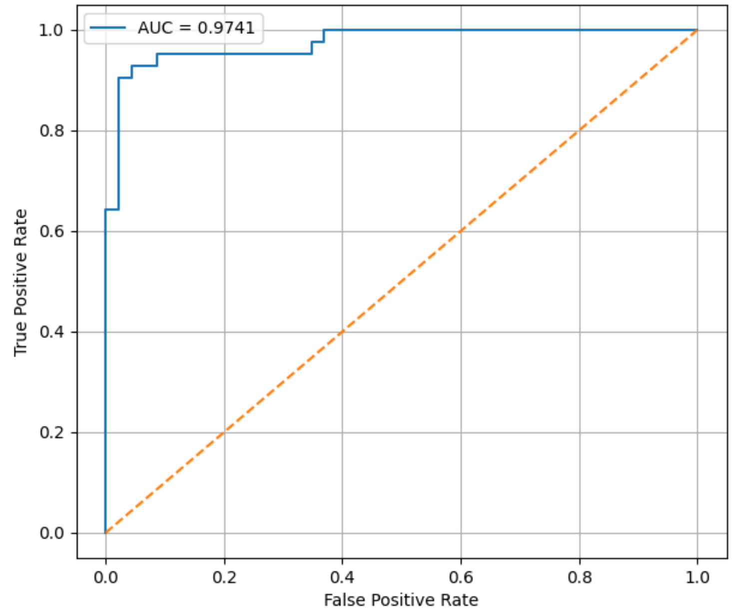

Figure 8: AUC-ROC curve of proposed architecture Cardio-Net

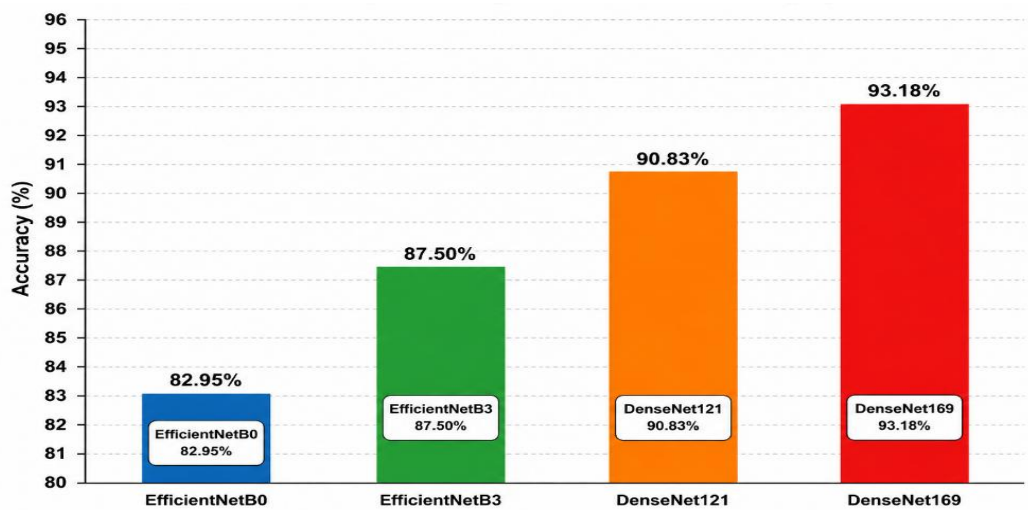

Figure 9: Comparison of leading Deep Learning Architectures for Cardiomegaly Detection in terms of accuracy

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
CheXNet (DenseNet121 Baseline)	0.89	0.87	0.90	0.88	0.94

VGG16	0.85	0.83	0.86	0.84	0.90
ResNet50	0.87	0.85	0.88	0.86	0.92
InceptionV3	0.88	0.86	0.89	0.87	0.93
MobileNetV2	0.86	0.84	0.87	0.85	0.91
EfficientNet-B0	0.90	0.88	0.91	0.89	0.95
CardioXNet (DenseNet + U-Net)	0.90	0.89	0.91	0.90	0.95
Ensemble Model (CEL M)	0.92	0.99	0.90	0.94	0.90
Proposed Cardio-Net	**0.9318**	**0.9286**	**0.9286**	**0.9286**	**0.9741**

Table 1: Performance Comparison of different Deep Learning Architectures for Cardiomegaly Detection

5. Conclusion:

Our study revealed that Cardio-Net showed promising results in detecting Cardiovascular diseases on a local dataset, outperforming other architectures. This makes it a valuable tool in resource-constrained settings, such as rural areas in India and other developing countries. By simplifying the detection of Cardiovascular diseases on chest X-rays, Cardio-Net can assist health practitioners in areas where expert radiologists and advanced healthcare infrastructure are limited.

