

# Heart Disease Evaluation Through Echocardiography Using CNN, ResNet50, VGG16, and Image Processing

Suvarna Potdukhe<sup>1</sup>, Akanksha Karale<sup>2</sup>, Aniket Deshmukh<sup>2\*</sup>, Shivani Ghare<sup>2</sup>, Mayuri Kadam<sup>2</sup>

## Abstract

Heart conditions stand out as primary contributors to untimely mortality among adults aged 30 and above, notably among those grappling with elevated cholesterol levels and diabetes. Detecting such ailments often necessitates the use of an echocardiogram, providing an intricate portrayal of the heart. However, precise analysis hinges on both the proper functioning of the echocardiogram apparatus and the proficiency of a skilled radiologist, a condition not always met. Manual scrutiny of echocardiograms to identify heart conditions proves to be an arduous endeavor prone to human fallibility, including misinterpretations, thus advocating for automation through image processing techniques like convolutional neural networks (CNN). This risk of misinterpretation escalates in remote locales where radiologist training might be deficient compared to urban centers, compounded by the potential presence of defective equipment. To tackle these obstacles, we introduce a system aimed at automating heart disease prediction based on echocardiograms. By minimizing human error, we aim to uphold consistent healthcare standards across urban and rural medical facilities. For the preliminary phase of our endeavor, we evaluated CNN, ResNet50, and VGG16 algorithms, ultimately selecting CNN due to superior accuracy. Specifically, our system concentrates on identifying angina pectoris, cardiovascular disease, coronary artery disease, and left ventricular hypertrophy (LVH). In initial testing, our CNN model achieved an accuracy rate of 95.27%.

**Keywords:** CNN (convolutional neural networks), echocardiography, ResNet50, VGG16, image processing

## INTRODUCTION

Heart conditions are increasingly prevalent among millennials and younger individuals owing to rising sedentary lifestyles and unhealthy eating habits. Common ailments associated with poor cardiovascular health include angina pectoris, left ventricular hypertrophy (LVH), cardiovascular diseases, and coronary artery diseases. These disorders can be diagnosed using echocardiography. Echocardiography, also known as ECG, is a painless, non-invasive procedure that evaluates the

### \*Author for Correspondence

Aniket Deshmukh

E-mail: [aniketdeshmukh951@gmail.com](mailto:aniketdeshmukh951@gmail.com)

<sup>1</sup>Assistant Professor, Department of Information Technology, RMD Sinhgad School of Engineering, Pune, Maharashtra, India

<sup>2</sup>Student, Department of Information Technology, RMD Sinhgad School of Engineering, Pune, Maharashtra, India

Received Date: June 04, 2024

Accepted Date: July 22, 2024

Published Date: November 07, 2024

**Citation:** Suvarna Potdukhe, Akanksha Karale, Aniket Deshmukh, Shivani Ghare, Mayuri Kadam. Heart Disease Evaluation Through Echocardiography Using CNN, ResNet50, VGG16, and Image Processing. International Journal of Information Security Engineering. 2024; 2(2): 25–35p.

electrical activity and rhythm of the heart. Ultrasound technology provides detailed images of the chambers and heart structures. These images were then reviewed by a physician or radiologist to identify any abnormalities that could indicate blockages, congenital defects, or weakened cardiac muscle. The accuracy of the diagnosis relies heavily on the expertise of the radiologist and the quality of the ECG equipment. Discrepancies in skilled personnel availability between rural and urban areas can affect diagnostic accuracy. In rural settings, there is a heightened risk of misdiagnosis due to factors such as electrode corrosion and unclean gel invasion, leading to noise in ECG readings. Proper earthing is crucial to prevent electrical interference

and ensure machine functionality, particularly in areas prone to electricity fluctuations. However, maintaining such safety measures can be challenging in underfunded rural healthcare facilities. Moreover, the manual classification of cardiac conditions requires judgment and expertise, which may be lacking among rural radiologists compared with their urban counterparts. This discrepancy can introduce human error, necessitate additional testing, or result in fatal outcomes. To address these challenges, a deep neural network model was employed in this study to analyze a vast dataset of echocardiograms and efficiently detect abnormalities.

## LITERATURE SURVEY

Abdi et al. [1] have displayed a strategy that employs a reverberated quality score to decide operator/radiologist changeability in information collection. A profound CNN demonstrated for scoring apical four-chamber (A4C) sounds was developed to achieve this. In this ponder, an authorized cardiologist evaluated 6,916 conclusion systolic images and gave them a score between (not satisfactory) and 5 (excellent). Two sets, preparation, approval, and test, were prepared from the picture sets. The arrangement plan and its parameters were chosen utilizing the molecule swarm optimization stochastic approach based on training-validation information. The cruel outright mistake between the experts' manual scores and the ultimate prepared model's scores extended from 0.71 to 0.58.

Stoitsis et al. [2] discussed the architecture of a computer-aided determination (CAD) framework, counting picture preprocessing, characterizing regions of interest, including extraction and determination, and classification. We present two cases to demonstrate the working of these concepts. Refinement of symptomatic and asymptomatic carotid atheromatous plaques is the subject of the primary illustration. Utilizing an examination of change (ANOVA), the foremost solid components of the assessed surface and movement highlight vector were chosen. Clustering delivered 74%, 79%, and 84% of the comes about procured.

Madani et al. [3] found that learning and computer vision calculations could accurately decode restorative photographs. They created data-efficient progressed machine learning classifiers for cardiology forecast errands with 91.2 accuracy for parallel cleared-out ventricular hypertrophy recognizable proof and 94.4 accuracy for the conclusion of 15-view still-image echocardiographic views. In addition, utilizing as much as 4% of the labeled information, they were able to create semi-supervised generative antagonistic organization models with 80 accuracy.

