Survey On Techniques For Cardiomegaly Prediction By Chest X-ray Images

Dena Ahmed Mohammed Hussein
College of Science for Women,
University of Babylon,
Babylon, Iraq
dina.hussein.gsci107@student.uobabylon.edu.iq
Orcid.org/0009-0004-1509-6778

Enas Hamood Al Saadi
College of Education for pure science,
University of Babylon,
Babylon, Iraq
pure.anas.ehmod@uobabylon.edu.iq
Orcid.org/0000-0002-1276-9605

DOI: http://dx.doi.org/10.31642/JoKMC/2018/100207

Received Mar. 18, 2023. Accepted for publication Jul. 14, 2023

Abstract-*Cardiomegaly is a condition characterized by an enlarged heart, which can be indicative of various underlying health issues. Early diagnosis of this condition lessens the patient's repercussions. The paper gives a thorough overview of the disease, its classifications, algorithms, and methods employed emphasizing the challenges encountered in this field. Traditional methods of diagnosing cardiomegaly rely on medical imaging techniques such as echocardiography or chest X-rays, which can be time-consuming and require specialized expertise to interpret. However, recent advances in deep learning algorithms have shown promise in accurately identifying cardiomegaly and its underlying causes from medical images. The use of deep learning algorithms in the diagnosis of cardiomegaly has the potential to improve both the speed and accuracy of diagnosis, leading to better patient outcomes and more efficient use of healthcare resources. Moreover, deep learning algorithms can potentially identify subtle changes in heart size over time, allowing for earlier detection and treatment of cardiomegaly.*

Keywords— Cardiomegaly, Deep Learning, Chest x-ray, Convolution Neural Network,CTR

I. INTRODUCTION

The heart is a crucial organ in the human body, and its malfunctioning can adversely impact other vital organs such as the brain and kidneys. The heart serves as a pump, circulating blood throughout the body, and cessation of its beating can result in death within minutes [1]. Figure 1 shows an image of a person with a normal heart and an image of a person with an enlarged heart.

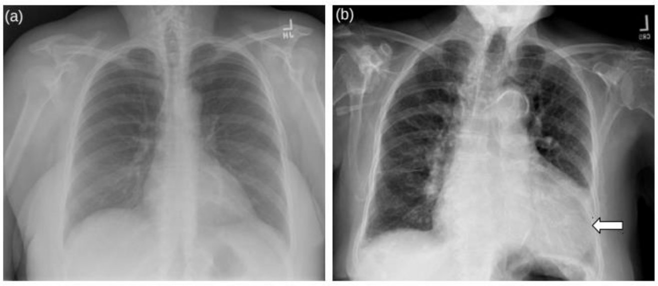

Fig.1. Presents chest X-ray (CXR) images of (a) a normal subject and (b) a patient diagnosed with cardiomegaly.

Diagnosis of cardiac abnormalities often involves a series of tests. Chest X-rays are a common imaging modality used to assess cardiomegaly due to their availability and low cost; radiologists typically use cardiothoracic ratio (CTR) values on anteroposterior chest radiographs. the cardiothoracic ratio (CTR) is a straightforward indicator used in clinical applications to assess the size of the heart during the manual examination, including under typical conditions (CTR between 0.42 and 0.50), mild to moderate cardiomegaly (CTR between 0.50 and 0.60), and severe cardiomegaly (CTR over 0.60)[2], These cases are shown in Figure 2, CTR can be estimated using three distinct methods:[3]

MRD: represents the width of the space between the right heart and midline.

MLD: stands for the left midline diameter of the heart.

ID: represents the chest's internal diameter.

