Fine-Tuned Convolutional Neural Network for Different Cardiac View Classification

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Abstract: In echocardiography, an electrocardiogram is conventionally utilized in the chronological arrangement of diverse cardiac views for measuring critical measurements. Cardiac view classification plays a significant role in the identification anddiagnosis of cardiac disease. Early detection of cardiac disease can be cured or treated, and medical experts accomplish this. Computational techniques classify the views without any assistance from medical experts. The process of learning and training faces issues in feature selection, training and classification. Considering these drawbacks, an effective rank-based deep convolutional neural network (R-DCNN) for the proficient feature selection and classification of diverse views of ultrasound images (US). Significant features in the US image are retrieved using rank-based feature selectionand used to classify views. R-DCNN attains

96.7% classification accuracy, and classification results are compared with the existing techniques. From the observation of the classification performance, the R-DCNN outperforms the existing state-of-art classification techniques.

Keywords: Cardiac view, neural network, ultrasound image, ranking, classification, and ReLU.

1. Introduction

Echocardiography plays a prominent role in imaging the cardiac and delivers a low-cost, non-invasive and broadly accessible diagnostic tool for the complete investigation of cardiac function and structure [1]. Heart sonographer's image uses ultrasound by placing the transducer beside the chest of the patient. The sound waves echoed on the internal structure of the heart wall that reflects conditions of the heart wall and velocity of blood flow.A two-dimensional cross section view of heart in a distinct orientation is captured by the ultrasound video [2, 3].

Numerous general cardiac views are categorized by the plane in which they are captured and they are taken by the cardiac specialist. The acquired images are utilised for the qualitative and quantitative investigation of the heart function [4]. Diversified cardiac views are utilised in the evaluation of significant measurements of cardiac are ejection fraction of left ventricular, aortic stenosis severity, abnormality of wall motion that is done by the clinician’s [5]. While investigating the multiple views, general or temporal synchronization turns to be as complicated one for accomplishing cardiac phases is the identical at every prompt in every views [6].

In the existing medical practices, transducer positioning and viewpoint capturing are essential for the manual participation in imaging and their interpretation [7]. The US images delineate the principal anatomical schema of heart and evaluate the incidence of disease. The investigation is done by the specialist and they interpret the echocardiogram for recognition of abnormality in the heart.The re-claiming of the desired information from a diverse viewpoint is a complex process and is subsequently utilized for the investigation as well as the diagnosis of disease [8]. The intervention of human and manual analysis is highly reduced with the advent of computational algorithms.

In the previous decades, cardiac view recognition scheme has shown incredible progression, and the cardiology-based decision making approachesareprogressed by the mechanism of similarity search and the relevant techniques [9]. The preliminary emphasis on the cardiac image analysis focuses on the automated detection feature from the images of ultrasound and then, the acquired features are employed in the similarity search and discrimination of disease. The automated classification has gained consideration amongst researchers and it has huge impact in the identification of abnormalities in cardiac functionality with the assistance of classified cardiac view [10, 11].

The ultrasound image poses noise and other irrelevant information that willdegrade the performance of the algorithm. The high dimensional and redundant featurescreates the diagnosis inaccurate. To overcome this issue, filtering and normalization is introduced during the process of pre-processing. The NL-means filter and body mass normalization are applied to improve the presence of the image. The selection of significant feature can enhance the classification accuracy. The classification is attained by the deep learning-based technique called DCNN.

The remaining of the article is organized as follows: diverse cardiac view classification techniques developed by different researchers are discussed in Section 2, the proposed feature selection and classification technique, R-DCNN is discussed in Section 3, feature selection and classifier outcomes are discussed in Section 4 and the article is concluded with future work suggestion in Section 5.

2. Related Works

Clinical investigation of disease identification is initiated with the views of heart image. An automatic classification with deep learning is attained to predict seven views of heart. Feature selection is not focussed in this approach and the process of learning is influenced by the redundant feature [12]. A learning framework with Echo-SyncNet is utilised in the classification of cardiac view and the 2D echo is used in this approach. The computational cost is huge for this technique [13].Deep learning is an evolving tool for examiningmedical images but it is not yet been broadly applied to echocardiograms, partially due to their composite format of multi-view [14].

Machine learning (ML) is a sub field of artificial intelligence (AI), whereas machines automaticallyretrieve the data by extracting needed or significant patterns from vast databases. Itcan be increasingly utilised within the medical field and definitelyreside within the field of cardiovascular diseases [15]. Automation of any tasks is accomplished by humans and some of the automation process are segmentation of image, cardiac structuralmeasurement and parameters related to functionality [16, 17]. The unsupervised, weak supervised and self-supervised based feature learning approachesacquire huge attention that aimin utilise the hugequantity of data [18].

