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Early-stage cardiomegaly detection and classification from X-ray images using convolutional neural networks and transfer learning

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ABSTRACT

Cardiomyopathy is a serious condition that can result in heart failure, sudden cardiac death, malignant arrhythmias, and thromboembolism. It is a significant contributor to morbidity and mortality globally. The initial finding of cardiomegaly on radiological imaging may signal a deterioration of a known heart condition, an unknown heart disease, or a heart complication related to another illness. Further cardiological evaluation is needed to confirm the diagnosis and determine appropriate treatment. A chest radiograph (X-ray) is the main imaging method used to identify cardiomegaly when the heart is enlarged. A prompt and accurate diagnosis is essential to help healthcare providers determine the most appropriate treatment options before the condition worsens. This study aims to utilize convolutional neural networks and transfer learning techniques, specifically Inception, DenseNet-169, and ResNet-50, to classify cardiomegaly from chest X-ray images automatically. The utilization of block-matching and 3D filtering (BM3D) techniques aimed at enhancing image edge retention, decreasing noise, and utilizing contrast limited adaptive histogram equalization (CLAHE) to enhance contrast in low-intensity images. Gradient-weighted Class Activation Mapping (GradCAM) was used to visualize the significant activation regions contributing to the model's decision. After evaluating all the models, the ResNet-50 model showed outstanding performance. It achieved perfect accuracy of 100 % in both training, and validation, and an impressive 99.8 % accuracy in testing. Additionally, it displayed complete 100 % precision, recall, and F1-score. These findings demonstrate that ResNet-50 surpassed all other models in the study. As a result, the impressive performance of the ResNet-50 model suggests that it could be a valuable tool in improving the efficiency and accuracy of cardiomyopathy diagnosis, ultimately leading to better patient outcomes.

1. Introduction

Cardiomegaly, also called enlarged heart, is a condition characterized by the enlargement and thickening of the heart muscle as seen in Fig. 1 (Innat et al., 2023). This may occur due to a range of underlying medical conditions such as hypertension, coronary artery disease, heart valve abnormalities, and specific genetic disorders (Enlarged heart - Symptoms, and causes - Mayo Clinic 2024). Individuals diagnosed with cardiomegaly must collaborate closely with their healthcare providers to effectively manage their condition and tackle any underlying health concerns. An enlarged heart can result from heart injury or specific heart diseases. Pregnancy and other short-term physical stresses can occasionally lead to an enlarged heart. An enlarged heart may be curable or a permanent ailment requiring lifelong care, depending on the underlying reason (Enlarged heart - Symptoms, and causes - Mayo Clinic 2024).

The symptoms of cardiomegaly, or an enlarged heart, might vary from person to person (Amin & Siddiqui, 2024). Some people may have no symptoms at all, while others may detect dyspnea, especially when they're lying down or first waking up. Cardiomegaly is also frequently indicated by abnormal cardiac rhythm and edema in the legs or abdomen. It's acute to speak with a medical expert if any of these signs are encountered. However these signs by themselves would not be sufficient to diagnose cardiomegaly, thus some kind of imaging method is required to gauge the size and function of the heart (Enlarged Heart (Cardiomegaly): Causes, Treatment, and More 2024). The dimensions of a normal adult heart are approximately 12–13 cm in length, 8–9 cm in

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width, and 6 cm in thickness, approximately 4–5.6 cm in diameter, with an average weight of 250–300 grams. An enlarged heart, known as cardiomegaly, is diagnosed when the heart exceeds 15.5 cm in length and/or weighs more than 450 grams, and diameter exceeds 5.6 cm [(Enlarged Heart (Cardiomegaly): What It Is, Symptoms and Treatment 2024; Cardiomegaly - an overview | ScienceDirect Topics 2024)].

A chest X-ray is a popular diagnostic technique for determining cardiomegaly (Mohare et al., 2019; Raghu Kumar et al., 2023). Medical personnel can evaluate the X-ray images to determine the dimensions and form of the heart and identify any anomalies that can point to cardiomegaly. Early diagnosis and treatment of cardiac disorders are made possible by this diagnostic instrument, which helps to avert future consequences (Ayalew et al., 2024). It is crucial for people experiencing symptoms like difficulty breathing, chest discomfort, or tiredness to promptly seek medical care and undergo relevant testing, including a chest X-ray if required, to ensure timely and efficient management of their heart health.

Early detection and treatment of cardiomegaly are essential to preventing more problems. Regular tests and symptom awareness can help with early detection and intervention, which can improve health outcomes. People must understand the signs and risk factors of cardiomegaly and get medical assistance if they see any worrying abnormalities. When worrying symptoms appear, it's imperative to see a doctor, and taking proactive steps to get diagnosed early can greatly impact overall health (Colizzi et al., 2020).

It has been determined that machine learning techniques, particularly deep learning, are more accurate than other techniques (Ayalew et al., 2022; Tamyalew et al., 2023). Using X-ray images, the authors in (Mohare et al., 2019; Que et al., 2018; Raghu Kumar et al., 2023) used deep learning techniques to diagnose cardiomegaly illness. Their study showed how sophisticated technology may be used to reliably diagnose cardiomegaly, a disorder marked by an enlarged heart. Through the use of deep learning algorithms, the authors were able to analyze X-ray images and identify patterns linked to cardiomegaly, thus giving medical personnel a more accurate and efficient diagnosis tool.

Our research introduces a specialized classifier for differentiating between normal and infected cases of cardiomegaly using chest X-ray images. We have developed an advanced deep learning model such as Convolutional neural networks (CNNs), and pre-trained CNN models such as Inception, Densely Connected Convolutional Networks (DenseNet-169), and Residual Networks (ResNet-50). To automate the diagnosis of cardiomegaly, to achieve accurate detection, and early identification before it leads to heart failure, and to decrease the likelihood of false negatives. In addition, we have incorporated contrast-limited adaptive histogram equalization (CLAHE) to improve the contrast of low-intensity images and employed a block-matching and 3D filtering (BM3D) method to eliminate multiplicative speckle noise from the chest X-ray images.

An overview of the remainder of the paper is provided below. Section 2 quickly summarizes recent research on cardiomegaly through the use of deep learning tools. Section 3 describes the methodology. This section also goes over the dataset that was used to train and evaluate the four models. Section 4 describes the evaluation technique, Sections 5 and 6 describe the results of each model and discussion respectively, and Section 7 concludes the research study.

2. Related works

In this part, we will delve into earlier publications centering on the diagnosis of cardiomegaly. These papers offer valuable perspectives into the established research and techniques employed in this area. By analyzing the discoveries and methodologies of these prior investigations (Mun et al., 2022), we can enhance our comprehension of the existing status of cardiomegaly diagnosis and pinpoint potential areas for additional research and advancement.

A convolutional attention mapping deep neural network for classification and localization of cardiomegaly on chest X-rays was presented by Innat et al. (2023). To efficiently classify and localize cardiomegaly, this work introduces a convolutional attention mapping deep learning network called Cardio-X AttentionNet. The authors updated the global average pooling (GAP) system with a weighting term to create a lightweight and effective Attention Mapping Mechanism (AMM). The suggested model is trained using the publicly available Chest X-Ray14 dataset. For the categorization of cardiomegaly, the best single model obtains overall precision, recall, F1-score measure, and area under curve scores of 0.87 %, 0.85 %, 0.86 %, and 0.89 %, respectively.