Alex Krizhevsky and others [4] for the ImageNet LSVRC-2010 competition in order to classify 1.2 million pictures, this study built a profound CNN with 650,000 neurons and 60 million parameters. Utilizing five convolutional layers, non-saturating neurons, a Graphics Processing Unit (GPU) implementation, and a dropout regularization strategy, they were able to get top-1 and top-5 blunder rates of 37.5%. A partitioned cycle of the demonstration was submitted, and with a top-5 blunder amid a testing rate of 15.3%, it was the possible victory of the ILSVRC-2012 competition. To extend the mechanized discovery and classification suggestive of echocardiograms, Khamis et al. [5] planned a multistage classification framework utilizing spatiotemporal extraction, Cuboid Finder, and administered lexicon learning (LC-KSVD) techniques. The discoveries illustrated that with a normal distinguishing proof rate of 95%, computerized categorization of echocardiography pictures appeared more promising than manual discovery.

According to Hubhanshi Singhal [6], there is a need for a therapeutic conclusion framework that can more precisely and accurately analyze cardiac conditions. An early arranging expectation and therapeutic conclusion framework was developed utilizing convolutional neural networks (CNNs). With more than 95 accuracy, CNNs that have been prepared to employ an altered adaptation of the backpropagation preparation strategy can both anticipate the nonappearance and nearness of heart disease.

Concurring inquiries by Bhavesh Patel, Nilam Harkulkar, and Swati Nadkarni [7], fake insights are the most compelling way to form judgments and expect cardiac infection precisely. To examine cardiac infections utilizing profound learning, the Cleveland dataset was utilized. CNN were utilized in the proposed study to recognize heart maladies. The test results show that their proposed work encompasses an exceptionally high degree of precision in foreseeing heart infections.

Zamzmi et al. [8] later assessed robotized methods for echocardiography information investigation. It incorporates the four essential objectives of assessing the quality of the research, categorizing the seas, partitioning the boundaries, and diagnosing illnesses. It also examines the shortcomings and drawbacks of current strategies and recognizes the foremost basic inquiries about ways. It too talks approximately how mechanized resound investigation is doing right presently Ravi Narayan Panda et al. [9] have considered different ways to robotize the forecast of heart malady, in arrange to estimate the malady early on, CNN recommended in this inquire about. This ponder compares the standard strategies, counting calculated relapses, K-nearest neighbors (KNN), Gullible Bayes, back vector machines, and neural systems, with CNN's proposed forecast show. The UCI machine learning store dataset for experimentation and 94% exact estimates of cardiovascular illness (CVD). Phalke et al. [10] evaluated several cardiac symptomatic categorization methods. In this study, The ECG numeric dataset begins with extraction and arrangement. At that point, employing a convolutional neural network (CNN), they extricate the characteristics that are required to be found and categorized. Concurring with these, CNN perform better than the current innovation. Execution measurements such as accuracy, precision, and F-measure must be calculated after classification. CNN performed better than KNN. convolutional neural network (CNN) are the best classifiers for heart malady determination on an accessible dataset, concurring with comparative measurements.

The Viren Viraj Shankar [11] information for this study was collected from genuine clinics and incorporated both organized and unstructured data. The exactness delivered by the show created ranged from 85% to 88%. Moreover, they suggested utilizing a few machine learning calculations over the preparation of information to predict the chance of illnesses to induce the finest precise machine learning calculation. This inquiry proposes that qualities can be changed to improve exactness.

Roldan et al. [12] reported that valve malady is a heart sign of systemic lupus erythematosus. In this study, 69 patients with systemic lupus erythematosus underwent transesophageal echocardiography and rheumatology. The information appeared that the frequency of valvular heart illness changes over time, indicating that it is transiently tied to other clinical aspects of lupus and is related to noteworthy dreariness and passing. The causes of the broadening within the walls of the heart were investigated in this study.

Kusunose et al. [13] surveyed the exactness of an Error Function (EF) (discharge division) expectation demonstrated in a learning database with mistakenly labeled pictures. A total of 340 patients were enlisted with five standard views and 10 pictures per cycle to prepare a convolutional neural arrangement. 5-fold cross-approval was utilized to evaluate the execution of the demonstration. Utilizing 10 care completely chosen pictures, the beat shows effectively recognized video with a general test accuracy of 98.1%. No steps were taken to reduce the overfitting of the model.

Mohammad MR Khan Mamun et al. [14] proposed a strategy for recognizing cardiac illness using firefly calculation (FA) with Convolutional Neural Networks (CNNs). FA finds the worldwide optima faster than other nature-inspired calculations, beating them. Two partitioned ECG databases were compared, and FA-CNN performed 88.25 better than the other machine learning strategies.

Soares et al. [15] developed four key points of interest from an audit of modern information extraction strategies: progressing picture quality, finding the cardiac window-seeing plane, measuring and

analyzing heart movement, and distinguishing and classifying cardiac maladies. The proper and cleared-out chamber and ventricles, as well as the classification of cardiac issues, were best distinguished and sectioned using profound learning calculations. The most noteworthy results were achieved using Convolutional Neural Network (CNN) models for all bunches. Wahlang et al. [16] investigated the use of profound learning approaches to echocardiography (reverberate). It employs 2D, 3D, and videographic pictures to classify the reverberation into typical or abnormal and videographic pictures to classify the different shapes of spewing forth. Deep learning methods outperformed SVM approaches, with Variational Autoencoder (VAE) outper-shaping Long Short-Term Memory (LSTM) for inactive 2D and 3D Doppler pictures and LSTM outflanking VAE for videographic pictures.

