Intracardiac Mass Detection and Classification Using Double Convolutional Neural Network Classifier

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ABSTRACT

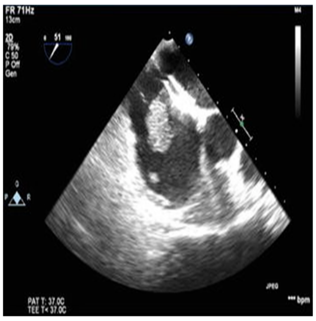
Identification and classification of intracardiac masses in echocardiogram is one of the significant processes in the diagnosis ofcardiovascular disease. Initially, the cropping over the specific region is done in order to make the definition of the mass area. Later on, as the second step the processing of globally unique denoising technique is being implied for the removal of speckle and in order to make the preservation of anatomical structured component in the image. This is defined in terms of preprocessing and it is carried out by Patch-based sparse representation. Subsequently the description of the mass contour and its interconnected wall of the artery are being done by the segmentation mechanism denoted as Linear Iterative Vessel Segmentation model. As the prefinal stage, the processing of boundary, texture and the motion features are being carried out through the processing by double convolutional neural network (DCNN) classifier in order to determine the classification of two different masses. Totally 108 cardiac masses images are being collected for accessing the effectiveness of the classifier. It is also realized with the various state of the art classifiers as projected the demonstration of the greatest performance that has been disclosed with an achievement of 98.98% of accuracy, 98.89% of sensitivity and 99.16% of specificity that has been resulted for DCNN classifier. It determines the explication that the proposed method is capable of performing the classification of intracardiac thrombi and tumors in the echocardiography and ensures for potentially assisting the medical doctors who are in the clinical practice.

Keywords: Cardiovascular Sickness; Echocardiogram; Cardiac Masses; Linear Iterative Vessel Segmentation; Multiscale Local Binary Pattern; Robust Back Propagation Neural Network.

INTRODUCTION

Intracardiac masses are irregular structures found in or near the heart. This structure can cause real cardiovascular problems and requires careful discovery and short-term resection and treatment. There are two basic types of dominant intracardiac masses: tumors and blood clots. Cancer shows the growth of parts of the body, Jomilham, through unpredictable tissue improvement [1-2]. Even though intra-cardiac differ only in pathology, they function similarly in electrophysiology. The Echocardiogram intracardiac tumor (Figure 1(a)) and thrombi

(Figure 1(b)) are shown in Figure 1.



a) Intracardiac Tumor

b) Intracardiac Thrombi

Figure1:(a) Intracardiactumor and (b) intracardiac thrombi

In numerous hospitals or medical clinics, echocardiograms recognizing bits of confirmation are finished by cardiologists manually.

RESEARCH BACKGROUND

Cardiovascular tumors are irregular patterns of the coronary heart. There are a few kinds of coronary tumors. The assessment of ultrasound images has been utilized effectively in the computer-aided design of cardiovascular infections, to distinguish the proof of necessary ultrasound emphasis in the early forecast of stroke [7], in the construction of an aid system with the selection based on fuzzy rules for the prognosis of coronary artery disease [8], and in the use of adaptive blocking adaptive methodologies in the dynamics of the wall and the plate of the carotid artery [9]. However, it is always difficult to differentiate the heart masses from comparable echocardiogram images from a defective image due to the presence of different weights and a high degree of noise, character drop, distortion, and lack of contouring [10].