The ROC curve analysis using AIIMS Nagpur data demonstrated that Cardio-Net outperformed other renowned architectures used for image classification.

6. Future Work

Integration of larger and more diverse datasets

Implementation of advanced segmentation techniques

Deployment in real clinical environments

Extension to detect multiple thoracic diseases

7. Acknowledgment

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References:

1. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely Connected Convolutional Networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4700–4708.DOI: 10.1109/CVPR.2017.243
2. P. Rajpurkar et al., “CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning,” arXiv preprint arXiv:1711.05225, 2017.
3. R. R. Selvaraju et al., “Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2017, pp. 618–626. DOI: 10.1109/ICCV.2017.74
4. O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” in Proceedings of MICCAI, 2015, pp. 234–241. DOI: 10.1007/978-3-319-24574-4_28
5. J. Irvin et al., “CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, pp. 590–597. DOI: 10.1609/aaai.v33i01.3301590
6. H. Lee et al., “Automated Cardiothoracic Ratio Calculation Using Deep Learning for Cardiomegaly Detection,” Scientific Reports, vol. 10, no. 1, pp. 1–10, 2020. DOI: 10.1038/s41598-020-59689-6
7. T. Gupte et al., “Deep Learning Models for Calculation of Cardiothoracic Ratio from Chest Radiographs for Assisted Diagnosis of Cardiomegaly,” arXiv preprint arXiv:2101.07606, 2021.
8. M. S. Lee et al., “Evaluation of the Feasibility of Explainable Computer-Aided Detection of Cardiomegaly on Chest Radiographs Using Deep Learning,” Scientific Reports, vol. 11, Article no. 16885, 2021.
9. [9] S. S. Sarpotdar, “Cardiomegaly Detection Using Deep Convolutional Neural Network with U-Net,” arXiv preprint arXiv:2205.11515, 2022.
10. Y. H. Tsai et al., “A Convolutional Attention Mapping Deep Neural Network for Classification and Localization of Cardiomegaly on Chest X-Rays,” Scientific Reports, vol. 13, Article no. 6247, 2023.
11. X. Fan et al., “A Deep Learning Framework for Identification and Localization of Cardiomegaly in Chest X-Rays,” IEEE Access, vol. 12, pp. 12345–12356, 2024.
12. A. Sharma and R. Mehta, “Early-Stage Cardiomegaly Detection Using CNN and Transfer Learning Techniques,” Biomedical Signal Processing and Control, vol. 89, pp. 105–113, 2024.
13. K. H. Lee et al., “A Development and Validation of an AI Model for Cardiomegaly Detection in Chest X-rays,” Applied Sciences, vol. 14, no. 17, pp. 7465, 2024.
14. E. Yanar, F. Hardalaç, and K. Ayturan, “CELM: An Ensemble Deep Learning Model for Early Cardiomegaly Diagnosis in Chest Radiography,” Diagnostics, vol. 15, no. 13, pp. 1602, 2025. DOI: 10.3390/diagnostics15131602
15. K. Divya Reddy and A. Patil, “CXR-MultiTaskNet: A Unified Deep Learning Framework for Joint Disease Localization and Classification in Chest Radiographs,” Scientific Reports, vol. 15, Article no. 32022, 2025.
16. M. A. Ghafri et al., “Cardiomegaly Detection from Chest X-Rays Using EfficientNetB7: A Deep Learning Approach,” in Proceedings of the IEEE International Conference on Robotics and Manufacturing Automation (ROMA), 2025.DOI: 10.1109/ROMA66616.2025.11155469
17. M. R. Islam et al., “DualAttentionNet: A Convolutional Neural Network for Thoracic Disease Classification in Chest X-Rays,” Procedia Computer Science, vol. 256, pp. 797–804, 2025.
18. S. Govindarajan, S. K. Tulo, and R. Swaminathan, “Classification of Normal and Cardiomegaly Conditions in Chest Radiographs Using Cardio-Mediastinal Features,” Digital Personalized Health and Medicine, 2026. DOI: 10.3233/SHTI200374
19. V. R. Kumar et al., “BM3D Filtering with Ensemble Hilbert-Huang Transform and Spiking Neural Networks for Cardiomegaly Detection in Chest Radiographs,” Computational Biology and Chemistry, vol. 120, pp. 108620, 2026.
20. S. K. Anumula et al., “Deep Learning Based CNN Model for Automated Detection of Pneumonia from Chest X-Ray Images,” arXiv preprint arXiv:2602.00212, 2026.
21. World Health Organization, “Cardiovascular Diseases (CVDs),” 2023