Raghu Kumar et al. (2023) et al. reported detecting cardiomegaly from CXR images using a 2D and 1D convolutional neural network-based classifier. The study proposes combining 2D and 1D grounded classifiers with convolution neural networks to achieve rapid cardiomegaly identification. Their pattern recognition system showed encouraging results; recall, precision, accuracy, and F1-score averages

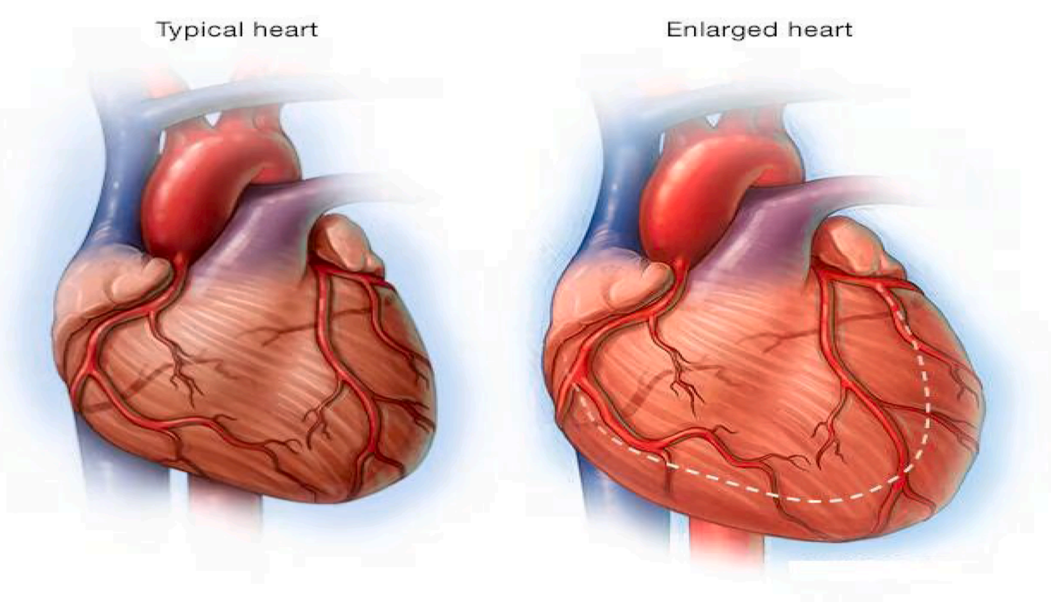

Fig. 1. Shows the normal heart size, and enlarged heart (Enlarged heart - Symptoms, and causes - Mayo Clinic 2024).

were all above 95 %, and screening irregularities were detected.

Automated detection for cardiomegaly based on deep learning was proposed by Que et al. (2018). Their suggested algorithm CardioXNet is a deep learning system that diagnoses cardiomegaly from chest X-rays using the cardiothoracic ratio and U-NET. This study has demonstrated the feasibility of autonomously identifying heart illness in medical images by combining deep learning segmentation (U-NET) with medical criterion. The suggested CardioXNet approach yields an F1-score of 94.34 %, 89.29 % for recall, 100 % for precision, and 93.75 % for accuracy.

Candemir et al. (2018) presented deep learning for grading cardiomegaly severity in chest X-rays. The study looks at the automatic identification of cardiomegaly in digital chest X-rays (CXRs) using deep convolutional neural networks. The Library of Medicine (NLM) Indiana Collection and the National Institutes of Health (NIH) chest X-ray dataset are two publicly accessible chest X-ray datasets that were utilized by the authors. The pre-trained VGG-16 model achieved an accuracy of 89.86, a sensitivity of 88.81, and a specificity of 90.91.

Hybrid classical quantum transfer learning for cardiomegaly detection in chest X-rays was presented by Decoodt et al. (2023). The authors created hybrid models of classical-quantum (CQ) transfer learning to identify cardiomegaly in CXRs. They combined a parameterized quantum circuit with a PyTorch-implemented classical network using Qiskit and PennyLane. Accuracy of up to 0.87, ROC, and AUC scores of up to 0.93 were attained for prediction.

Problems encountered in the previous studies: Analysis of chest X-ray images is vital for diagnosing cardiomegaly as it enables healthcare practitioners to precisely evaluate the heart's size and condition, facilitating prompt intervention and treatment. It is crucial to recognize that past research in this area has certain drawbacks in cardiomegaly detection using deep learning techniques. These challenges include an imbalance in class distribution during data manipulation, a small amount of dataset, classification results that were not accurate, and the extraction of features from images lacking adequate preprocessing techniques such as intensity equalization and noise reduction from X-ray images. Furthermore, deep learning models' explainability and interpretability require enhancement to assure transparency and clinician trust. Integration into clinical processes and real-time processing capabilities are also understudied, as is model performance in edge instances like early-stage cardiomegaly or images with confounding circumstances. To mitigate these constraints and uphold the precision and reliability of the results, this study must focus on overcoming these deficiencies. Our deep learning approach for automated cardiomegaly disease categorization achieves excellent accuracy while decreasing false-negative cases. Also, we implemented image enhancement techniques: advanced techniques such as block-matching 3D filtering and contrast limited adaptive histogram equalization are used to increase the quality and clarity of X-ray images, which is critical for correct diagnosis. The following are noted as this paper's main contributions:-

1. A novel CNN model was developed, and compared with the transfer learning model for better identification of cardiomegaly disease.
2. The BM3D image filtering algorithm was the most suitable filtering algorithm for cardiomegaly chest X-ray medical images.
3. Contrast limited adaptive histogram equalization was used to improve the contrast of low-intensity cardiomegaly chest X-ray images.
4. ResNet-50 features achieved high training, validation, and testing accuracy of 100 %, 100 %, and 99.8 %, respectively.

3. Methodology

3.1. Data collection

A dataset was generated from 4400 original images, of which 2200 were normal (Chest X-ray Images 2024) and 2200 were cardiomegaly infected, gathered from the online repositories (Cardiomegaly Disease Prediction Using CNN 2024) as shown in Fig. 2. Following preprocessing to improve image quality with techniques such as Block-Matching and 3D Filtering (BM3D) for noise reduction and Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement, the dataset was divided into training, validation, and testing groups. Using a five-fold cross-validation procedure, the dataset was divided such that 70 % of the data was used for training the models, 10 % of the data was used for validating the models during training to tune hyperparameters and avoid overfitting, and 20 % of the data was used for final testing to evaluate the model's performance on unseen data. This technique ensures that models are trained, validated, and tested on discrete subsets, encouraging generalization while limiting overfitting, and improving the model's performance evaluation reliability.

3.2. Image preprocessing

Image preprocessing is a vital step that occurs after acquiring image data. It involves modifying the images to enhance quality and optimize performance during model training (Tamyalew et al., 2023). Techniques such as normalization, resizing, and noise reduction are applied to prepare data for the next stages of the machine learning pipeline. The original three-channel images were reduced from 1024 × 1024 to 224 × 224 pixels to minimize computation and faster processing (Ayalew et al., 2023, Bezabh et al., 2024). All subsequent procedures have been applied to the reduced images.