SVM is a supervised machine learning technique that is utilised for the classification as well as the regression analysis and it coordinates with the general distinct observation of values. [19]. The medical images are categorized by the Back Propagation Neural Network with Support Vector Machine (SVM). The features for the classificationis retrieved by the histogram and statistical methods. The views of the medical images are categorized with the support of reclaimed features [20].

Additionally, the classification is achieved by the neuro fuzzy inference system that makes the classification simple [21]. The categorization of views are accomplished by the MLboostingapproach, which is an integration of multi-object features detection and local-global features. The views of the cardiac image isframed based on the design of the spatial portion to the template. The views are categorized based on the frames acquiredfrom the video and in end-diastolic [22]. The drawbacks in the existing system namely training, existence of redundant feature and training is considered in designing the proposed Rank based DCNN technique.

3. Proposed Methodology: Cardiac View Classification

This section explains the proposed classification technique along with the pre-processing and feature selection. The overall block diagram is given in Figure 1.

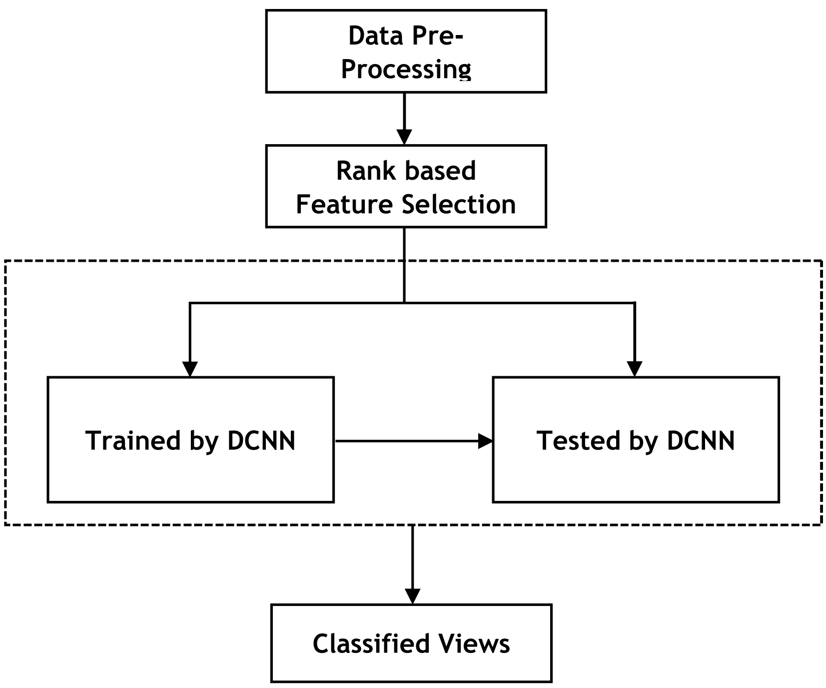

Figure 1. Overall Block Diagram of R-DCNN

In Figure 1, the entire flow of R-DCNN that is pre-processing, feature selection and classification approaches are given.

3.1. Pre-Processing

NL-means filter

The process of de-noising is a difficult task in US image and occurrence of speckle artifacts removal is a complicated process that is independent of heart wall and tissue. The US images necessitatesdistinctive filters due to the signal that dependent of intensity in image speckle. The unwanted material in the US image is eliminated by the NL-means filter, which is further normalized by body mass normalization [23]. Formulation of Bayesian function initiates NL-means filter and it is corresponding to experimental estimator $\widehat{EE}(BY_{x_m})$ and it is denoted as,

$$\widehat{EE}\left(BY_{x_m}\right) = \frac{\frac{1}{|\Delta_{x_m}|}\sum_{y=1}^{|\Delta_{x_m}|} EE\left(BY_y\right)pb\left(uBY_{x_m}\right)|EE\left(BY_y\right)}{\frac{1}{|\Delta_{x_m}|}\sum_{y=1}^{|\Delta_{x_m}|} pb\left(uBY_{x_m}\right)|EE\left(BY_y\right)}$$

---------- (1)

where the blocks are indicated as BY_{x_m}, probability density function (PDF) for the experimental estimator is indicated as $pb\left(uBY_{x_m}\right)|EE(BY_y)$ of uBY_{x_m} thatdelivers noise-free and unknown patches of $EE(BY_y)$. The unknown value of $EE(BY_y)$ is calculated by the substitution of $EE(BY_x)$ for $EE(BY_y)$ and the acquired experimental estimator is equated as,

$$\widehat{EE}\left(BY_{x_m}\right) = \frac{\sum_{y=1}^{|\Delta_{x_m}|} u\left(BY_y\right)pb\left(uBY_{x_m}\right)|u\left(BY_y\right)}{\frac{1}{|\Delta_{x_m}|}\sum_{y=1}^{|\Delta_{x_m}|} pb\left(uBY_{x_m}\right)|u\left(BY_y\right)}$$

---------- (2)

where the pdf of uBY_{x_m}indicates$pb\left(uBY_{x_m}\right)|u(BY_y)$ and it is conditional to $u(BY_y)$.