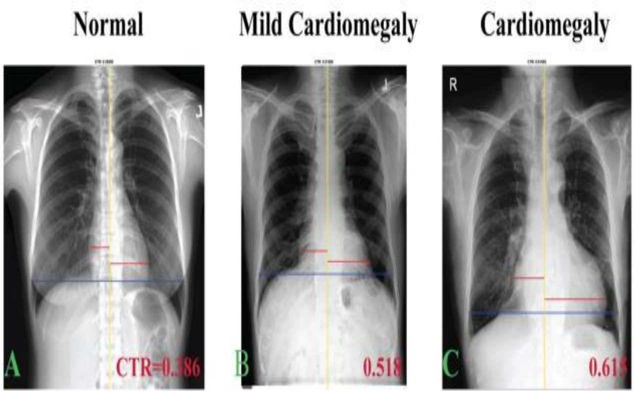

Fig.2. Shows cases of heart enlargement.

On the other hand, this manual technique requires a significant amount of time, and the results of the diagnosis are contingent on the reader's views and previous experience. However, the manual marking of organ boundaries and the computation of CTR are time- and labor-intensive processes that may lead to errors. Recent advances in computer vision techniques and machine learning, specifically Deep learning, are a subset of machine learning that uses artificial neural networks to learn patterns and features in large datasets [4]. These algorithms can be trained on labeled medical images to automatically detect features indicative of cardiomegaly and classify images based on the underlying cause, showing potential for automating the identification of cardiac abnormalities in X-ray images [5].

This paper aims to utilize deep learning concepts such as convolutional neural networks(pre-processing the chest x-ray, creating a mask, diagnosing disease), and they were able to achieve successful predictions of this condition. These effective techniques demonstrate the potential of deep learning algorithms in medical image analysis for accurate and efficient detection of cardiomegaly and its underlying causes, as well as discuss the potential benefits and limitations of this approach.

II.CHALLENGES FOR CARDIMEGALY DETECION

The detection of cardiomegaly poses several challenges, primarily due to the variability in the presentation of cardiac enlargement and the potential overlap with other pulmonary and cardiac pathologies. Additionally, detecting the early stages of cardiomegaly, when the heart is only slightly enlarged, can be particularly challenging and requires highly sensitive and specific imaging techniques. Furthermore, the interpretation of cardiac imaging requires specialized training and experience, as the subtleties of cardiac anatomy and function can be complex. These challenges highlight the importance of developing accurate and reliable methods for the detection of cardiomegaly, which can aid in the timely diagnosis and treatment of this serious cardiac condition [6].

III.TYPE OF CARDIOMEGALY DATASET

The ChestX-ray14 dataset and the NIH Chest X-ray dataset are two frequently employed datasets for detecting cardiomegaly, containing more than 100,000 frontal-view chest radiographs obtained from over 30,000 patients, including those with cardiomegaly. Additionally, the Shenzhen and Montgomery County (MC) datasets, composed of chest radiographs obtained from tuberculosis screening programs, are other publicly available datasets utilized for identifying cardiomegaly. These datasets have been leveraged in numerous research endeavors to develop and validate machine-learning models for the detection of cardiomegaly, with the ultimate objective of improving diagnostic accuracy and patient outcomes [7].

In preparation for inputting a deep learning network with a dataset, it is necessary to standardize the chest X-ray images. Given that the images originate from diverse medical facilities and were captured using varying equipment, histogram equalization is employed to ensure consistency across all images. To effectuate modifications of individual pixel values, the following approach is recommended:

$$g_{i,j} = \left\lfloor (L-1) \sum_{n=0}^{f_{i,j}} p_n \right\rfloor, \qquad (1)$$

where L represents the picture's greatest intensity, gi,j represents the density of the output at location (i,j), fi,j represents the density of the original image at position (i,j), pn represents the percentage of pixels that have density n, and L represents the total number of pixels[8].