3.3. Contrast enhancement

Once the image has been processed and resized, we can improve the quality of low-intensity areas by utilizing contrast limited adaptive histogram equalization (CLAHE). This method is particularly beneficial for enhancing the overall image quality, especially in low-light or low-contrast conditions (Ayalew et al., 2024). CLAHE enhances images by setting a threshold for the original image's histogram. When the histogram exceeds the threshold, it is trimmed and the surplus is evenly distributed to each gray level. Clip Limit: Determines the threshold for contrast limiting. It determines the maximum slope of the cumulative distribution function (CDF) of the histogram. Commonly set between 2.0 and 4.0. The typical "limit contrast" is set to 40, with a block size of 8 × 8. This method effectively reduces noise and highlights the contrast between local vessels and the background in images (Fan et al., 2020).

3.4. Image noise removal

After the dataset has been processed, image sizes adjusted, and the contrast of low-intensity images improved, the next step involves applying block-matching and 3D filtering (BM3D) to reduce image noise. BM3D is a widely acclaimed de-noising algorithm renowned for its capability to remove unwanted noise while retaining image details (Pakdelazar & Rezai Rad, 2011). Utilizing BM3D enhances the overall quality of the images, making them more suitable for scrutiny and presentation. This phase is crucial in ensuring that the images are noise-free, thereby improving the accuracy of subsequent image processing and analysis tasks. Particularly in the field of medical imaging, where image accuracy and clarity are critical for correct diagnosis and treatment, BM3D has shown great effectiveness in enhancing image quality through noise reduction without losing vital image detail. BM3D's effective noise removal from medical images offers increased diagnostic accuracy and improved visualization of anatomical structures, opening the path for better patient care (Qu et al., 2024).

3.5. Proposed system architecture

As seen in Fig. 3, the system architecture is the first part of the suggested deep learning-based approach for classifying and diagnosing

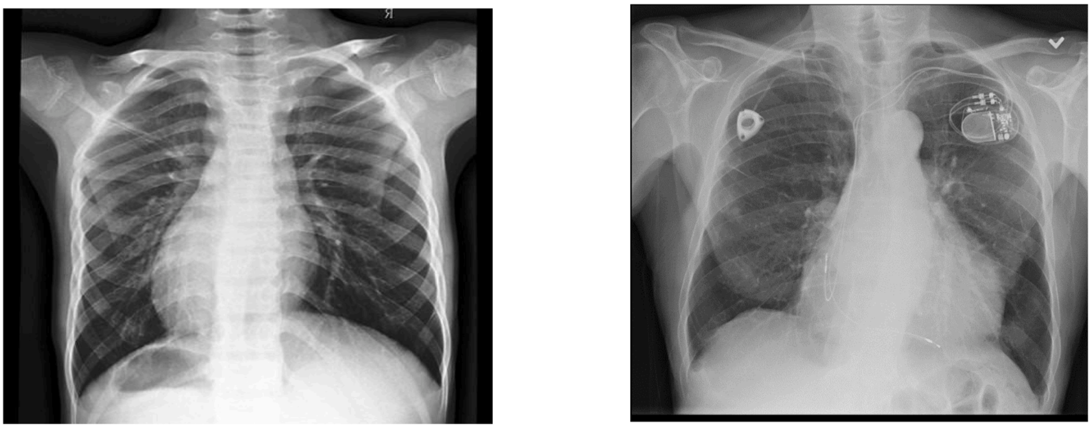

Fig. 2. Shows the normal image is on the left, and the cardiomegaly image is on the right.

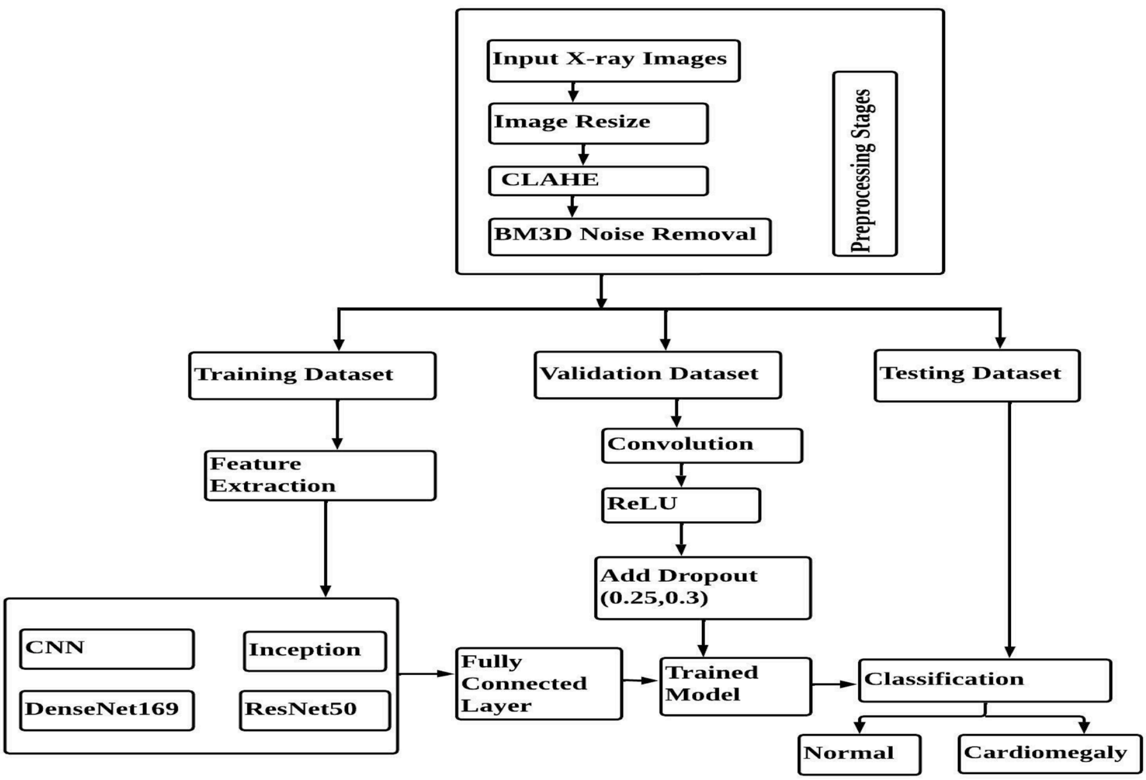

Fig. 3. Proposed model system architecture.

cases of cardiomegaly. In this phase, we collected images of both patients with cardiomegaly and healthy individuals. Following acquisition, the images were pre-processed utilizing BM3D filtering, and CLAHE methods to increase their quality. Following the processing of the samples, feature learning was achieved by employing CNN to extract pertinent information from the input image. The chest X-ray images were processed using CNN methods to extract feature vectors. To train the classification model, the features obtained through CNN methods were inputted into the model. The sigmoid function learning approach in CNN is employed throughout the preprocessing, training, validation, and testing stages. After developing the proposed models, they were capable of extracting features that could be utilized for classifying cardiomegaly diseases as either normal (healthy) or cardiomegaly infected. This classification was achieved through the use of a fully connected layer in the deep learning classifier.