A fully automated classification technique has not been suggested in the past near the distinction of intracardiac loads on echocardiograms. This classification consists of four stages, such as noise removal, segmentation, feature extraction, and mass classification. Usually, different types of noises are present in ultrasound images, the structure of which also contains beneficial anatomical information. In addition to extracting the essential facets of the image and protecting the anatomical details, it is necessary to obtain a pleasant diagnosis. Usually, different types of noise removal strategies are available, such as pixel intensity correction [11,12,13], median filter-based preprocessing [14], speckle-decreasing anisotropic diffusion (SRAD) found preprocessing [15-16], and preprocessing based on wavelet transformation strategies[17]. As nearby noise decreases procedures, they balance the standard inhomogeneous zones and keep up the edges and realities. These filters are effective at removing stains, but they also remove great small runs. Regarding segmentation, the massive contour artifacts reduction [18], the staging [19], the Animated-Looking Mannequin [20], the fuzzy techniques [21], and the sketch reduction [22] were evaluated. Despite the way that these strategies may be valuable for express different kinds of images, they fail in partitioning heart masses and the improvement of the heart chamber at a particular stage in the cardiovascular cycle. At the systolic level, the chamber limits so much that it loads up with an intracardiac mass, covering the atrial divider as far as possible. Exciting endeavors have been made in computer-aided classification applications, such as the synthetic multilayer ANN [23-24] and SVM [25]. In [26], a scattered illustration approach is implemented for the classification of tumors and thrombi in intracardiac ultrasound images. In [27], F-FDG intake in cardiac tumors can distinguish benign and malignant cardiac tumors and predict survival. In [28-29], discussed the latest developments in the fields of cardiovascular imaging and related machine learning in the fields of video acquisition and reconstruction, image analysis, diagnosis, evaluation, and prognostic information derivation. In [30], the prevalence of malignant diseases, which are increasing globally. The development of modern diagnostic tools guarantees improved early detection.

PROPOSED INTRACARDIAC MASSES DETECTION AND CLASSIFICATION

This section discusses the operation of the proposed intracardiac mass detection and classification system based on the Patch-based sparse representation, GLCM-LBP based DCNN classifier. The proposed system consists of five stages, such as frame separation, noise removal, segmentation, feature extraction, and mass classification. To deal with the intracardiac issue the proposed work thought of the course of action of a DCNN Classifier for intracardiac disease identification and classification. This technique is needed to manage the differentiation of patterns. The structure first transfers all images to a specific level, and transfer all images to a specific level. Examples of noise-free usage using Patch-based rare representations are much clearer, with different types of features. The extracted features could be used for making the classification model. This classification model framework, we can finally predict the intracardiac infection masses. Finally, the proposed framework recommends clinical treatment or guidance dependent on our anticipated intracardiac disease result. In this research work, a total of 340 images were tested. In this process, 240 images were collected from Vinayaka Mission's Kirupananda Variyar Medical College & Hospital, Salem, Tamilnadu.

PATCH-BASED SPARSE REPRESENTATION

The nearness of speckle noise in echocardiogram images disrespects the image quality and influences the edges and exquisite details of the image, which makes demonstration progressively troublesome. In this manner, image pre-processing is fundamental for the removal of speckle-noise, which helps in the improvement of computer-aided classification of intracardiac diseases. Therefore, Patch-based sparse representation has been utilized in image pre-processing for this work. First, an adaptive median filter is used to detect the heart image and obtain the initial guidance image. Second, you will learn rare patch-based sparse representation from the images in this guide; third, a normalization method with weighted $l_1, -l_1$ is provided to punish the candidate noise that is heavier than the remaining pixels. The alternating direction minimization algorithm is derived to solve the normalized model. Experiments were carried out under speckle noise levels of 30% to 90%.

LINEAR ITERATIVE VESSEL SEGMENTATION

First, interpret the image using the neutrosophic set, which calculates the spatial information of the image. Then, the error in the image defined by combining the spatial information and the intensity information also uses this value to configure the error filter. Indeterminacy filters reduce the uncertainty of their respective strength and spatial information. A graph of the image, use the uncertain filtered value to represent the weight of each pixel, and use the neuron value to redefine the energy function. The result of segmentation in this work is produced using an ultrasound intracardiac image with three classes. Each type contains a three-dimensional component vector related to every pixel alongside the class name.