IV.CARDIOMEGALY DETECTION TECHNIQUES

Medical imaging systems aid in the detection and treatment of diseases by providing a wealth of information that can be automatically and accurately analyzed using algorithms and computer technologies[9].This automated analysis eliminates the need for manual intervention in the diagnostic process. To obtain medical images, specialized medical equipment must be utilized instead of a conventional digital camera. The techniques employed in disease detection systems can be classified into two categories: machine learning, which requires comparatively less data and time, but may yield less accurate results that sometimes require manual intervention; and deep learning, which relies on artificial intelligence principles and necessitates a larger quantity of data over an extended period of time but can achieve higher accuracy. The acquisition of a database is an essential and imperative component of the diagnostic process. Figures 3 and 4 demonstrate the most essential approaches utilized in these domains, according to the charts below:

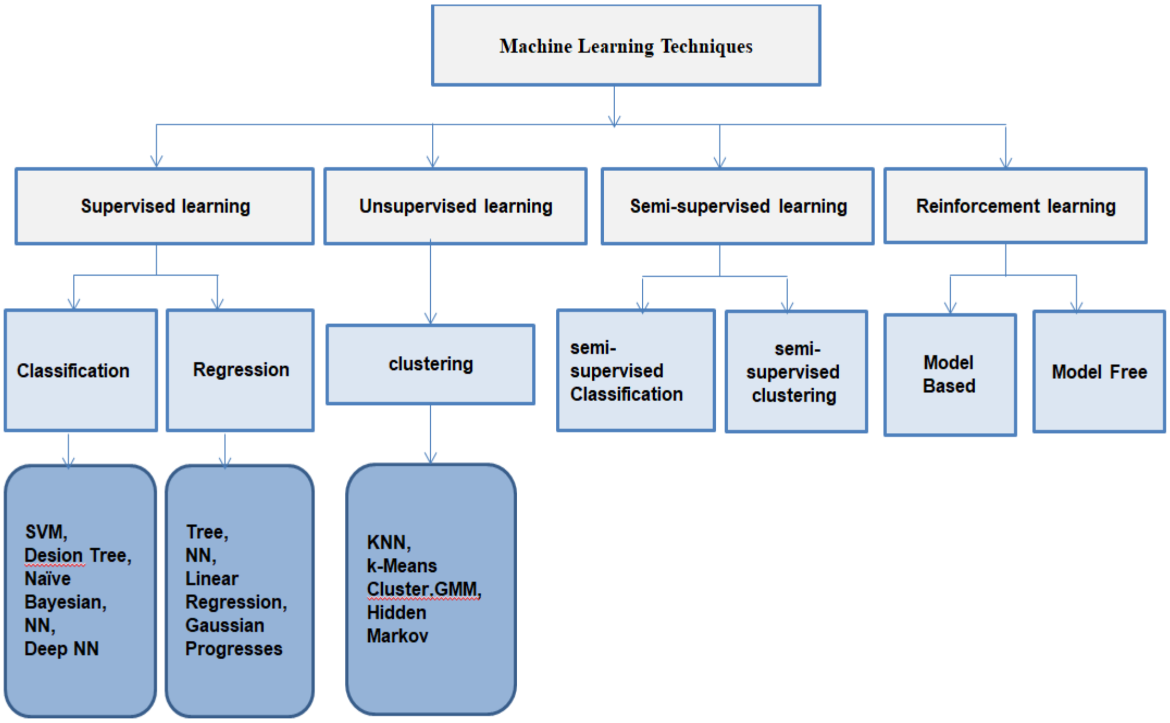

Fig.3.Machine Learning Techniqes

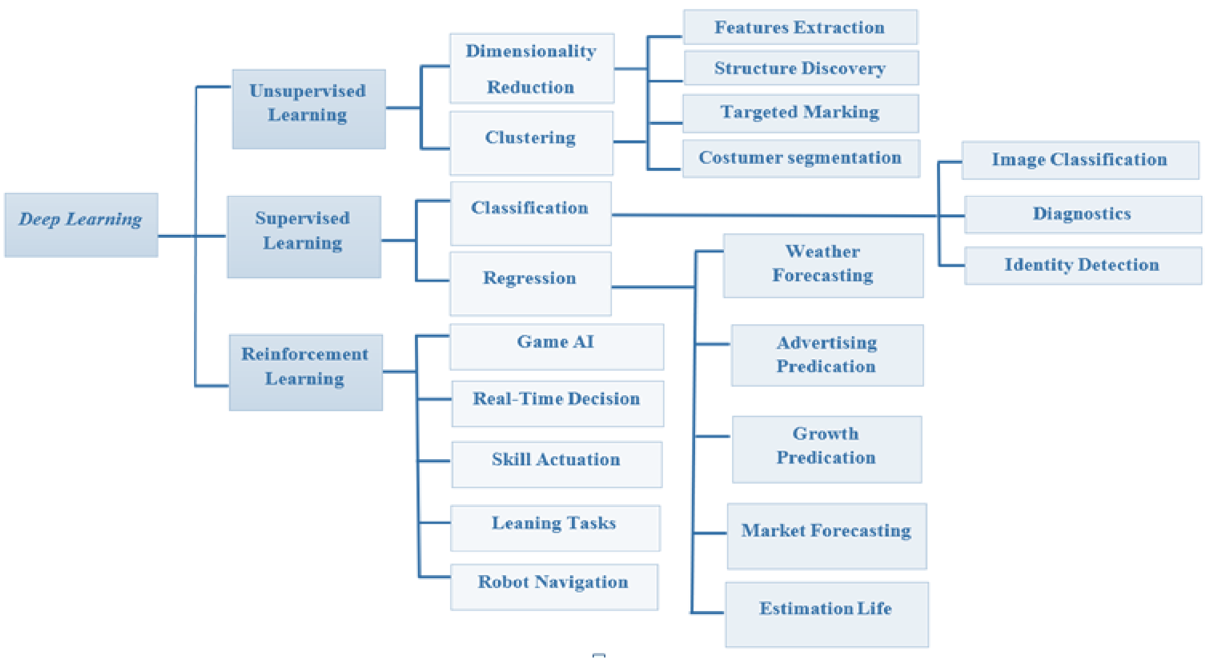

Fig.4.Deep Learning Techniqes.

V. CARDIOMEGALY DETEECTION SYSTEM

There are many comprehensive summaries of prior research provided, Table I highlights the most recent advancements employed in the early detection of cardiomegaly. Additionally, Figure 6 illustrates the typical workflow followed by diagnostic systems,which involves a series of steps encompassing thorough image processing, as depicted in the accompanying diagram. The process is organized into three distinct stages, outlined as follows:

1. **First Stage(Pre-processing):**The initial stage involves preparing the input image by resizing it, enhancing and eliminating any noise present. Medical imaging devices often introduce noise, which can impede accurate disease diagnosis. Hence, it is essential to purify the image by addressing issues such as noise, uneven lighting, blurring, and other distortions. Numerous techniques are available for improving the input image quality, such as spatial or frequency filters.

2. **Second Stage (Mask Creation):** In the biomedical domain, where labeled data is often limited, developing a supervised learning system capable of effectively extracting specific details from large datasets can be challenging. This challenge is particularly prominent in the biomedical field, where the manual creation of unique masks and precise localization of diseases in each image is typically required. This stage involves identifying pixels within each image that correspond to regions affected by the disease and utilizing them to generate a new image of identical dimensions to the original. As shown in Figure 5. It should be noted that extensive medical expertise may not always be necessary for identifying the disease area, as conditions like cardiomegaly can be diagnosed by observing significant thickening, which forms the basis of the diagnosis.