3.6. Feature extraction

3.6.1. Convolutional neural networks

One type of deep neural network that is used to evaluate visual images is called a convolutional neural network (CNN) (Bezabih et al., 2023). In addition to an input and output layer, it has several hidden layers. CNN models are utilized for training and validating the input data of each dataset (Alzubaidi et al., 2021). The data is processed through many layers containing filters, such as kernels, pooling, fully connected layers, and the sigmoid function, which is applied to classify objects between probabilistic values of 0 and 1 (Asnake et al., 2024). 3 × 3 kernel size and five convolution layers in total have been utilized. Stride size, the third parameter, determines how the filter convolves around the feature map. Two-step stride sizes have been employed. Additionally, Adam was utilized for optimization and the Rectified Linear Unit (ReLU) was employed as the activation function in this study

(Tamyalew et al., 2023). Due to the blurring effect of average pooling on images, which hinders sharp feature distinction, max pooling was selected as the pooling layer to address the highest output in a rectangular area (Ayalew et al., 2024). Subsequently, a flattened layer was applied after the pooling layer in our model to streamline the entire network (Abeje et al., 2022). The final layer of the deep learning network consists of a dense layer activated by the sigmoid function, receiving the flattened output from the last convolutional layer. This final layer is used for binary classification, distinguishing between normal and cardiomegaly-infected cases. As seen in Table 1, several hyperparameter tuning strategies were used to improve the convolutional neural network (CNN) model's performance in detecting early-stage cardiomegaly from X-ray images. The model was trained with a fixed kernel size of 3 × 3 with "same" padding, Adam optimizer, and ReLU activation function for the majority of the layers, switching to Sigmoid in the output layer to forecast probability. A learning rate of 0.001 was chosen, and training was spread throughout 50 epochs with a batch size of 64 and 50 iterations each epoch. To reduce overfitting, dropout regularization was used across several layers at rates of 0.3, 0.2, and 0.15. Throughout training, validation parameters like as accuracy and loss were maintained, with early halting based on validation performance to avoid overfitting and ensure robust generalization. This systematic approach to hyperparameter tuning and validation strategy allowed the model to achieve peak performance in reliably diagnosing cardiomegaly, demonstrating its potential to improve diagnostic accuracy and clinical outcomes in medical imaging applications.

3.6.2. Transfer learning

Along with CNN, we utilized pre-trained models like Inception, DenseNet-169, and ResNet-50. Transfer learning is an effective method that empowers a model to utilize the knowledge acquired from an existing model, enabling it to achieve exceptional performance without the need for extensive computational resources (Abuhayi et al., 2024). By preserving the initial parameter values of the existing model, the new model can promptly adjust to new tasks and datasets, making it a proficient and impactful approach in machine learning (Mazumder et al., 2024). Advanced architectural models like Inception, DenseNet-169, and ResNet-50 were utilized and adjusted for detecting cardiomegaly (Shah et al., 2023).

4. Evaluation techniques

The model or proposed solution's performance has been assessed using several metrics, such as precision, recall, F1-score, confusion matrix, and accuracy. These metrics are widely employed to evaluate the model's effectiveness and dependability in producing precise results. By examining these metrics, we can obtain a valuable understanding of the model's performance and make informed judgments regarding its potential impact and suitability for specific uses.

Table 1
CNN model hyperparameters and their values applied in our model.

HyperParameters	Value
Kernel size	3 × 3 for all layers
Padding	Same
Optimizer	Adam
Pooling	Max pooling (2)
Activation function	ReLU, Sigmoid
Learning rate	0.001
Epoch	50
Batch size	64
Iteration	50
Dropout	0.3, 0.2, and 0.15

5. Experimental results

In this study, we conducted four different experiments to evaluate the model, which we will discuss in this section. Each of the four models was trained using a combination of low-intensity images enhanced with CLAHE and filtered images using the block-matching and 3D filtering technique, which is specifically tailored for medical images. To conduct experiments, we utilized a Google compute engine instance called Google Collaboratory (colab). The Colab notebooks used for experimentation were Jupyter-based and functioned similarly, to a Google Docs object. These notebooks also included pre-configured versions of key machine learning and artificial intelligence libraries, such as TensorFlow, Matplotlib, and Keras. The model was developed using the GPU and Python programming language. These resources allowed for efficient and effective experimentation in the field of deep learning.

5.1. CNN feature extraction

In this CNN model, we have attained an accuracy of 99.8 % for training, 99.4 % for validation, and 98.5 % for testing accuracy. As the number of epochs increases, both the training and testing accuracy improve, while the training and validation loss decreases. This trend is clearly shown by the training and validation loss curves in Figs. 4 and 5 respectively. Fig. 4, below indicates that the validation accuracy closely matches the training accuracy, implying the lack of overfitting in our deep learning model. The training and validation accuracy and losses show a linear trend in Fig. 5, suggesting that the network was trained well and can make precise predictions.

5.2. Inception feature extraction

The Inception Layer consists of a mix of the 1 × 1 Convolutional layer, 3 × 3 Convolutional layer, and 5 × 5 Convolutional layer, with their output filter banks merged into one output vector for the next stage's input (Szegedy et al., 2015). Utilizing Inception for feature extraction has helped us identify and detect cardiomegaly cases, enhancing our ability to analyze and diagnose the condition. By leveraging Inception's capabilities, we have improved our accuracy in addressing cardiomegaly cases, ultimately leading to better patient care and outcomes. Inception has played a significant role in advancing our efforts in medical imaging and diagnosis, enabling us to make informed decisions and provide improved treatment for patients with cardiomegaly. This Inception model achieved 98.6 % accuracy for training, 96.8 % for validation, and 96 % for testing accuracy. Fig. 6, shows how training and validation accuracy changes with epoch count. The graph suggests that with more epochs, both training and validation accuracy significantly increase. The Fig. 7, below shows how the validation loss

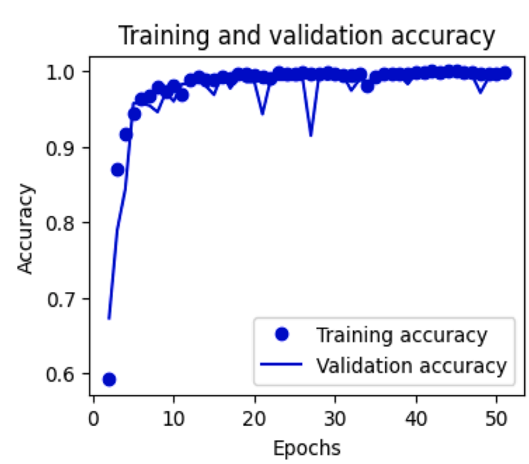

Fig. 4. Training and validation accuracy of the CNN model.

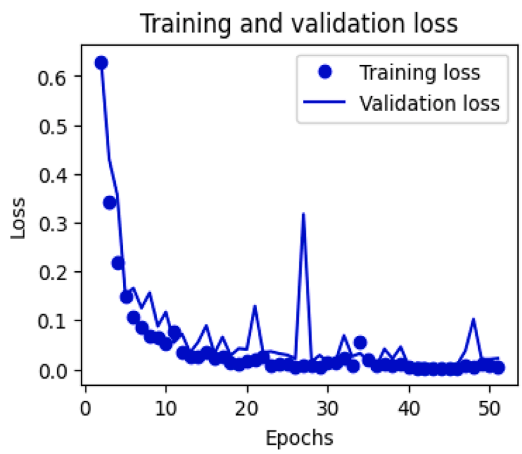

Fig. 5. Training and validation loss of the CNN model.