MULTISCALE LOCAL BINARY PATTERN STRATEGY (MS-LBP) WITH GLCM

This paper proposes a content-based image retrieval method, which focuses on the extraction and reduction of multiple features. Discrete wavelet transform is first applied to RGB channels to extract the approximate values and precise coefficients of the image multi-level decomposition. Therefore, both the approximation and the exact coefficient are computationally valid, and are suitable for the main rotating local binary mode that presents a rotation-invariant texture. For patches in the local neighborhood, measure the descriptor as a reference and obtain the image of the rotation invariant function. The proposed method contains the complete structure information extracted from the local binary pattern, and uses the size information to extract additional information to obtain additional discriminative power. Then use GLCM technology to capture the dominant rotated local binary mode image and extract the statistical characteristics for texture image classification.

To develop feature indicators, the MS-LBP approach first involves a asymmetrical neighborhood circularly around each pixel and a dark estimate of the neighboring pixels in the focal pixels' dim estimation. For example, the threshold yield has two types of data: character and scale. Be that as it may, the scale data, gives the size of the difference, for example, the amount is higher than the neighboring pixel or smaller than the confidence inside the pixel. To achieve dark surface invariance, the LBP approach uses only local neighborhood comparisons for binarization. Therefore, a binary property vector is given by dividing the amount by one of the neighboring pixels is more interesting than the internal pixel The feature extraction algorithm computes the Selected Features similarity at each pixel and finally calculates the similarity of the cumulative pixels. The proposed method extracts 12 features, such as PSNR, MSE, contrast, variance, homogeneity, collection, skewness, energy, mean, entropy, standard deviation, and kurtosis. The results of feature extraction for various images are depicted in Table 1.

Table 1. Result of Feature Extraction with various sample images

Features	Normal (Mean±SD)	Cardiac Tumor (Mean±SD)	Cardiac Thrombi (Mean±SD)
Standard deviation	1.5643± 0.4011	0.0818±1.9196	0.3145±0.0218
Contrast	0.0854±0.0142	0.02834±0.0324	0.0742±0.0672
Correlation	0.7298±0.0126	0.1266±0.2407	0.5603±0.0236
Energy	1.7843±0.0248	0.7856±0.3889	0.9362±0.0278
Entropy	2.2432±0.1737	0.7250±0.9234	0.5213±0.1340
Homogeneity	2.1247±0.0207	0.9367±0.0158	0.9349±0.0054
LBP1	3.2234±0.1361	1.4278±0.4938	1.7799± 0.217
LBP2	3.3437±0.0252	1.5358±0.0340	1.7743±0.894
LBP5	1.7631±0.1972	0.4963±0.6536	0.6498±0.3908
LBP9	1.9570±0.0324	0.4676±0.0504	0.5564±0.1113
Mean intensity	3.1278±0.02719	0.9413±0.0218	1.26134±0.0267

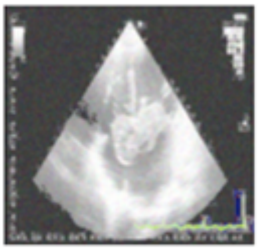
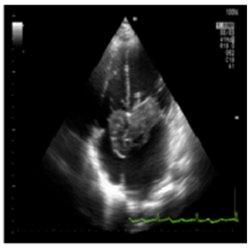
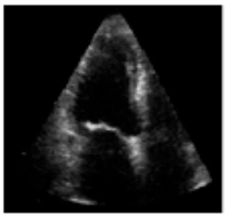
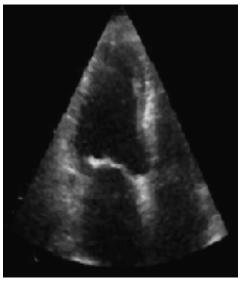
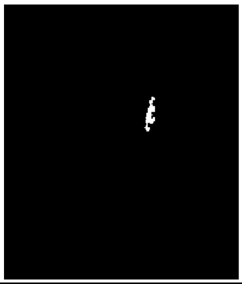
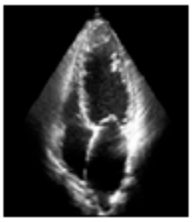
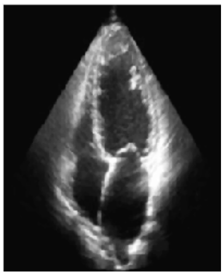
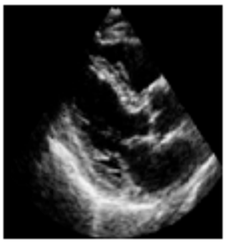
DOUBLE CONVOLUTIONAL NEURAL NETWORK (DCNN)