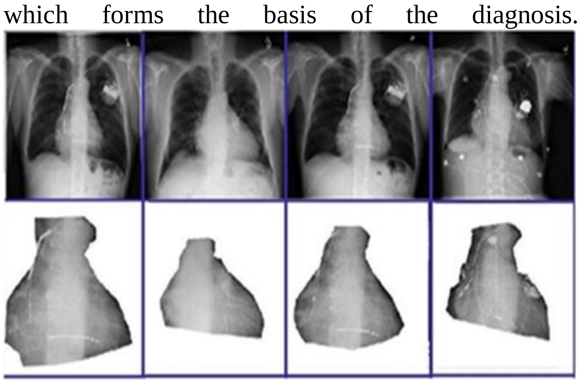

Fig.5. Depicts four manually created masks for cardiomegaly localization

3. **Third Stage (Cardiomegaly Diagnosis):** Once a mask of the cardiomegaly chest X-ray image has been created, and the affected area has been localized, the next step is diagnosing cardiomegaly.

4. This is achieved by training various data samples using chest X-ray images and developing a model capable of automatically diagnosing test data. Deep learning and machine learning algorithms are commonly employed for this purpose.

In summary, a cardiomegaly detection system incorporates image processing techniques and machine learning algorithms to facilitate the early identification and diagnosis of an enlarged heart.With the ultimate goal of assisting healthcare professionals in accurate and efficient detection of the condition.

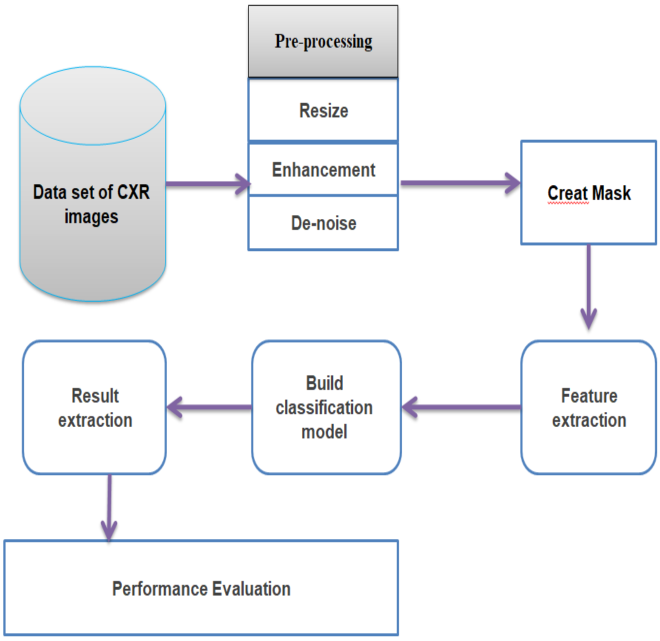

Fig. 6 .Flowchart of cardiomegaly detection system

Table I: Illustrated Several Technologies Used in Cardiomegaly Detection.

Author	Techniques	Dataset	Performance		
			Accuracy (%)	*Sensitivity (%)*	*Specificity (%)*
Haralabos Bougias, et al.[10]	VGG19	Chest x-ray images from PACS	84,5	84	83
	VGG16			81	81
	SqueezeNet			80	80
	InceptionV3			64,1	77,1
Isarun Chamveha, et al.[8]	U-Net with VGG16 encoder	NIH	67.1	0.81	0.69
		CheXpert	69.8	0.69	0.70
Diego A. Cardona Cardenas, et al.[11]	EfficientNet, ,	PadChest,OpenI-NIH	0.910	0.760	0.945
	MobileNet		0.901	0.822	0.919
	InceptionNet		0.886	0.869	0.890
Abdelilah Bouslama, et al.[12]	U-Net	ChestX-ray8	94		
HYUN YOO, et al.[13]	ResNet and Explainable Feature Map	NIH	80		
Chia-Hung Lin, et al.[14]	Classification of Posteroanterior Chest X-Ray Images Using a Multilayer 1D Convolutional Neural Network	NIH	98.00		
Muhammad Arsalan, et al.[15]	X-RayNet_1	JSRT, Montgomery County (MC) and Shenzhen X-Ray sets	96.27		
	X-ray Net_2		98.10		
Tanveer Gupte.et al. [16]	Attention UNET	NIH/ two private hospitals (D1, D2), and a private dataset which was collected from population screening (which we name as D3)		0.96	0.81
	SE-Resnext UNET			0.87	0.86
	Efficient Net			0.94	0.83
Mu Sook Lee. et al.[6]	Standard U-Net and XLSor Model: Method1 segmentation	Two public datasets CXRs,JSRT,	91	95	87