Body Mass Normalization (BMN)

BMN reduces the role of body mass such that the correlation amongbody mass and muscle size, wherethe value is close to zero. The ratio scaling approach is important among the thickness across traversal position of valve and in body mass when any correlation is not present in the wall region. The proportionand scaling-based normalization is ineffective for these ultrasound images. Hence, BMN scheme is utilised for the normalisation and prepares the US image for feature selection [24].

3.2. Feature Selection

Features are determined as a functional elements of distinct measurements of US image and substantial characteristics in the images are identified. A group of identified feature that helps the classification model to spot the significant or needed patterns in the US image that is determined as a class label. The group feature includesdefinite irrelevant and redundant features whereas the computational cost is huge to process the irrelevant or redundant features. Those features are eliminated by the process of feature sub-selection that can eventually minimize the dimensionalityof the data [25].

From theUS images of echocardiogram 117 features are extracted and optimal features are elected by rank-based feature selection method. This will accomplish the learning or training process simpler and the best classification accuracy is achieved. The significant selection of feature is characterized as ranking the feature and selection of feature subset. The features are ordered based on their significance and ordered to reclaim the needed features. Outline of the rank-based feature selection is given in Algorithm 1.

Algorithm 1. Feature Ranking

Input: Group of features in US image →GF

Output: Top ranked(TR) feature→ TR

Ranking Technique

1. Critieria_of_Eva (C)→Features //Criteria for feature evaluation
2. Ordering→Feature_by_Rank(Features) //Descending order

Return (Top ranked(TR) feature)

The subset selection process is initiated for the selectionof feature and it utilises aninclusive search process. If a dataset encompasses of N count of initial features and it is probable for subset 2N. The optimal feature setdecides the performance of the classifier and the proficient accuracy is gained.

Table 1. US image Features

Particular	Feature Count
Statistics of first order (entropy, mean, mode, variance, kurtosis, energy, median, skewness)	05
Matrices based on the level of haralick spatial grey	23
Difference statistics based on the level of gray (entropy, mean, energy and contrast)	03
Neighbourhood Gray Tone Difference Matrix (NGTDM)	04
Statistical feature matrix (SFM) (coarse, period, contrast, roughness and feat)	03
Fractal Dimension Texture Analysis (FDTA)	03
Law Features	06
Shape (perimeter, area, and perimeter^2/area)	03
Spectral Features	364
Others	03
Total	

3.3. Classification – Deep Convolutional Neural Network (DCNN)

The optimal features retrieved fromrank-based feature selection is classified with the support of Deep Convolutional Neural Network (DCNN) with Rectified Linear Unit (ReLu), which acts as an activation function [26, 27]. DCNN is has two stages such aslearning of feature and classification. The feature learning stage in DCNN has convolution and pooling layer. The classification phase in DCNN has the fully connected and softmax layer. The Deep CNN facilitates learning process of features acquired from imageand the process of classification is simple that classifies the features based on the labels. The outline of Deep CNN classifier is illustrated in Figure 2.

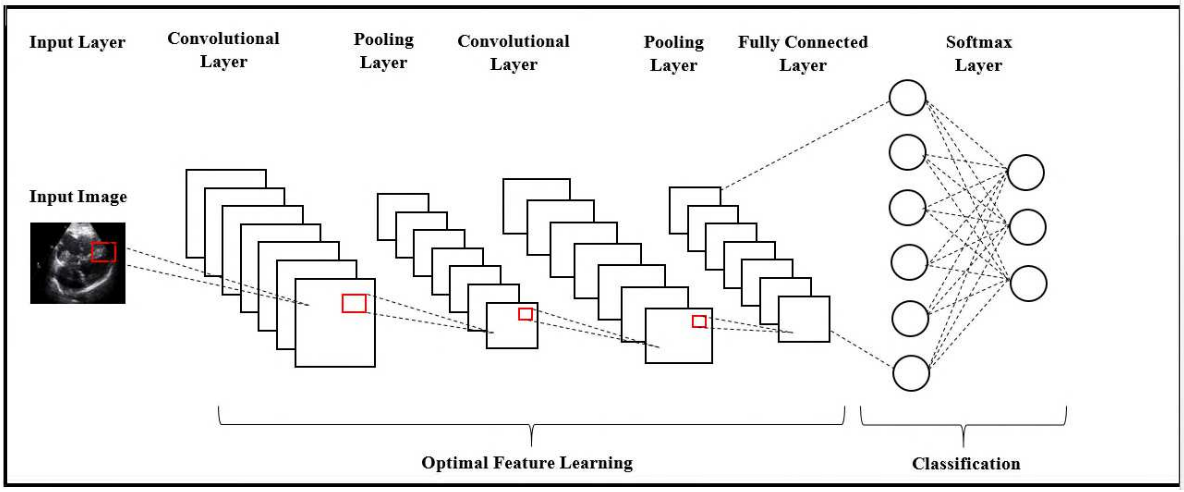

Figure 2. Outline of Deep CNN with RELU

Convolution Layer

In this layer numerous filters slide over the input feature and the process of summation is attained as element by element that utilised multiplication technique. The input information receptive rate of is then estimated as the output value of this layer. The weighted summation rate is measured as an input element of US image of the succeeding layer. The main focus area of this layer is slide to fill the supplementary pixels values that is in the resultant value of the convolutional layer. Eachprocedure in the convolution layer is denotedas stride, size of filter, and zero padding.