Chayakrit Krittanawong and Hafeez Ul Hassan Virk have taken an overview [17] of 103 cohorts totaling 3,377,318 people who met the incorporation criteria out of 344 qualified ponderers. The pooled Area under the curve (AUC) for boosting calculations was 0.88 (95% CI 0.84–0.91), while the pooled AUC for custom-built calculations was 0.93 (95% CI 0.85–0.97). The combined AUCs for the back vector machine (SVM), boosting, and Convolutional Neural Network (CNN) approaches were 0.92 (95% CI 0.81–0.97), 0.91 were observed (95% CI 0.81–0.96), and 0.90, for occurrence (95% CI 0.83–0.95), respectively. Although there are insufficient considerations for each calculation to utilize the meta-analytic method, SVM may outflank the other calculations in certain scenarios. Clinicians may discover this data by selecting the most suitable calculations for their dataset and deciphering the results.

Jing Wanga and Xiaofeng Liuc Center [18] according to this consider, a down-to-earth end-to-end system may be utilized to automatically assess multi-view echocardiograms 1308 patients gotten five-view echocardiograms that were recorded, with names demonstrating malady and key-frames for the standard. Diminishing arranging parameters and progressing the approach to the unequal lesson issue required the utilization of positive preparation tests and profundity shrewd separated convolution-based multichannel systems.

Wilson Soares de Siqueira [19], a framework for writing audits (SLR), will be conducted using fake insights (Artificial Intelligence) methods utilized in transthoracic echocardiography Transthoracic Echocardiography robotization. More than 800 papers on the subject were revealed by the overview, and 45 papers were selected to make a complete ponder. The discoveries classified the key examinations into three categories: deciding the cardiac vision arrangement, looking at the heart working, and deciding cardiac sicknesses.

Rajesh N, Maneesha T, Shaik Hafeez, and Hari Krishna [20]—the Gullible Bayes procedure, choice trees, ID 3, KNN clustering, and CNN performed other picture identification and classification calculations, which are the most vital data. The A4C perspective was the foremost open, but CNN consistently had the finest exactness. The larger part of the distributions, be that as it may, did not improve their information filtration strategy or grow the number of pooling layers, which had a negative impact on the model's last expectations.

## PROPOSED SYSTEM

### Dataset Collection and Preprocessing

Gathering and preprocessing datasets. There were 2398 images in the dataset downloaded from Kaggle. The dataset was further split into two segments: test photos were included in one segment and training images were included in the other. The following are images with data distributions: all of the algorithms in our exploratory investigation were fed training data from 606 photographs of angina pectoris, 599 images of cardiovascular disease, 592 images of coronary artery disease, and 601 images of patients with LVH disease; the remaining images in the testing folder are as follows: LVH (#34), coronary artery disease (#24), angina pectoris (#29), and cardiovascular disease (#24). This testing dataset was chosen at random and used to assess the accuracy of the model. The preprocessing stage of

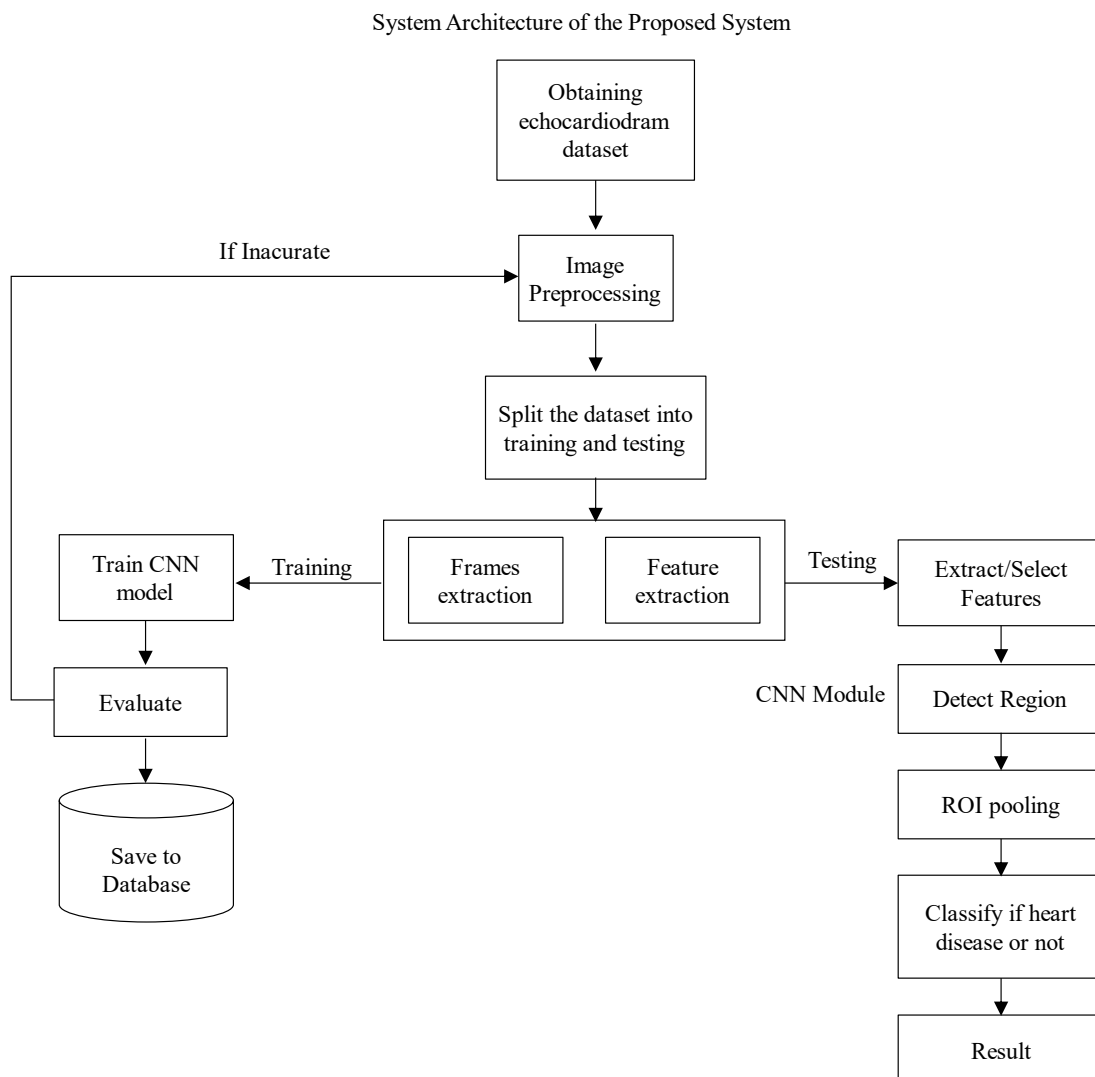
the photo creation restricted them to  $400 \times 400$  pixels. The machine learning models were fed by these trimmed photos, which contained less noise. In our first investigation, we employed algorithms such as VGG-16, ResNet-50, and CNN. Greyscale conversion is the process of converting RGB colors (three-channel pictures) to grayscale (single-channel pictures), where 255 represents white and 0 represents black. Echocardiogram images can be converted from color to grayscale, which reduces the input data complexity and expedites training.