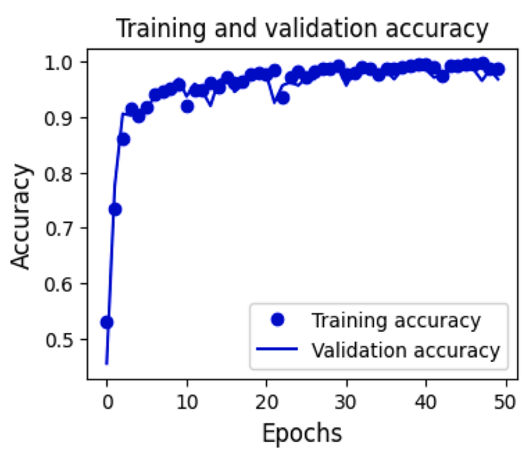

Fig. 6. Training and validation accuracy of the Inception model.

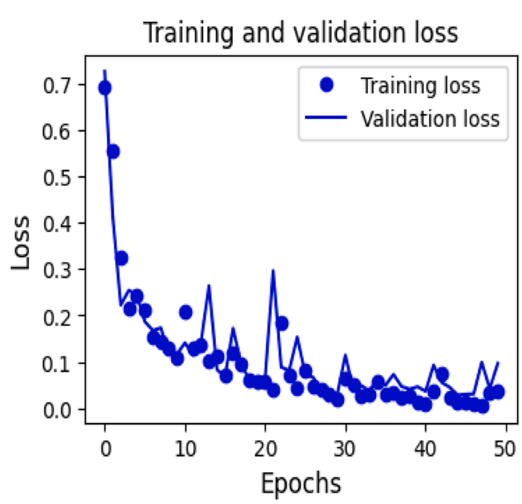

Fig. 7. Training and validation loss of the Inception model.

fluctuates with the number of epochs, while the training loss remains constant. After further examination, it is noted that there is a significant decrease in training loss when reaching 50 epochs, improving the network's accuracy and efficiency. The final training loss at the end of all epochs is 0.04 while and validation loss is 0.09. Overall, this inception model shows significantly lower accuracy in comparison to the other three experiments.

5.3. DenseNet-169 feature extraction

Deep Convolutional Networks (DCNNs) are popular for image recognition due to their unique convolutional and pooling layers. However, as the network becomes deeper, there is a problem of gradient vanishing, which DenseNets solves by directly connecting all layers with equal feature sizes. DenseNet-169 architecture allows for obtaining more generic features with a deeper network (Dhaka et al., 2021). Feature extraction was performed using the pre-trained DenseNet-169, a 169-layer Convolutional Neural Network architecture. It includes one initial convolution and pooling layer, 3 transition layers, and 4 dense blocks. Each dense block has two convolution layers: one 1×1 and one 3×3. The final classification layer utilizes a global average pooling of 7×7 and a fully connected layer with sigmoid activation (Varshni et al., 2019). This DenseNet-169 model attained 100 % accuracy for training and validation, as well as 99.7 % for testing accuracy. Fig. 8, demonstrates that the validation accuracy closely aligns with the training accuracy, suggesting no overfitting in our model. Fig. 9, illustrates that the training and validation loss decreases consistently with the number of epochs increases, indicating no underfitting problem in the DenseNet-169 model. This model exhibits notably superior accuracy compared to the preceding two experiments.

5.4. ResNet-50 feature extraction

Residual Networks (ResNet-50), created by Microsoft Research in 2015, is a CNN architecture with 50 layers including 48 convolutional layers, one MaxPool layer, and one average pool layer, forming networks by stacking residual blocks (Mukti & Biswas, 2019). ResNet-50 is a robust image classifier that excels when trained on extensive datasets, producing cutting-edge outcomes. Its notable feature is the incorporation of residual connections, enabling the network to master residual functions for mapping input to output (Dai et al., 2024). Therefore we apply ResNet-50 to solve a complex problem, we stack some additional layers in the deep neural networks which results in improved accuracy and performance in the detection of cardiomegaly cases. The performance of the ResNet-50 model is remarkable, achieving a flawless 100 % accuracy in both training and validation and an outstanding testing accuracy of 99.8 %. This showcases the model's strength and dependability in precisely cardiomegaly cases. Such exceptional performance attests to the effectiveness of ResNet-50 in managing intricate tasks with great accuracy. This ResNet-50 model shows significantly better accuracy than the previous three experiments. The graph provided in Fig. 10, illustrates the correlation between epoch count and training and validation accuracy fluctuation. Upon examination, the graph reveals that an increase in epochs results in a significant rise in training accuracy, while validation accuracy experiences a gradual increase followed by a decrease. The Fig. 11, below illustrates the fluctuation of loss in the

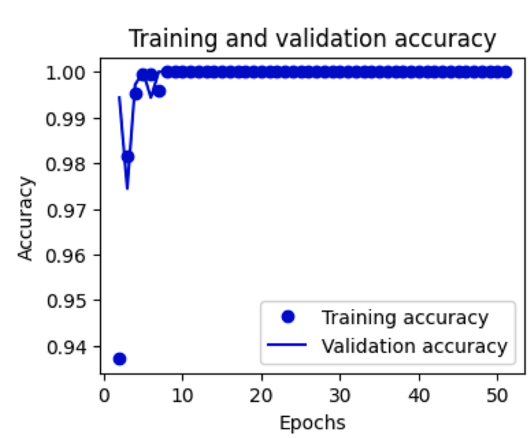

Fig. 8. Training and validation accuracy of DenseNet-169 model.

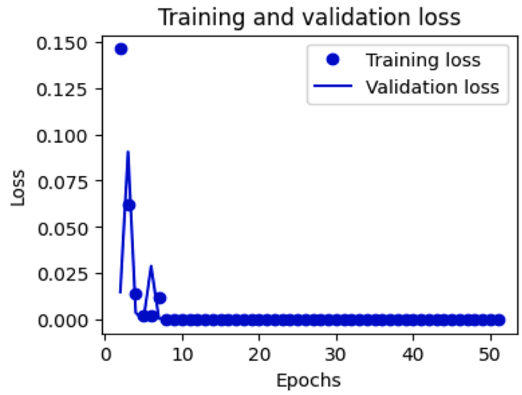

Fig. 9. Training and validation loss of DenseNet-169 model.

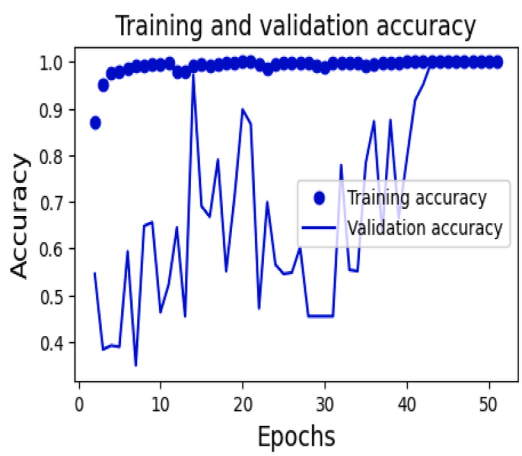

Fig. 10. Training and validation accuracy of the ResNet-50 model.

network as epochs increase. It is evident that training loss significantly decreases and stabilizes near zero by epoch 50, resulting in a more accurate and efficient network. Meanwhile, validation loss fluctuates before eventually decreasing towards 0 by epoch 50. To mitigate the risk of overfitting, we put in place multiple approaches to verify that the ResNet-50 model's impressive accuracy truly reflects its ability to generalize. To address this issue, we have put in place numerous tactics. In the beginning, we used methods like data augmentation to enhance the variety of the training data, which helped decrease the chances of overfitting. Moreover, our results have been confirmed through cross-validation, ensuring the model's ability to perform well on various data subsets, and we also incorporated regularization methods, such as dropout layers and L2 regularization, within the model architecture to prevent overfitting. At last, as shown in Fig. 10, the training and validation accuracy follow the same trend after epoch 40, and in Fig. 11, the training and validation loss follow the same trend after epoch 30, suggesting a consistent and applicable model. All these measures together make sure that the model's high accuracy is not due to overfitting but truly demonstrates its ability to accurately detect cardiomegaly.