The activation function in the DCNN is Rectified Linear Unit (ReLU) and it accelerates the convergence of stochastic descent gradient [28]. The execution of ReLU is simple and it is exploited by assigning thresholds where the rate of activation function value is mapped to zero. It returns zero if it gets negative value and t is returned if it receives positive (pt) value. The ReLU (AF_ReLU) is given as,

$$AF\_ReLU = \max(0, pt)$$

where the positive value is denoted as pt, and the activation function of DCNN is denoted as AF_ReLU.

The gradient approach in this layer stops learning process when the AF_ReLU value extents to zero and activation of DCNN is accomplished in that scenario that is ReLU (AF_ReLU). The activation function in this layer l is equated follows,

$$AF\_ReLU_l = \begin{cases} pt & pt > 0 \\ o \times pt & pt \leq 0 \end{cases}, o$$

where the predefined parameter is denotes as o and it is initially assigned with the value of 0.01.

Pooling Layer

The pooling layer reduces the dimension of the output information of US image and the most familiar max pooling approach is utilized, whichdenote the maximum pooling filter value. The max pooling is a most capablemethod and it deliversnotable down sampling size of input information. Max pooling approach is highly effective than averaging and summation approaches.

Fully Connected Layer

This layer learns the combination of non-linear information of the high range features, which is denoted by the output of convolutional layer. The non-linear function and values in this space is learned by this layer.

Softmax Layer

In softmax layer, the view classification is attained and softmax function is employed in the output layer, which isincluded as a normalized value of exponent of output view of US image. This denotes the probability of output and softmax function is distinguished. Moreover, the exponential pixel rate proliferates the probability to highest level. The softmax function and their estimation is equated as,

$$Opt_x \frac{e^{z_x}}{\sum_{x=1}^{C} e^{z_x}}$$

where output that is US image view of the softmax is denoted as $opt_x$for the number of output is x, z_x is the considered as output x before the layer softmax, and whole count of the output layer is denoted as C. The class labels for the US image views are classified in the softmax layer.

4. Result and Discussion

This section describes about the results acquired from the feature selection and classification process. Additionally, the performance of the proposed approach is compared and contrasted with the existing technique. In this research work, about 600 ultrasound images withdifferent cardiac views are used and 35% of the image is incorporated in the process of training where the remaining images are utilisedin the testing phase. The imageutilised image in this research work has 90 DPI with the resolution of 300*340. The experiment is done on the Matlab of windows operating system(OS) with 4GB of RAM and a 500GB hard disk capacity. The US images used in this experimentation is captured from the US video. The input US image is given in Figure 3.

Figure 3. US image

4.1.Analysis of Pre-processing

The noise and other unwanted information in the image is removed and normalized by NL-means filter and body mass normalization. The pre-processed image is converted to grey-scale that highlight the necessary information in the US image [29]. The pre-processed sub-coastal view, Mid-esophageal view, apical four chamber and apical two chamber view is given in Figure 4.

Figure 4 (a). Subcostal View

Figure 4 (b). Mid-Esophageal View

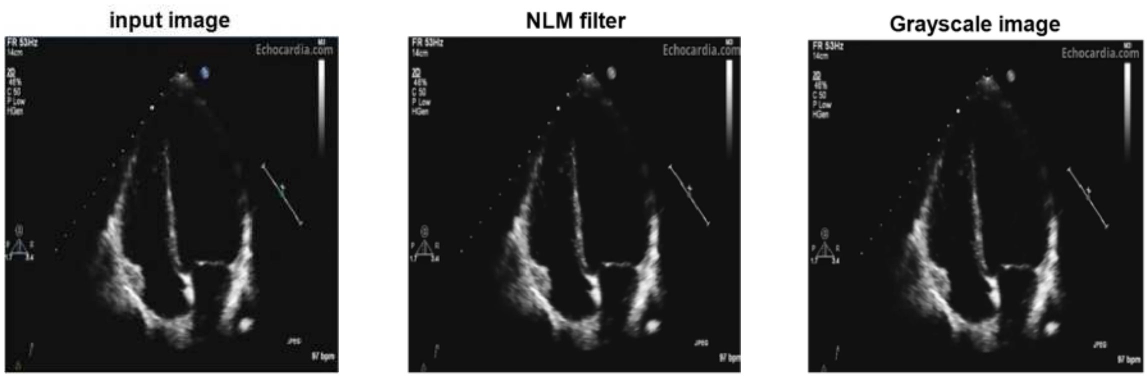

Figure 4 (c). Apical four Chamber View

Figure 4 (d). Apical two Chamber View

Figure 4. Pre-Processed US image

In Figure 4 pre-processed and grey scale image are given. Figure 4 (a) depict sub-coastal view, Figure 4 (b) depict Mid-esophageal view, Figure 4 (c) depict apical four chamber and Figure 4 (d) depict apical two chamber view.