### System Architecture

The given in Figure 1 is the system architecture of the proposed model.

### Algorithms Applied

**VGG-16:** The VGG-16 method employs convoluted layers to find hidden patterns in data that are invisible. There are 16 layers in this architecture. The  $400 \times 400$  images were resized to  $224 \times 224$ , the minimum size required as an input file for the VGG-16 model. The first block consisted of two convolutional layers, each of which had  $64 \ 3 \times 3$  filters. A max-pooling layer, which has a pooling function and divides the spatial dimensions into half, comes after these layers have a  $2 \times 2$  pooling size. Similar to Block 1, the second block had two  $3 \times 3$  convolutional layers with 128 filters each, followed by a max-pooling layer. Three convolutional layers and  $256 \ 3 \times 3$  filters constitute the third block. A

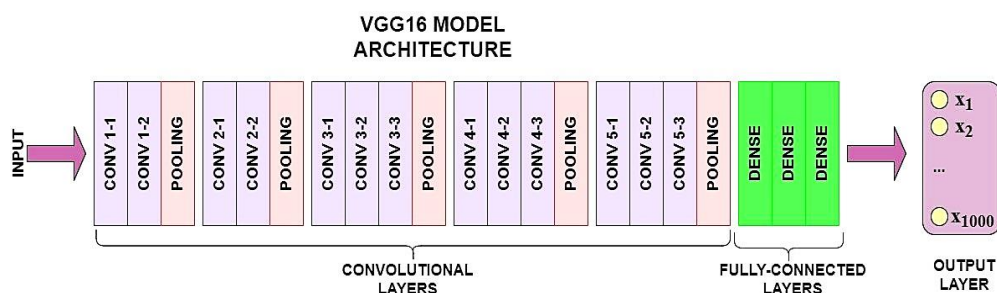


**Figure 1.** System architecture.

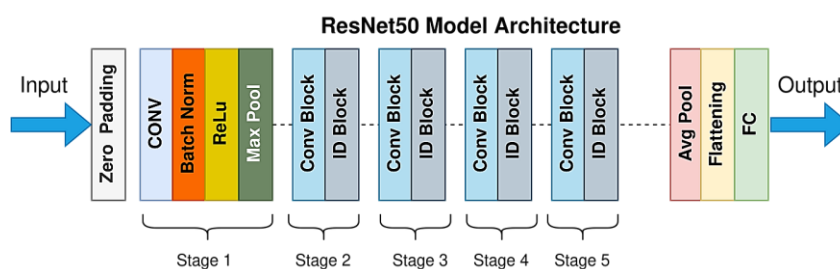
max-pooling layer is added after the convolutional layers. The fourth block consisted of a layer for maximum pooling after three convolutional layers with 512 3x3-sized filters each. Following the three convolutional layers with 512 3x3-sized filters each, the fifth block has a max-pooling layer. The final output of the max-pooling layer was compressed into a one-dimensional vector with 25 088 elements. Consequently, the features were configured for the fully connected layers, as shown in Figure 2.

*ResNet-50:* ResNet-50 is another pre-trained model with 50 layers, most of which are convolutional layers. Microsoft developed it in 2015, intending to extract features from a set of input photographs. The total number of layers in the network, which includes convolutional, batch normalization, and fully connected layers, is indicated by the number “50” in ResNet-50. The basic blocks of the ResNet-50 architecture have a similar structure. The max-pooling layer is followed by several convolutional layers, typically with  $3 \times 3$  filters, within each block. As we get deeper into the network, each block has a greater number of filters to gather more complicated data. By reducing the spatial dimension and downsampling the feature maps, the max-pooling layers enable the network to focus on the most crucial attributes, as shown in Figure 3.