5.5. Confusion matrixes and Grad-CAM visualization

According to the ResNet-50 confusion matrix, which is presented in Fig. 12, 440 of the 440 cardiomegaly-positive patients have been identified properly using our suggested model from the chest X-ray images. None of the 440 patients who tested positive for cardiomegaly were incorrectly classified as negative for cardiomegaly. Similar to this, 439 of 440 normal individuals have received the proper diagnosis based on their chest X-ray images. Only 1 patient has ever been misdiagnosed as

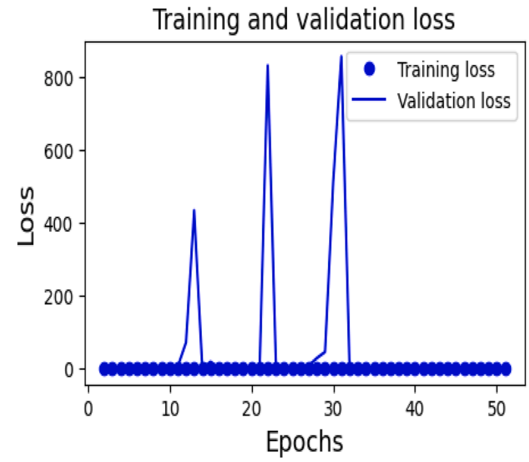

Fig. 11. Training and validation loss of the ResNet-50 model.

having cardiomegaly. Our proposed model exhibits high precision and reliability in accurately detecting cardiomegaly and differentiating it from normal cases. This accuracy is essential for providing prompt and precise medical care for patients, highlighting the potential of incorporating advanced technology in healthcare diagnostics.

Our model can also process low-quality or incorrectly positioned X-rays, and we have incorporated multiple image preprocessing techniques in the model development phase. Initially, we utilized sophisticated preprocessing methods like Block-Matching and 3D Filtering (BM3D) to reduce noise, and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance contrast. These techniques aim to enhance image quality and minimize the negative effects of low-quality X-rays. Furthermore, we purposely included a variety of image qualities in our training dataset and employed data augmentation methods to replicate different image quality and position variations. This method seeks to improve the durability of the model in practical situations. Additionally, we evaluated the model using X-rays of different quality and alignment, and it showed good performance.

Gradient-weighted Class Activation Mapping (Grad-CAM) is a visualization tool for understanding and interpreting CNN decisions. It gives visual explanations for judgments made by CNN-based models by highlighting the regions in the input image that are most important for the prediction (Tang et al., 2021). The heatmap visualization for the four CNN models employing Grad-CAM is displayed in Fig. 13. An example of a correctly diagnosed CXR image for the Normal class and Cardiomegaly class is shown in these figures. The regions shown in dark red are the most important for the CNN model's decision-making, while the regions highlighted in dark blue are the least important. The location where the CNN models extracted the "features" during the prediction phase is indicated by the dark red patch.

6. Discussion

Our four proposed methods for identifying and diagnosing cardiomegaly were extensively tested using X-ray images and evaluation standards. We implemented CNN, Inception, DenseNet-169, and ResNet-50 from pre-trained models to extract features, along with a sigmoid classifier. Results in Table 2 and Fig. 14, display the performance metrics for training, validation, testing, and precision, recall, and F1-score of the models in recognizing cardiomegaly disease. In all experiments, image enhancement was used to boost low-intensity contrast and BM3D noise filtering was applied, resulting in improved accuracy compared to the initial dataset. This research utilized X-ray images for binary classification of cardiomegaly and healthy individuals with CNN and pre-trained methods. ResNet-50 demonstrated superior performance over CNN, Inception, and DenseNet-169. As shown in Table 3, our study

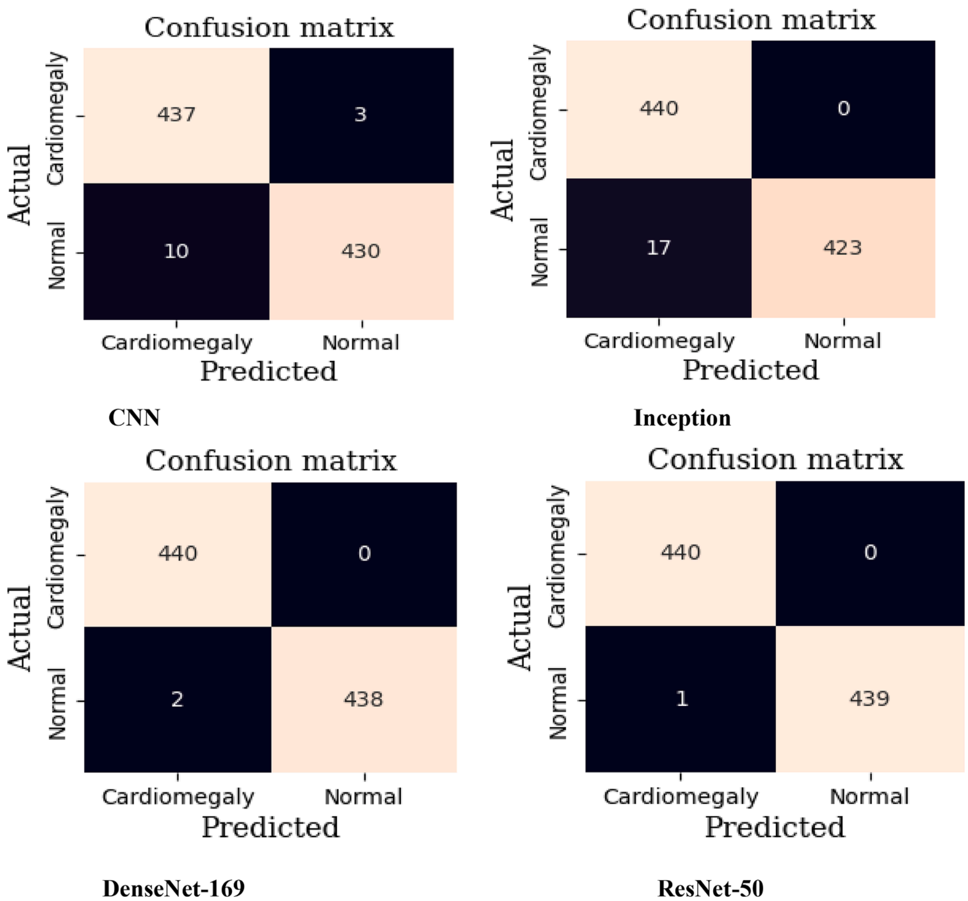

Fig. 12. Confusion matrixes of the different proposed cardiomegaly detection models.