4.2.Analysis of Classification

The R-DCNN and the existing techniques SVM [19], histogram features with BPNN [20], neuro-fuzzy system [21] and ML-boosting [22] are compared for the evaluation of the performance. The classification performance is investigated by the performance metrics namely accuracy, sensitivity, specificity [30], F1-Score and Matthews correlation coefficient (MCC).

4.2.1. Accuracy

Classification summarizes the classification model performance as the count of exact prediction (True Positive and True Negative) divided by the total count of the prediction (TP, TN, False Positive and False Negative). The classification model is evaluated with the accuracy attained during the process of classification. The algorithm with highest accuracy is determined as best classifier. The accuracy for different image count and different algorithms is given in Table 2 and illustrated in Figure 5. The accuracy value is estimated as,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Table 2. Comparison of Accuracy

Algorithm	No of Images				
	200	300	400	500	600
SVM	86	86.5	85	84	83
histogram features with BPNN	95	90	80	85	87.5
Neuro fuzzy	91	90.9	90.5	89	88
ML-BOOSTING	80.3	75.5	67.5	70.9	74.9
R-DCNN	97.55	97.1	96	96.9	96.7

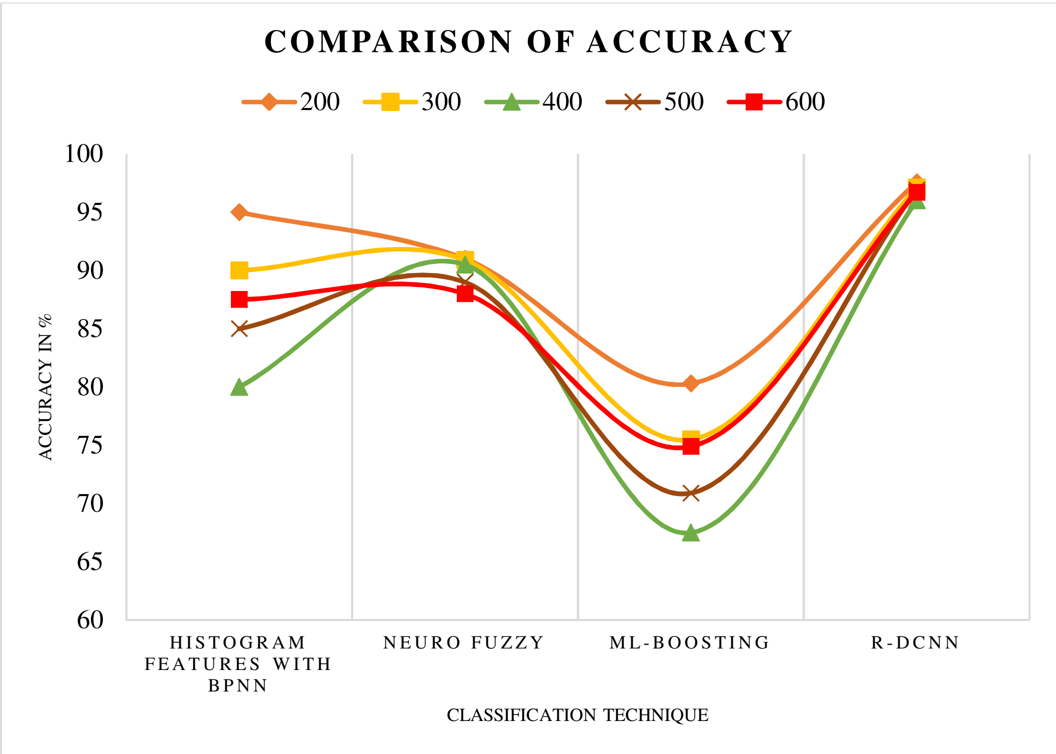

Figure 5. Comparison of Accuracy

In Figure 5, the accuracy value for the image count 200, 300, 400, 500, 600 is depicted and the R-DCNN is compared with the existing approaches. For image count 600, the R-DCNNachieves accuracy value of {13.7%, 9.2%, 8.7%, 21.8%} for {SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting}, respectively. The accuracy value of R-DCNN is higher and it shows that the proposed classification model is best.