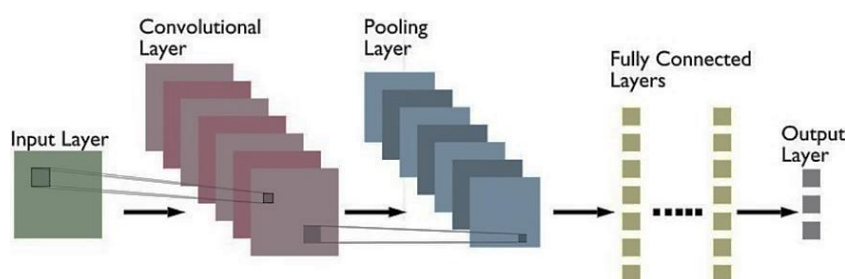
*Convolutional neural networks:* CNN are a common type of artificial neural network used for image and video recognition. It is composed of several layers that learn to identify the features in the input data by applying convolutional filters. Convolutional layers were used for feature extraction, pooling layers were used to reduce dimensionality, and fully linked layers were used for classification. CNNs can be used for classification after training on labeled data to identify patterns and features in the input



**Figure 2.** Architecture of VGG-16.



**Figure 3.** Architecture of ResNet50.



**Figure 4.** CNN Architecture.

data. The dimensions of the input images were  $224 \times 224$  pixels. The training and validation data are defined in the dataset directories. The CNN architecture consists of four convolutional layers, followed by layers for max-pooling and flattening, two dense layers, and a SoftMax-activated output layer for multiclass classification. An optimizer, loss function, and accuracy metric were included in the CNN model compilation process, as shown in Figure 4.

## RESULT AND DISCUSSION

### Accuracy of Models

- *VGG16*: Our proposed system's VGG16 model on data produced an initial training accuracy of 91.31% and a validation accuracy of 73.02%, as shown in Figure 5.
- *ResNet-50*: Our proposed ResNet-50 model produced an initial training accuracy of 94.23% and a validation accuracy of 75.33%. Similarly, the models were not able to reach 92.57% testing accuracy. The ResNet-50 model of our proposed system achieved an initial training accuracy of 94.23% and a validation accuracy of 75.33%. Similarly, the models were not able to achieve a testing accuracy of up to 92.57%, as shown in Figure 6.

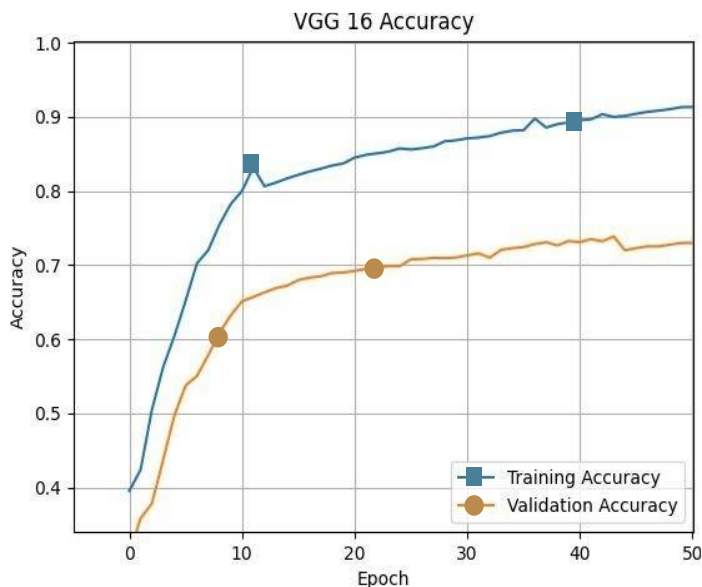


Figure 5. Accuracy graph of VGG16 model.

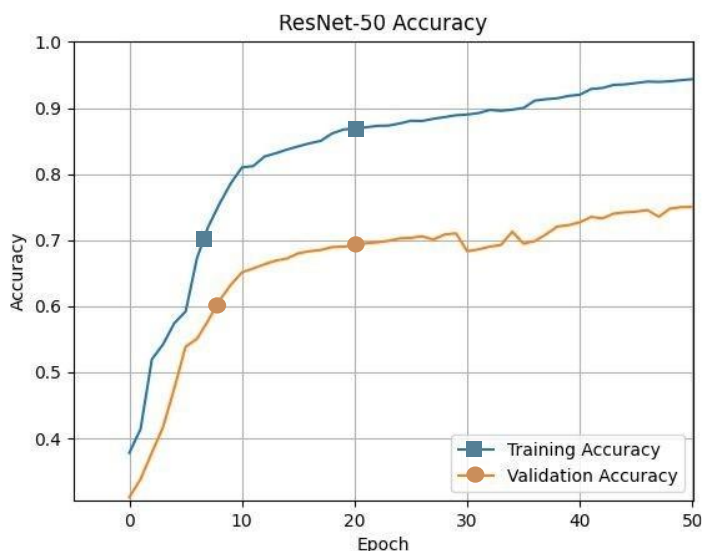
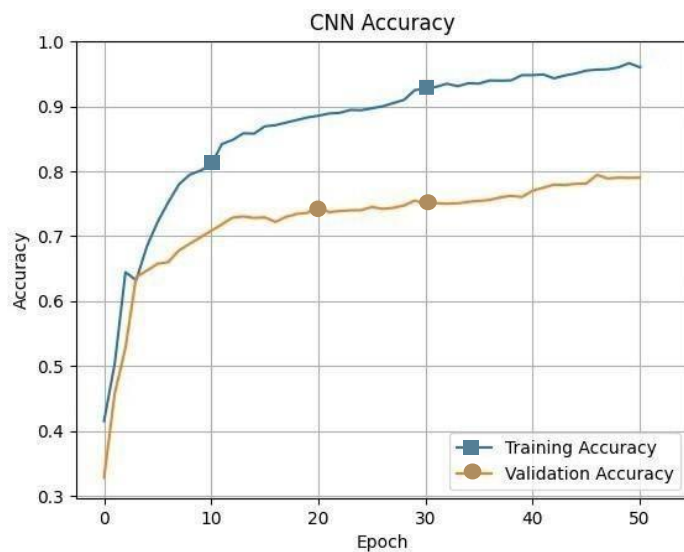


Figure 6. The ResNet-50 model's accuracy graph.