	Method1 segmentation	Montgomery, and in-house PA	92	94	88
Qiwen Que1.et al[17]	CardioXNet	ChestX-ray8	93.75		

VI. METRICS FOR EVALUATION PERFORMANCE

In this section, an overview of several evaluation techniques is provided, highlighting the importance of utilizing diverse approaches to assess model performance. Specifically, accuracy, recall, precision, and the F1 measure are discussed as effective methods for evaluating classification algorithms [18]. Additionally, the following terms are defined:

- true positive (TP), which pertains to instances of positive occurrences that are correctly classified.
- false negative (FN), which refers to instances of positive occurrences that are mistakenly classified.
- false positive (FP), which pertains to instances of negative occurrences that are erroneously classified.
- true negative (TN), which denotes instances of negative occurrences that are correctly classified.

$$accuracy = \frac{tp + tn}{tp + tn + fp + fn} \qquad (2)$$

$$precision = \frac{tp}{tp + fp} \qquad (3)$$

$$recall = \frac{tp}{tp + fn} \qquad (4)$$

$$f1_{score} = \frac{2 \times precision \times recall}{precision + recall} \qquad (5)$$

VII.CONCLUSION

This paper presents a comprehensive overview of the cardiomegaly disease, including its classification algorithms and techniques employed in this field. The utilization of deep learning algorithms in detecting and diagnosing cardiomegaly through chest X-rays has exhibited significant promise. Employing sophisticated techniques and algorithms, such as convolutional neural networks.The aforementioned algorithms have yielded high efficacy and accuracy compared to traditional methods, with the potential to automate the detection process and significantly enhance patient outcomes via early identification and intervention. Nevertheless, further investigation is essential to refine and enhance these algorithms. In summary, this study's outcomes demonstrate the significant potential of deep learning algorithms for the diagnosis and management of cardiomegaly.

ACKNOWLEDGMENT

THIS STUDY HAS BEEN CONDUCTED, IN PART, AT THE COLLEGE OF SCIENCE FOR WOMEN, COMPUTER SCIENCE DEPARTMENT, UNIVERSITY OF BABYLON, WITH SUPPORT FROM THE MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH IN IRAQ.ACKNOWLEDGMENTS IN THE UNNUMBERED FOOTNOTE ON THE FIRST PAGE.

REFERENCES

[1] A.Yadav, L.Gediya1, A.Kazi," Heart Disease Prediction Using Machine Lerning". International Research Journal of Engineering and Technology, Volume: 08 Issue: 09 | Sep 2021.

[2] T.Gupte,M.Niljikar,M.Gawali,V.Kulkarni,A.Kharat, A.Pant," Deep Learning Models for Calculation of Cardiothoracic Ratio from Chest Radiographs for Assisted Diagnosis of Cardiomegaly".2021, IEEE, DOI: 10.1109/icABCD51485.2021.9519348.

[3] M.Nawaz,T.Nazir,J.Baili,M.Attique ,YJin Kim , J.Hyuk Cha," C Xray-EffDet: Chest Disease Detection and Classification from X-ray Images Using the EfficientDet Model",2023, https://doi.org/10.3390/diagnostics13020248.

[4] J. X. Wu et al., "Limitations of cardiothoracic ratio derived from chest radiographs to predict real heart size: comparison with magnetic resonance imaging," Insights Imaging, vol. 12, no. 1, pp. 47824–47836, 2022, doi: 10.1109/ACCESS.2022.3171811.