4.2.2. Sensitivity

Specificity is the ratio of TN values out of all the samples that has no condition. Sensitivity is determined as the detection of TP values and accuracy of the US image is evaluated with this technique.The sensitivity for different image count and different algorithms is given in Table 3 and depicted in Figure 6. The sensitivity value is estimated as,

$$Sensitivity = \frac{TP}{TP + FN}$$

Table 2. Comparison of Sensitivity

Algorithm	No of Images				
	200	300	400	500	600
SVM	85	85.7	86	86.7	87
histogram features with BPNN	78	78.1	78.9	81	81.3
Neuro fuzzy	92	92.9	93.6	93.7	93.9
ML-BOOSTING	69	69.8	70.3	71	70.9
R-DCNN	95.6	96.3	96.6	97.7	97.8

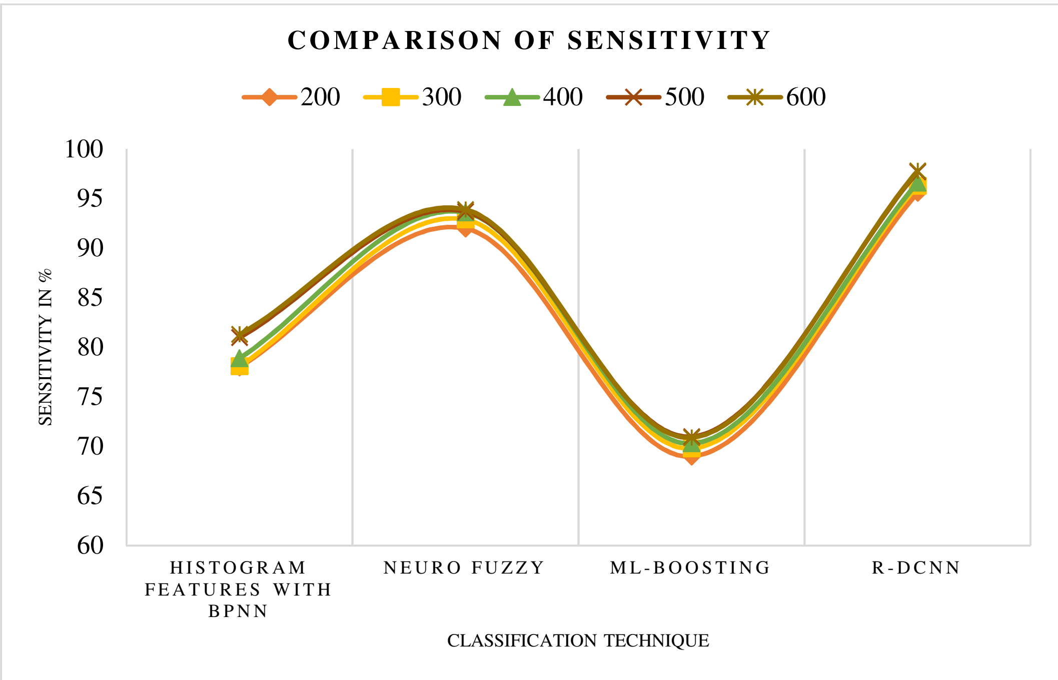

Figure 6. Comparison of Sensitivity

In Figure 6, the sensitivity value for the image count 200, 300, 400, 500, 600 is depicted and the R-DCNN is compared with the existing approaches. For image count 600, the R-DCNN achieves sensitivity value of {10.8%, 16.5%, 3.9%, 26.7%} for {SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting}, respectively. The sensitivity value of R-DCNN is higher and it shows that the proposed classification model is best.

4.2.3. Specificity

Specificity signify the proportion of negative or incorrectly classified values out of all the instances in the dataset and it is specified as the rate of TN. Calculation of specificity supports the detection accuracy in the whole classification sample. The specificity for different algorithms and image count is given in Table 4 and illustrated in Figure 7. The specificity value is estimatedas,

$$Specificity = \frac{TN}{TN + FP}$$

Table 3. Comparison of Specificity

Algorithm	No of Images				
	200	300	400	500	600
SVM	63.5	64.4	66.5	66.4	69.5
histogram features with BPNN	79.3	79.1	79.9	82.8	83.3
Neuro fuzzy	88.3	89.6	91.1	92.5	93.1
ML-BOOSTING	68.9	69.5	71.1	71..5	72
R-DCNN	93.7	95.9	96.5	97.3	98