**Figure 7.** CNN model's accuracy graph.

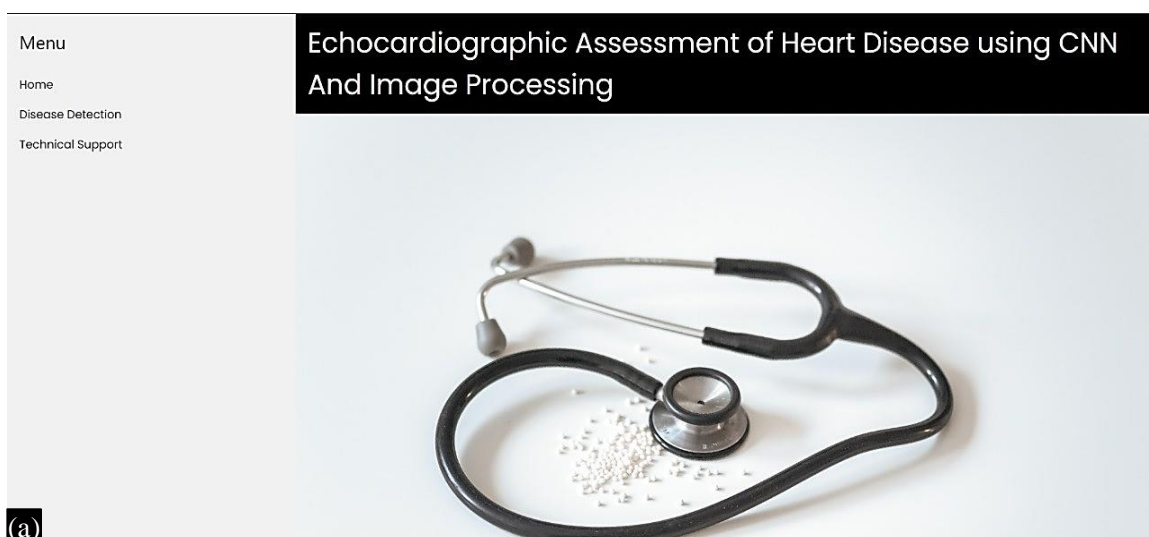
- *Convolutional neural networks:* With the available data, the CNN model in our recommended method yielded a first validation accuracy of 79.16% and a first training accuracy of 96.43%. Our objective is to build models that are effective enough to reach a testing accuracy of 95.27%, in line with how models have produced high levels of validation accuracy, as shown in Figure 7.