The main purpose of the proposed Double Convolutional Neural Network (DCNN) is to provide a model similar to the internal system of cardiac quality classification, In order to analyze various systems based on experience, the ultimate goal of these algorithms is to be able to generate the possibility of learning streams in artificial networks, and provide deep learning to diagnose the network like the human brain. The network contains some new and unusual features that can improve performance and reduce training time. High network size has become an important issue, and several effective techniques have been used to prevent overfitting. The final network consists of 5 layers and 3 layers, and depending on the depth, removing each convolutional layer (each containing more than 1% of the model parameters) will result in a lower yield. The net has eight layers of weight. The first five are convolutional, and the remaining three are fully connected.

After the explanation, the model can explain the Double CNN architecture. As shown in the figure below, there are eight layers with weights in the model, the first five layers are the same Convolution layer, and the remaining three layers are fully connected layers. The second, fourth, and fifth convolutional layer kernels are connected to the previous MAP kernel on the same GPU. The third kernel in the convolutional layer is connected to all kernel maps in the second layer. Neurons are connected from neurons in the fully connected layer to previously connected neurons. The response normalization layer follows the first and second convolutional layers. The largest pooling layer follows the full layer and the fifth convolutional layer. Non-linear ReLU is implemented at the output of each convolutional layer and fully connected layer.

RESULTS AND DISCUSSIONS

The input images (image 1-6), the result of the patch based sparse representation and the LIVS are shown in Figure 7.

Input Images	Result of Preprocessing	Result of Segmentation	Type of cardiac mass
 Input Image-1			Thrombi
 Input Image-2			Thrombi
 Input Image-3			Tumor
 Input Image-4			Tumor