[5] D.Grant, B.W. Papież, G.Parsons, L. Tarassenko & A.Mahdi." Deep Learning Classification of Cardiomegaly Using Combined Imaging and Non-imaging ICU Data",2021. https://doi.org/10.1007/978-3-030-80432-9_40.

[6] M. S. Lee et al., "Evaluation of the feasibility of explainable computer-aided detection of cardiomegaly on chest radiographs using deep learning," Sci. Rep., vol. 11, no. 1, pp. 1–11, 2021, doi: 10.1038/s41598-021-96433-1.

[7] S. Sarpotdar, "Cardiomegaly Detection using Deep Convolutional Neural Network with U-Net". doi.org/10.48550/arXiv.2205.11515.

[8] I. Chamveha,T. Promwiset, T. Tongdee, P. Saiviroonporn, and W. Chaisangmongkon, "Automated Cardiothoracic Ratio Calculation and Cardiomegaly Detection using Deep Learning Approach," pp. 1–11, 2020, [Online]. Available:http://arxiv.org/abs/2002.07468. :doi.org/10.48550/arXiv.2002.07468

[9] P.Kora , C. Pin Ooi , O.Faust ,et al," Transfer learning techniques for medical image analysis: A review",2022. https://doi.org/10.1016/j.bbe.2021.11.004.

[10] H. Bougias, E. Georgiadou, C. Malamateniou, and N. Stogiannos, "Identifying cardiomegaly in chest X-rays: a cross-sectional study of evaluation and comparison between different transfer learning methods," Acta radiol., vol. 62, no. 12, pp. 1601–1609, 2021, doi: 10.1177/0284185120973630.

[11] D. Cardenas, J. Ferreira Junior, R. Moreno, M. Rebelo, J. Krieger, and M. Gutierrez, "Multicenter Validation of Convolutional Neural Networks for Automated Detection of Cardiomegaly on Chest Radiographs," pp. 179–190, 2020, doi: 10.5753/sbcas.2020.11512.

[12] A. Bouslama, Y. Laaziz, and A. Tali, "Diagnosis and precise localization of cardiomegaly disease using U-NET," Informatics Med. Unlocked, vol. 19, no. January 2021, 2020, doi: 10.1016/j.imu.2020.100306.

[13] H.Yoo, S. Han, and K. Chung, "Diagnosis Support Model of Cardiomegaly Based on CNN Using ResNet and Explainable Feature Map," IEEE Access, vol. 9, pp. 55802–55813, 2021, doi: 10.1109/ACCESS.2021.3068597.

[14] C. H. Lin et al., "Posteroanterior Chest X-ray Image Classification with a Multilayer 1D Convolutional Neural Network-Based Classifier for Cardiomegaly Level Screening," Electron., vol. 11, no. 9, 2022, doi: 10.3390/electronics11091364.

[15] M. Arsalan, M. Owais, T. Mahmood, J. Choi, and K. R. Park, "Artificial intelligence-based diagnosis of cardiac and related diseases," J. Clin. Med., vol. 9, no. 3, 2020, doi: 10.3390/jcm9030871.

[16] T. Gupte, M. Niljikar, and M. Gawali, "Deep Learning Models for Calculation of Cardiothoracic Ratio from Chest Radiographs for Assisted Diagnosis of Cardiomegaly" . ://doi.org/10.48550/arXiv.2205.11515.

[17] Q.Que,4 , Z. Tang, R.Wang , Z. Zeng ,J.Wang , M. Chua1 , T.Sin Gee, X.Yang , B. Veeravalli," CardioXNet: Automated Detection for Cardiomegaly Based on Deep Learning",IEEE, DOI: 10.1109/EMBC.2018.8512374.

[18] J. WU,, C. PAI, C.KAN,et al," Chest X-Ray Image Analysis With Combining 2D and 1D Convolutional Neural Network Based Classifier for Rapid Cardiomegaly Screening",2022.IEEE, DOI: 10.1109/ACCESS.2022.3171811.