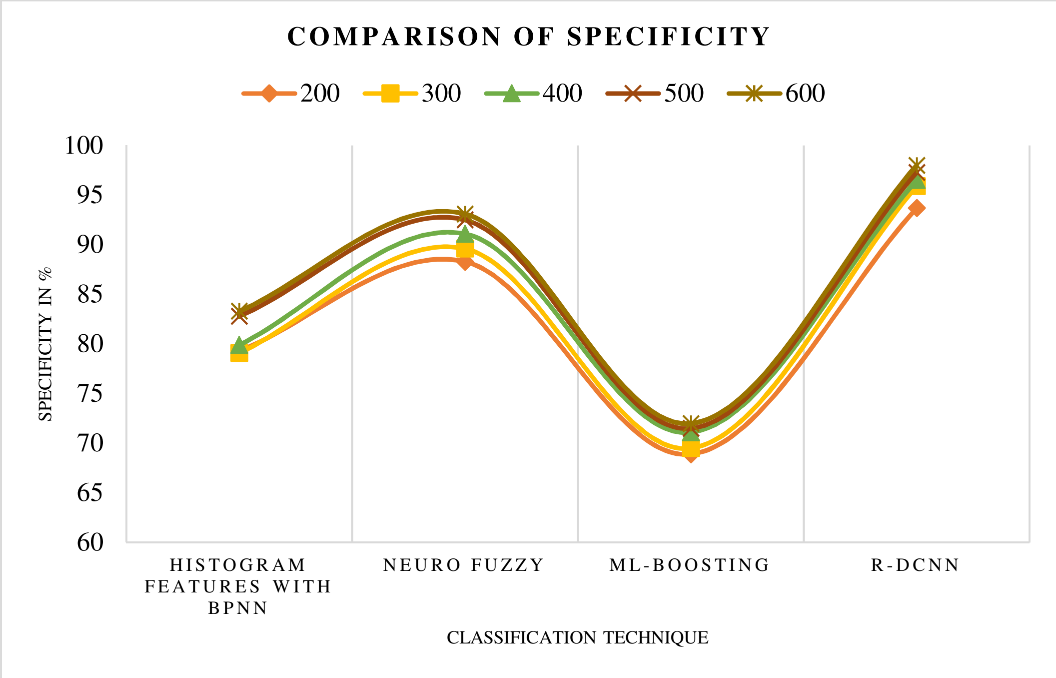

Figure 7. Comparison of Specificity

In Figure 7, the specificity value for the image count 200, 300, 400, 500, 600 is depicted and the R-DCNN is compared with the existing approaches. For image count 600, the R-DCNN achieves specificity value of {18.5%, 14.7%, 4.9%, 26%} for {SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting}, respectively. The specificity value of R-DCNN is higher and it shows that the proposed classification model is best.

4.2.4. F1-Score

Table 4. Comparison of F1-Score

Algorithm	No of Images				
	200	300	400	500	600
SVM	68.5	65.4	66.5	66.9	70.4
histogram features with BPNN	78.8	79.6	81.9	83.8	89.8
Neuro fuzzy	88.8	89.6	92.1	93.5	94.1
ML-BOOSTING	67.9	70.6	72.6	73.6	73.8
R-DCNN	93.9	94.8	95.5	95.8	96

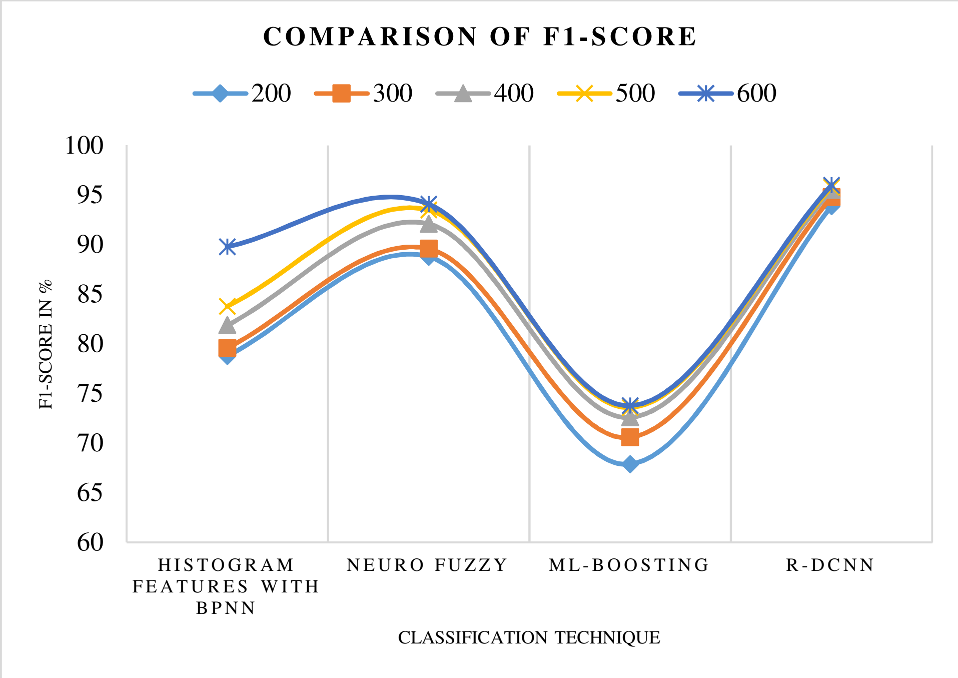

Figure 8. Comparison of Specificity

In Figure 8, the F1-Score value for the image count 200, 300, 400, 500, 600 is depicted and the R-DCNN is compared with the existing approaches. For image count 600, the R-DCNN achieves F1-Scorevalue of {18.5%, 14.7%, 4.9%, 26%} for {SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting}, respectively. The F1-Score value of R-DCNN is higher and it shows that the proposed classification model is best.