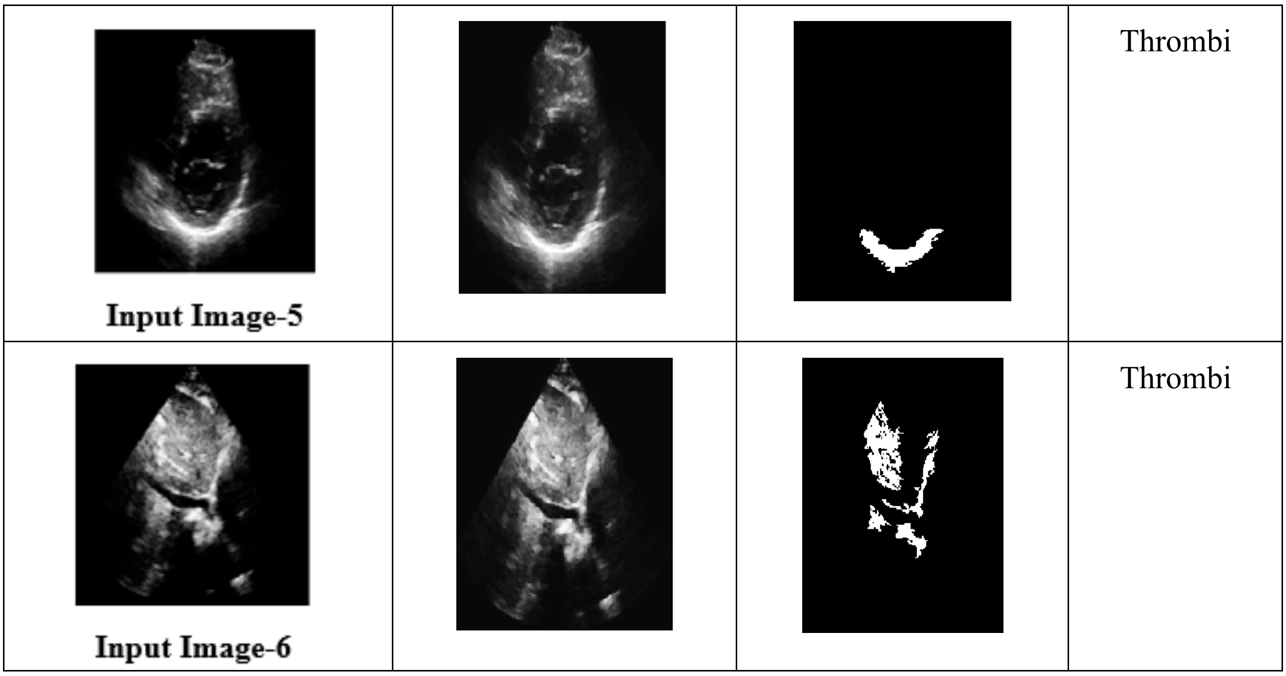


Figure 2. Preprocessing and Segmentation results of different Intra-Cardiac masses

The simulation result of the preprocessing and segmentation of different samples is shown in Figure 2. The performance analysis of preprocessing with different filters is listed in Table 2. Table 2 depicts that introduced patch based sparse representation denoise approach attains a better response to image preprocessing. The evaluation of MSE for different echocardiogram images and are compared with various methods, and it illustrates clearly that the proposed method has produced a low mean squared error value and significant PSNR as compared with other filtering methods.

Table 2. Performance evaluation of filtering response

Parameters	Filters	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6
MSE	Gaussian	14.394	13.869	15.698	14.782	13.698	15.695
	Mean	11.553	11.569	13.692	12.089	10.859	13.126
	AVM	7.753	8.693	9.630	8.963	7.631	8.425
	Patch	7.134	8.325	9.120	8.389	7.178	7.987
PSNR(in dB)	Gaussian	30.895	32.569	33.698	31.896	32.584	33.698
	Mean	33.886	34.875	37.960	34.871	35.612	36.742
	AVM	41.646	40.894	41.467	40.569	41.871	41.968
	Patch	40.567	40.432	40.675	40.256	41.287	41.438

Table 3 discusses the global consistency error (GCE) between different methods. It measures the extent to which one segmentation can be viewed as a refinement of the other. The proposed LIVS has low GCE rate conventional K-means clustering and fuzzy C-means (FCM) clustering methods.

Table 3. Performance evaluation of Global Consistency Error

Parameters	Segmentation method	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6
GCE	K-means clustering	0.4634	0.4567	0.4890	0.4725	0.4604	0.4464
	FCMclustering	0.4378	0.4398	0.4504	0.4567	0.4306	0.4257
	LIVS	0.3624	0.3534	0.3467	0.3354	0.3613	0.3698
DICE Coefficient	K-means clustering	0.74	0.72	0.78	0.75	0.76	0.77
	FCM clustering	0.84	0.85	0.87	0.86	0.86	0.89
	LIVS	0.95	0.99	0.97	0.95	0.98	0.97

From Table 4 and Figure 3, it is depicted that the introduced DCNN approach attains a high accuracy value while classifying the exact tumor and thrombi location from the echo-cardiogram images. The discussed system efficiency is evaluated on 6 different echo-cardiogram images. From the analysis, the DCNN attains the maximum specificity results when compared to the state of art approaches RBPNN, SVM, ANN, Sparse Representation, SVM-PSO, and KCR. The successful computation of 12 different features in the proposed method helps to recognize the intra-cardiac mass tumor with maximum accuracy (98.89%) compared to other classifiers. The method effectively computes the output value $V_h = \sum_{n=1}^{N_{Hid}} w_{nh} y_n$ also minimizes the deviation while calculating the output value.