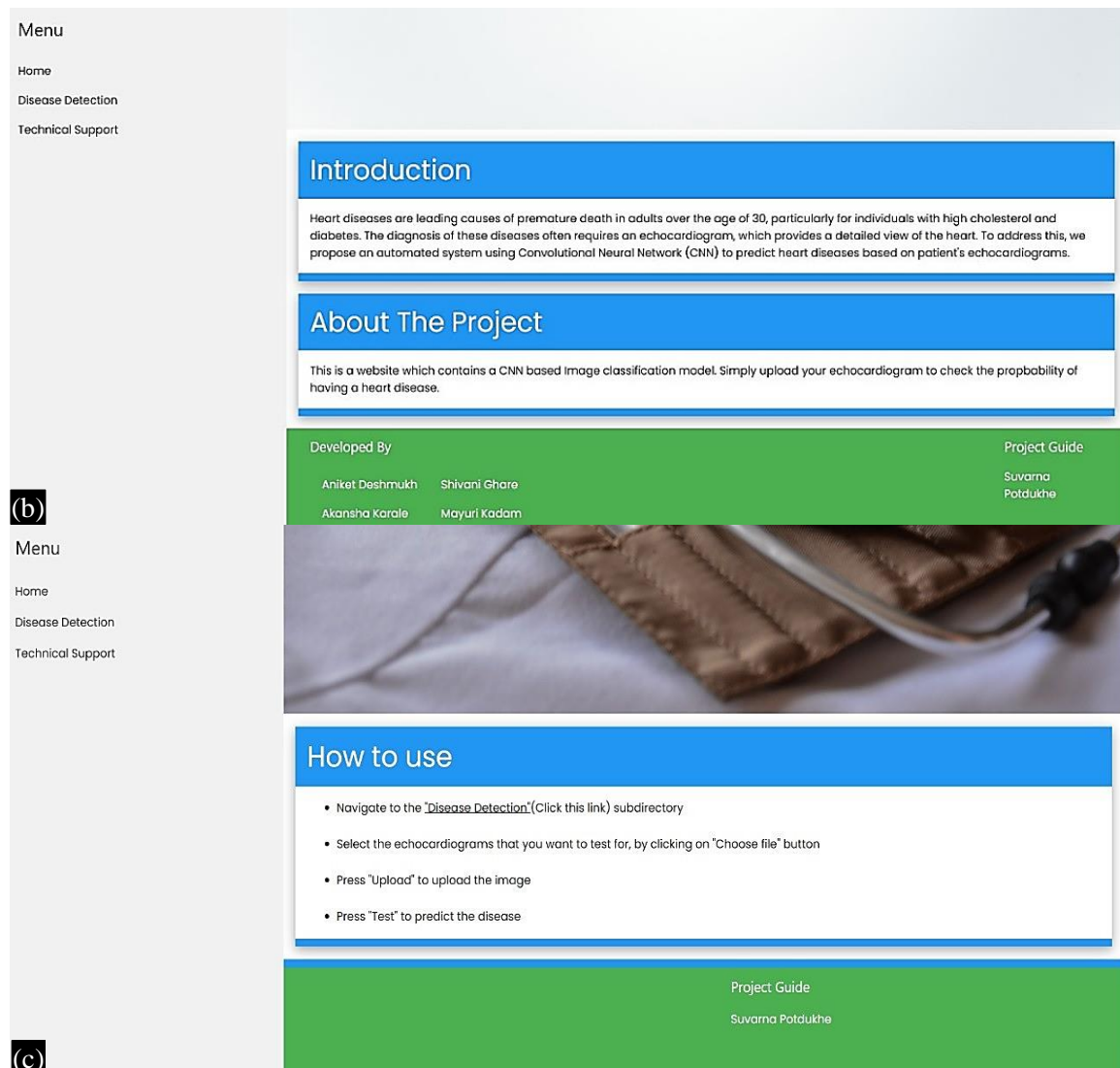
### Comparing the Accuracy of Models

When comparing CNN, ResNet50, and VGG16, ResNet50 often provided the best accuracy owing to its deep residual learning framework. VGG16 offers a good balance between performance and complexity, whereas a basic CNN serves as a good starting point but may fall short on more complex datasets. The choice of model should consider the specific requirements of the task, available computational resources, and the need for model interpretability, as shown in Table 1 and Figures 8(a)–(c) and 9.

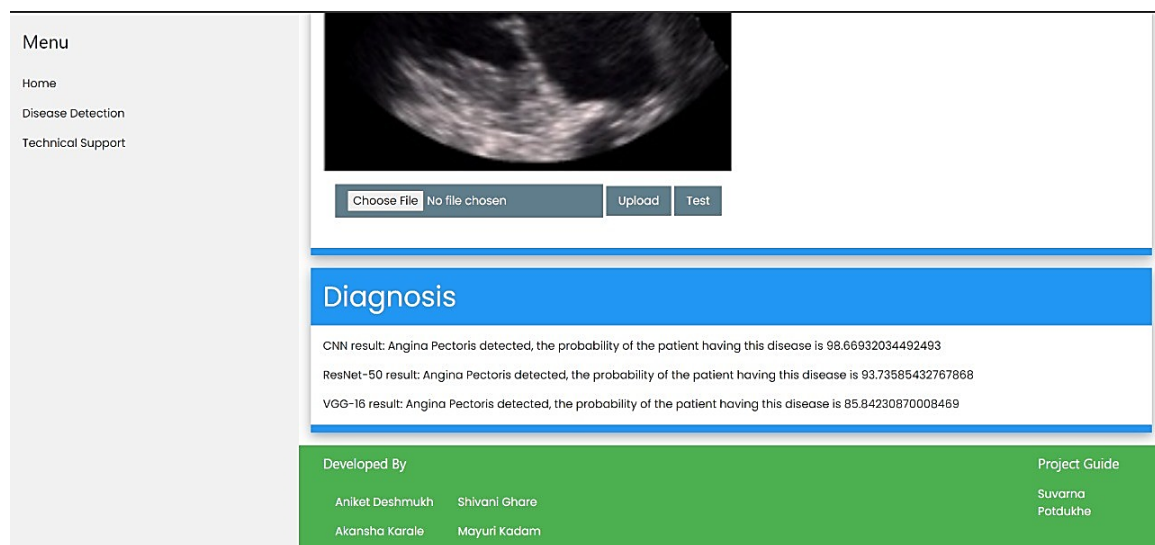
**Table 1.** Accuracy scores of models.

S.N.	Algorithm name	Training accuracy	Testing accuracy
1.	CNN	96.43%	95.27%
2.	ResNet-50	94.23%	92.57%
3.	VGG-16	91.45%	87.09%





**Figure 8.** (a) Front-end of web application, (b) Front-end of web application, and (c) Front-end of web application.



**Figure 9.** Classification functionality of web application.

---

## CONCLUSION

In conclusion, our endeavors in the field of image processing demonstrated significant performance variations among different deep learning models. Through comprehensive experimentation and evaluation, it was observed that the CNN model exhibited the highest accuracy with a testing accuracy of 95.27%. In contrast, both the VGG-16 and ResNet50 models exhibited relatively low testing accuracies of 87.09% and 92.57%, respectively. These results underscore the importance of selecting appropriate deep learning architectures for specific tasks, as the superior performance of the CNN model emphasizes its suitability for our image processing tasks. The notable accuracy achieved by CNN suggests its effectiveness in accurately classifying and analyzing images, positioning it as a viable option for future image processing applications. The outcomes of this contribute to the existing body of knowledge in the field and provide valuable insights for researchers and practitioners alike, emphasizing the significance of considering various deep learning models in image processing tasks to optimize accuracy and enhance overall performance.

## Acknowledgments

The corresponding authors would like to extend their sincere appreciation and gratitude to Mr. Saurabh Parhad for his invaluable guidance, unwavering support, and constant encouragement throughout the review process. Their expertise and insightful suggestions greatly contributed to the success of this study. Additionally, the authors would like to express their heartfelt thanks to their friends and family members for their unwavering support and understanding during this study. Their encouragement and belief in their abilities have been instrumental in overcoming challenges and reaching the completion of this work.