4.2.5. MCC

MCC is the most reliable and significant aspect of classification whereas the goodness of the classification model is identified by MCC. The model with high MCC denotes the effectiveness of the classifier. The MCC for different algorithms and image count is given in Table 5 and illustrated in Figure 9. The MCC value is estimated as,

$$MCC = \frac{\sqrt{TP \times TN - FP \times NM}}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Table 5. Comparison of MCC

Algorithm	No of Images				
	200	300	400	500	600
SVM	64.7	65.5	66.3	66.9	68.3

histogram features with BPNN	78.3	78.9	79.5	83.2	84.3
Neuro fuzzy	88.9	89.1	92.5	93.3	93.5
ML-BOOSTING	67.9	68.3	71.1	71.6	73
R-DCNN	94.6	95.5	96.1	96.3	97

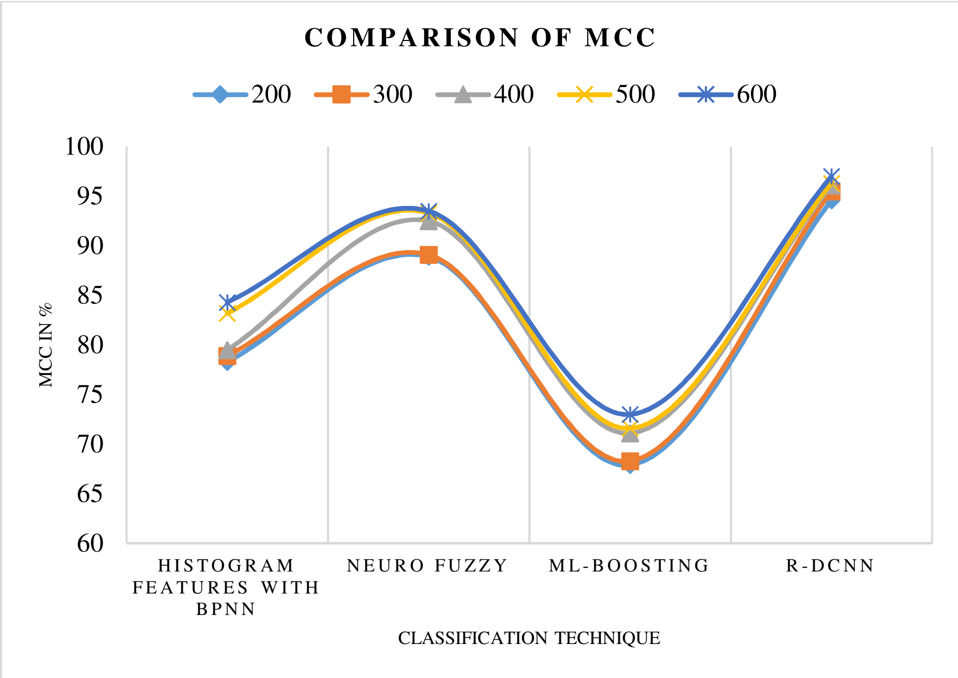

Figure 9. Comparison of MCC

In Figure 9, the MCC value for the image count 200, 300, 400, 500, 600 is depicted and the R-DCNN is compared with the existing approaches. For image count 600, the R-DCNN achieves MCC value of {28.7%, 12.7%, 3.5%, 24%} for {SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting}, respectively. The MCC value of R-DCNN is higher and it shows that the proposed classification model is best.

5. Conclusion

US image of cardiacis classified that helps in the abnormality identification. The position modification and functional abnormal in the heart are detected by the imaging techniques. Early diagnosis of cardiac disease can increase the survival rate and can be cured. The conventional approaches needs medical experts in the diagnosis of disease and the estimation of different view also time consuming. To solve this issue computational techniques are initiated to classify the views.In this also, itfaces issues like feature selection, training and classification. Considering these drawbacks, an effective rank-based deep convolutional neural network (R-DCNN) proposed. The pre-processing in done by speckle filter and features are selected using rank-based technique. R-DCNN attains 96.7% classification accuracy, and classification results are compared with the existing techniques namely SVM, histogram features with BPNN, neuro-fuzzy system and ML-boosting. From the observation of the classification performance, the R-DCNN outperforms the existing state-of-art classification techniques. In future, the approach can be extended with optimization and artificial intelligence approaches.

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Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

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Conflict of Interest: Conflict of Interest is not applicable in this work.

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