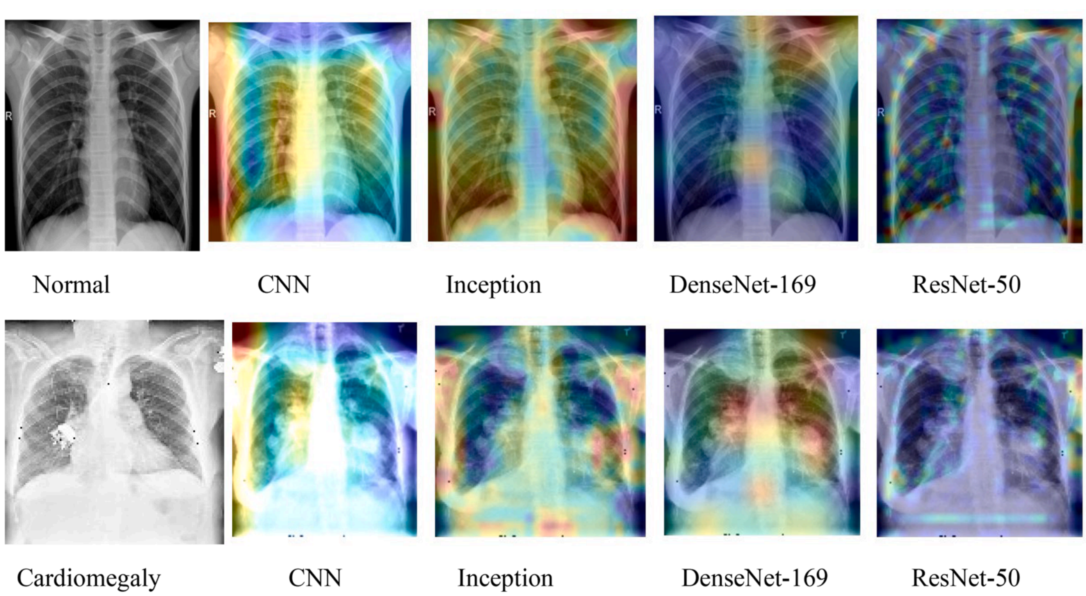

Fig. 13. Shows the visualization of significant regions in the CXR images using Grad-Cam.

indicates that the cardiomegaly diagnosis model has surpassed previous research in terms of training, testing accuracy, and speed. This advancement is important for improving diagnosis precision and speed. It indicates a significant improvement in cardiomegaly diagnosis accuracy, potentially leading to better patient results. The suggested ResNet-50 has demonstrated a notable enhancement in both detecting cardiomegaly capacity and efficiency in actual clinical settings. The proposed method is a cost-effective solution for diagnosing cardiomegaly. This is important in real clinical settings where quick and accurate diagnosis is crucial for timely patient care. Improved accuracy and faster run time make our model a valuable tool for clinical use, ultimately improving patient care. Clinically, the speed and precision of

Table 2
Shows the summary model's performance in precision, recall, F1-score, training, validation, and testing accuracy, as well as, training and testing time.

Models	Class	Precision (%)	Recall (%)	F1-score (%)	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)	Training time (minutes)	Testing time (seconds)
CNN	Cardiomegaly	98	99	99	99.8	99.4	98.5	0:2:22	1s, 22ms
	Normal	99	98	99					
Inception	Cardiomegaly	96	100	98	98.6	96.8	96	0:12:04	3s, 100ms
	Normal	100	96	98					
DenseNet-169	Cardiomegaly	100	100	100	100	100	99.7	0:11:38	8s, 284ms
	Normal	100	100	100					
ResNet-50	Cardiomegaly	100	100	100	100	100	99.8	0:26:37	4s, 140ms
	Normal	100	100	100					

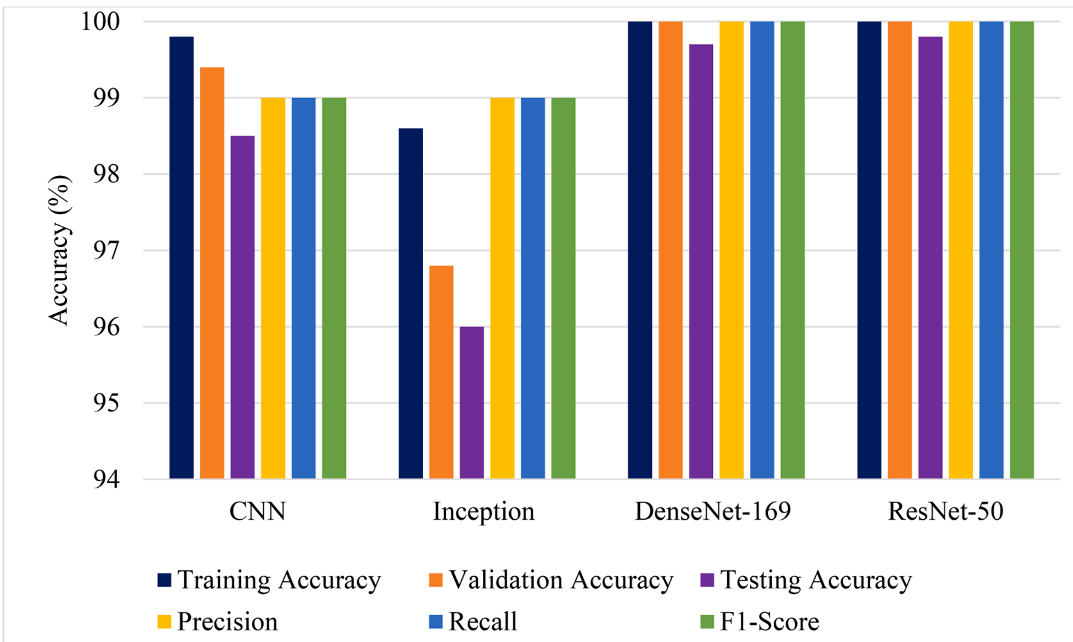

Fig. 14. Shows a comparison of classification results achieved through four models.

Table 3
Shows a comparison among previous existing methods in cardiomegaly detection.

Authors	Classes	Methods	Image no.	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
(Innat et al., 2023)	Non-Cardio, Cardio	CNN	30,805	87	85	86	85
(Raghu Kumar et al., 2023) et al.	Cardiomegaly, Normal	CNN	35,038	95	95	95	–
(Que et al., 2018)	Cardiac, Thoracic	VGG16	2′630	100	89.29	94.34	93.75
(Candemir et al., 2018)	Cardiomegaly, Normal	CNN	4000	83.92	92.58	88.73	88.24
(Decoodt et al., 2023)	Cardiomegaly, Normal	DenseNet-121, AlexNet	224,316	84.8	93.1	–	87
Proposed model	Cardiomegaly, Normal	CNN, Inception, DenseNet-169, and ResNet-50	4400	100	100	100	99.8

diagnosing cardiomyopathy from chest X-ray images could be greatly increased by including ResNet-50 and other CNN models in diagnostic procedures. These models can speed up initial evaluations by automating the detection process, which may cut down on delays in diagnosis, allow for prompt intervention, will also reduce workflow in radiology departments, eventually benefiting both healthcare professionals and patients. The CNN for the cardiomegaly diagnostic model takes almost two minutes to train and one second to test, as Table 2 illustrates. In contrast, the proposed ResNet-50 model takes 26 minutes to train and 4 seconds to test. This suggests that in actual clinical settings, the suggested study will aid in enhancing the precision and speed of cardiomegaly detection. As a result, the model's effective run time is essential to its usability and usefulness in clinical settings. The recommended methodology reduces the amount of time needed for training and testing, providing a financially viable option for cardiomegaly identification. This is particularly helpful in real-world clinical settings because rapid patient treatment depends on an accurate and timely diagnosis.