## REFERENCES

1. Abdi AH, Luong C, Tsang T, Allan G, Nouranian S, Jue J, et al. Automatic quality assessment of echocardiograms using convolutional neural networks: Feasibility on the apical four-chamber view. *IEEE Trans Med Imaging*. 2017;36(5):1221–30. DOI: 10.1109/TMI.2017.2690836. PubMed: 28391191.
2. Stoitsis J, Valavanis I, Mougiakakou SG, Golemati S, Nikita A, Nikita KS. Computer-aided diagnosis based on medical image processing and artificial intelligence methods. *Nucl Instrum Methods Phys Res A*. 2006;569(2):591–5. DOI: 10.1016/j.nima.2006.08.134.
3. Madani A, Ong JR, Tibrewal A, Mofrad MRK. Deep echocardiography: Data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease. *NPJ Digit Med*. 2018;1:59. DOI: 10.1038/s41746-018-0065-x. PubMed: 31304338.
4. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. *Commun ACM*. 2017;60(6):84–90. DOI: 10.1145/3065386.
5. Khamis H, Zurakhov G, Azar V, Raz A, Friedman Z, Adam D. Automatic apical view classification of echocardiograms using a discriminative learning dictionary. *Med Image Anal*. 2017;36:15–21. DOI: 10.1016/j.media.2016.10.007. PubMed: 27816858.
6. Singhal S, Kumar H, Passricha V. Prediction of heart disease using CNN. *Am Int J Res Sci Technol Eng Math*. 2018;23:257–61.
7. Harkulkar N. Heart disease prediction using CNN, deep learning model. *Int J Res Appl Sci Eng Technol*. 2020;8(7):875–81. DOI: 10.22214/ijraset.2020.32671.
8. Zamzmi G, Hsu LY, Li W, Sachdev V, Antani S. Harnessing machine intelligence in automatic echocardiogram analysis: Current status, limitations, and future directions. *IEEE Rev Biomed Eng*. 2021;14:181–203. DOI: 10.1109/RBME.2020.2988295. PubMed: 32305938.
9. Mehmood A, Iqbal M, Mehmood Z, Irtaza A, Nawaz M, Nazir T, et al. Prediction of heart disease using deep convolutional neural networks. *Arab J Sci Eng*. 2021;46(4):3409–22. DOI: 10.1007/s13369-020-05105-1.
10. Phalke A, Sondur S. Deep learning-based heart disease prediction. *Asian J Converg Technol*. 2019;5(1):1–4.

11. Shankar V, Kumar V, Devagade U, Karanth V, Rohitaksha K. Heart disease prediction using CNN algorithm. *SN Comput Sci.* 2020;1:170. DOI: 10.1007/s42979-020-0097-6.
12. Roldan CA, Shively BK, Crawford MH. An echocardiographic study of valvular heart disease associated with systemic lupus erythematosus. *N Engl J Med.* 1996;335(19):1424–30. DOI: 10.1056/NEJM199611073351903. PubMed: 8875919.
13. Kusunose K, Haga A, Inoue M, Fukuda D, Yamada H, Sata M. Clinically feasible and accurate view classification of echocardiographic images using deep learning. *Biomolecules.* 2020;10(5):665. DOI: 10.3390/biom10050665. PubMed: 32344829.
14. Mamun MMRK, Alouani A. FA-1D-CNN implementation to improve diagnosis of heart disease risk level. *Proceedings of the 6th World Congress on Electrical Engineering and Computer Systems and Sciences (EECSS'20); 2020 Aug; Prague, Czech Republic (Virtual Conference).* Paper No.: ICBES 122. DOI: 10.11159/icbes20.122.
15. de Siqueira VS, Borges MM, Furtado RG, Dourado CN, da Costa RM. Artificial intelligence applied to support medical decisions for the automatic analysis of echocardiogram images: A systematic review. *Artif Intell Med.* 2021;120:102165. DOI: 10.1016/j.artmed.2021.102165. PubMed: 34629153.
16. Wahlang I, Maji AK, Saha G, Chakrabarti P, Jasinski M, Leonowicz Z, Jasinska E. Deep learning methods for classification of certain abnormalities in echocardiography. *Electronics.* 2021;10(4):495. DOI: 10.3390/electronics10040495.
17. Krittanawong C, Virk HUH, Bangalore S, Wang Z, Johnson KW, Pinotti R, et al. Machine learning prediction in cardiovascular diseases: A meta-analysis. *Sci Rep.* 2020;10:16057. DOI: 10.1038/s41598-020-72685-1. PubMed: 32994452.
18. Wang J, Liu X, Wang F, Zheng L, Gao F, Zhang H, et al. Automated interpretation of congenital heart disease from multi-view echocardiograms. *Med Image Anal.* 2021;69:101942. DOI: 10.1016/j.media.2020.101942. PubMed: 33418465.
19. de Siqueira VS, de Castro Rodrigues D, Dourado CN, Borges MM, Furtado RG, Delfino HP, et al. Machine learning applied to support medical decision in transthoracic echocardiogram exams: A systematic review. *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC), Madrid, Spain. 2020.* pp. 400–7. DOI: 10.1109/COMPSAC48688.2020.0-215.
20. Rajesh N, Maneesha T, Hafeez S, Krishna H. Prediction of heart disease using machine learning algorithms. *Int J Eng Technol.* 2018;7(2.32):15714. DOI: 10.14419/ijet.v7i2.32.15714.