Table 4. Performance analysis of accuracy with different classifier.

Sample Input Images	Classification accuracy (%)						
	ANN	SR	KCR	SVM	SVM-PSO	RBPNN	**DCNN**
Image 1	85.72	90. 32	91.88	92.02	93.82	97.35	**98.62**
Image 2	84.89	91.47	92.90	92.93	94.84	97.39	**98.32**
Image 3	85.29	90.58	91.49	92.40	94.15	97.58	**98.97**
Image 4	85.78	90.98	92.22	93.93	94.55	97.85	**99.14**
Image 5	85.90	91.03	91.46	92.95	93.25	97.69	**98.81**
Image 6	84.35	91.48	92.58	93.85	94.67	97.61	**99.21**

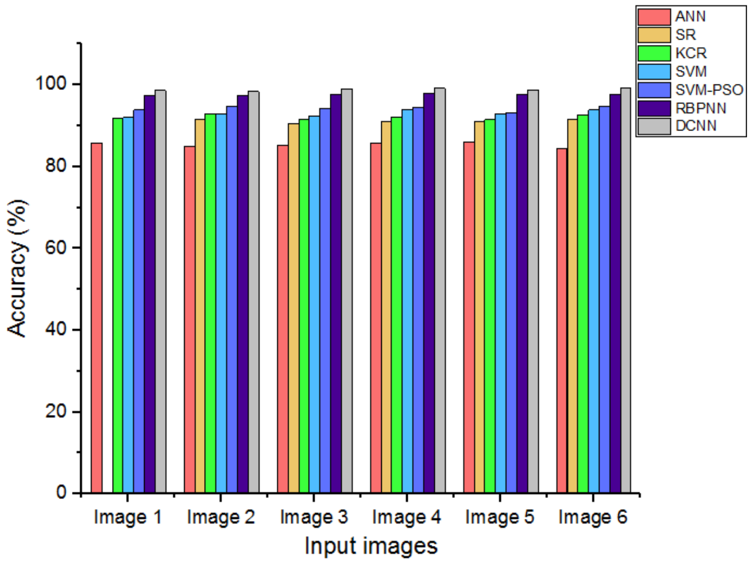


Figure 3. Result of Accuracy analysis with different classifier

The proposed DCNN approach attains the maximum sensitivity value while selecting the exact tumor location from the echo-cardiogram images. The discussed system efficiency is evaluated the six different echo-cardiogram images. From the analysis, the DCNN attains the maximum sensitivity results when compared to the state of art approaches such as RBPNN, SVM, ANN, Sparse Representation, SVM-PSO, and KCR. Based on the tabular value, sensitivity results in the graphical analysis are illustrated in Figure 10.

RUN TIME ANALYSIS

The running time of the proposed method was calculated for each processing and it took about 435.165 seconds to analyze and identify the cardiac masses, where it took 268.78 seconds to eliminate the noise and to segment the masses, took 127.21 seconds.

CONCLUSION

In this work, a double convolutional neural network classifier is proposed to detect and classify intra-cardiac masses by echocardiogram images. The proposed system consists of four stages, such as noise removal, segmentation, feature extraction, and mass classification. Initially, the noise is diminished from echocardiogram images utilizing the patch based sparse representation. The masses were automatically segmented dependent on the LIVS strategy followed by texture features extracted utilizing the GLCM with MS-LBP method. These features were used to separate the intracardiac mass from the echocardiogram images using DCNN with a polynomial kernel for texture mixing. This research clearly states that the proposed DCNN method achieves the best accuracy ratio compared with conventional RBPNN, Sparse Representation, SVM-PSO, SVM, ANN, and KCR methods. The accuracy, sensitivity, and specificity suggested by the DCNN system are 98.98%, 98.89%, and 99.16%, More prominent productivity and basic execution make the DCNN approach helpful for cardiologists to make anticipation before medical surgery.

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