Our evaluation indicates that the ResNet-50 and other models are highly successful in detecting early or subtle cases because of their advanced ability to extract features and their high rates of accuracy. In particular, the model's capacity to identify minor irregularities is backed by its reliable results in different test situations and its high accuracy in detecting cardiomegaly. These findings show that our models can detect early indicators of cardiomegaly with great accuracy, essential for earlier treatment and better management of patients. This feature is important in a clinical setting because it enables treatment to start early and enhances patient care, which could lead to better results for patients. Moreover, our model gives further insights into the utilization of visualization methods like Grad-CAM, aiding in comprehending the model's focus on possible early signs of the condition. This demonstrates how our model aids in early detection and its possible influence on clinical procedures.

Additionally, the model performed consistently across different subgroups within the dataset we used, including age, gender, and ethnicity. It maintained high accuracy in detecting cardiomegaly across various age groups, genders, and ethnic backgrounds, demonstrating robustness and removing bias. Performance metrics such as accuracy, precision, recall, and F1-score were stable across these subgroups, suggesting that the model generalizes well and does not exhibit significant disparities.

Comparing our proposed models' performance against that of human radiologists would reveal important information about its potential clinical utility in diagnosing cardiomegaly from chest X-ray images. While the model achieved 99.8 % accuracy in testing, as well as perfect (100 %) precision, recall, and F1-score, radiologists contribute considerable clinical skills and contextual understanding to image interpretation. They take into account elements such as patient history, clinical symptoms, and other diagnostic tests, all of which are important for making thorough diagnostic conclusions. Integrating the ResNet-50, and other models into clinical practice could help radiologists by giving quick and uniform preliminary assessments, thereby increasing diagnostic efficiency and aiding in early detection. However, the model's performance needs to be evaluated against human radiologists across varied patient groups and clinical contexts to verify its reliability and generalizability.

Ethical considerations are essential when applying AI for medical diagnosis to ensure patient privacy, decision-making openness, and equitable access to healthcare benefits. Addressing biases in AI algorithms, training healthcare personnel, and following ethical rules and regulatory frameworks are all critical for ensuring patient-centered care and encouraging trust in AI technology in healthcare. To address the biases issue, we have ensured that our dataset is varied and inclusive, and have used methods like data augmentation and meticulous selection of training data. We also used a balanced and representative dataset to minimize these biases. Furthermore, we addressed the significance of continual assessment and modification of the model in various healthcare settings to prevent unintentional biases. Concerning privacy issues, it is important to note that all patient information utilized in our research was anonymized following ethical standards and regulations, as we sourced our dataset from an international online repository on Kaggle. We emphasize the importance of following secure data handling procedures and maintaining strict access controls while implementing our models in clinical settings. We aim to build trust in AI-based diagnostics and ensure our technology benefits healthcare and protects patient rights.

Implementing the ResNet-50 model for clinical use requires various essential stages and tackles numerous obstacles. At the start, it is crucial to integrate with current electronic health record (EHR) systems and imaging databases to guarantee smooth data access and processing in clinical workflows. This integration requires creating interfaces that allow the model to interact with X-ray images and integrate its results into radiological evaluations. Furthermore, the model must go through extensive clinical validation to confirm that its accuracy remains constant in various patient demographics and imaging scenarios. This involves ongoing adjustment influenced by clinical input to respond to changing practices and demographics. Radiologists and healthcare professionals need to undergo training to understand the model's features and effectively interpret its results. Continuous assistance is required to deal with any operational problems that may come up. Adherence to regulations and maintaining strong data security are essential for meeting medical device mandates and safeguarding patient data.

In addition to that, implementing the ResNet-50 model to detect cardiomegaly from chest X-ray images demands careful evaluation of constraints. These include the challenges of extending binary classification to multi-class scenarios for various cardiac conditions, and imaging equipment, and the computational demands required for practical clinical implementation. Furthermore, the deployment of such models necessitates the use of critical infrastructures such as computers, servers, and dependable internet connectivity to enable real-time image processing and model inference, which is critical for efficiently integrating AI-driven diagnostic tools into clinical workflows. Addressing these difficulties necessitates extensive planning and resource allocation to ensure the model's reliability, scalability, and ethical application in healthcare settings. Also, integrating the model into current clinical systems could be challenging from a technical perspective, demanding meticulous planning to guarantee seamless data flow and compatibility. Moreover, it is crucial to address opposition to new technologies by showcasing the advantages of the model and offering thorough training to promote acceptance.

In general, integrating the ResNet-50 model into medical processes can improve diagnostic speed by supplying automated initial evaluations. This enables radiologists to concentrate on complicated cases and analyze findings with additional context. The model can rapidly detect potential cases of cardiomegaly, making the diagnostic process more efficient, reducing workload, and enhancing patient care in the end. Taking proactive steps to address these deployment challenges will be essential for maximizing the potential benefits of the model in clinical practice.

Our binary classification is limited by the size of our dataset, which was carefully selected for detecting cardiomegaly and normal cases. To address this issue, we recognize the importance of further research to enhance the model's functionalities. Creating classification systems that can distinguish between different cardiac conditions would offer a more detailed diagnostic tool.

7. Conclusion

This study involves training a deep learning model to automatically classify cardiomegaly in chest radiograph images. Additionally, techniques such as BM3D for noise reduction, and CLAHE for contrast enhancement in low-intensity images are used to improve the model's performance. The suggested model effectively forecasts if a specific chest X-ray shows cardiomegaly or normality, aiding in early and accurate diagnosis crucial for prompt patient care, especially in regions with limited radiologists. This study aims to enhance medical accuracy by enabling early cardiomegaly detection to improve healthcare and prevent unfavorable consequences like death. Based on our observations, we found that the performance of CNN and other pre-trained models such as Inception, DenseNet-169, and ResNet-50 was accurate. After careful consideration of the results, we decided to use ResNet-50 for the detection and identification of cardiomegaly. The ResNet-50 model consistently demonstrated the highest level of accuracy across four experiments, achieving 100 % training accuracy, 100 % validation accuracy, 99.8 % testing accuracy, and 100 % accuracy for precision, recall, and F1-Score. Our automated cardiomegaly diagnosis model has the potential to transform the measurement process, possibly eliminating the requirement for manual screen drawing, and ultimately saving millions of hours for radiologists in clinical settings. This development holds the promise of significantly enhancing the efficiency and precision of cardiomegaly diagnosis, delivering ultimate advantages to both medical professionals and patients.

Authors Contributions

Aleka Melese Ayalew: Conceptualization, Methodology, Software, and Writing – original draft. Belay Enyew**:** Data curation, Methodology, Review & editing. Yohannes Agegnehu Bezabh**:** Software, Investigation. Visualization, **Biniyam Mulugeta Abuhayi:** Investigation, Resources, Validation. **Girma Sisay Negashe:** Formal analysis, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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