Fine-tuned convolutional neural network for different cardiac view classification

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Abstract
In echocardiography, an electrocardiogram is conventionally utilised in the chronological arrangement of diverse cardiac views for measuring critical measurements. Cardiac view classification plays a significant role in the identification and diagnosis 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, there is 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 selection and 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-the-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-sectional view of heart in a distinct orientation is captured by the ultrasound video [2, 3].

Numerous general cardiac views are categorised 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 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 synchronisation turns to be as complicated one for accomplishing cardiac phases which 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 utilised 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 approaches are progressed 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 will degrade the performance of the algorithm. The high-dimensional and redundant features create the diagnosis inaccurate. To overcome this issue, filtering and normalisation are introduced during the process of pre-processing. The NL-means filter and body mass normalisation 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 organised as follows: diverse cardiac view classification techniques developed by different researchers are discussed in Sect. 2, the proposed feature selection and classification technique, R-DCNN, is discussed in Sect. 3, feature selection and classifier outcomes are discussed in Sect. 4, and the article is concluded with future work suggestion in Sect. 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 examining medical 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 subfield of artificial intelligence (AI), whereas machines automatically retrieve the data by extracting needed or significant patterns from vast databases. It can be increasingly utilised within the medical field and definitely reside within the field of cardiovascular diseases [15]. Automation of any tasks is accomplished by humans, and some of the automation processes are segmentation of image, cardiac structural measurement and parameters related to functionality [16, 17]. The unsupervised, weak supervised and self-supervised-based feature learning approaches acquire huge attention that aim in utilise the huge quantity of data [17].

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. [18]. The medical images are categorised by the Back Propagation Neural Network with Support Vector Machine (SVM). The features for the classification are retrieved by the histogram and statistical methods. The views of the medical images are categorised with the support of reclaimed features [19].

Additionally, the classification is achieved by the neuro fuzzy inference system that makes the classification simple [20]. The categorisation of views is accomplished by the ML boosting approach, which is an integration of multi-object features detection and local–global features. The views of the cardiac image are framed based on the design of the spatial portion to the template. The views are categorised based on the frames acquired from the video and in end-diastolic [21]. The drawbacks in the existing system, namely training, existence of redundant feature and training, are 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 Fig. 1.

In Fig. 1, the entire flow of R-DCNN that is pre-processing, feature selection and classification approaches is given.
3.1 Pre-Processing

3.1.1 NL-means filter

The process of de-noising is a difficult task in US image, and occurrence of speckle artefacts removal is a complicated process that is independent of heart wall and tissue. The US images necessitate distinctive filters due to the signal that depends on intensity in image speckle. The unwanted material in the US image is eliminated by the NL-means filter, which is further normalised by body mass normalisation [22]. Formulation of Bayesian function initiates NL-means filter, and it is corresponding to experimental estimator $\hat{EE}(BY_{x_m})$ and it is denoted as:

$$\hat{EE}(BY_{x_m}) = \frac{\frac{1}{|\Delta_m|} \sum_{y=1}^{|\Delta_m|} EE(BY_y) pb(uBY_{x_m}) |EE(BY_y)|}{\frac{1}{|\Delta_m|} \sum_{y=1}^{|\Delta_m|} pb(uBY_{x_m}) |EE(BY_y)|}$$

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

$$\hat{EE}(BY_{x_m}) = \frac{\sum_{y=1}^{|\Delta_m|} u(BY_y) pb(uBY_{x_m}) |u(BY_y)|}{\frac{1}{|\Delta_m|} \sum_{y=1}^{|\Delta_m|} pb(uBY_{x_m}) |u(BY_y)|}$$
where the pdf of \( u_{BY_{x_m}} \) indicates \( pb(u_{BY_{x_m}}|u(BY_y)) \), and it is conditional to \( u(BY_y) \).

### 3.1.2 Body mass normalisation (BMN)

BMN reduces the role of body mass such that there is the correlation among body mass and muscle size, where the 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 proportion and scaling-based normalisation is ineffective for these ultrasound images. Hence, BMN scheme is utilised for the normalisation and prepares the US image for feature selection [23].

### 3.2 Feature Selection

Features are determined as a functional element of distinct measurements of US image, and substantial characteristics in the images are identified. A group of identified features 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 includes definite 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 minimise the dimensionality of the data [24].

From the US 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 characterised 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 \( \rightarrow GF \)
Output: Top ranked(TR) feature \( \rightarrow TR \)
Ranking Technique
    1. Criteria_of_Eva(C) \( \rightarrow \) Features  //Criteria for feature evaluation
    2. Ordering \( \rightarrow \) Feature_by_Rank(Features)  //Descending order
Return (Top ranked(TR) feature)
```

The subset selection process is initiated for the selection of feature, and it utilises an inclusive search process. If a dataset encompasses of N count of initial features, it is probable for subset 2 N. The optimal feature set decides the performance of the classifier, and the proficient accuracy is gained (Table 1).
3.3 Classification—deep convolutional neural network (DCNN)

The optimal features retrieved from rank-based feature selection are classified with the support of Deep Convolutional Neural Network (DCNN) with Rectified Linear Unit (ReLU), which acts as an activation function [25, 26]. DCNN is has two stages such as learning 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 image, and the process of classification is simple that classifies the features based on the labels. The outline of deep CNN classifier is illustrated in Fig. 2.
3.3.1 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. Each procedure in the convolution layer is denoted as 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 [27]. 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 as follows:

$$AF_{ReLU} = \left\{ \begin{array}{ll}
pt & pt > 0 \\
o \times pt & pt \leq 0
\end{array} \right., o$$

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

3.3.2 Pooling layer

The pooling layer reduces the dimension of the output information of US image and the most familiar max pooling approach is utilised, which denote the maximum pooling filter value. The max pooling is a most capable method, and it delivers notable down sampling size of input information. Max pooling approach is highly effective than averaging and summation approaches.

3.3.3 Fully connected layer

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

3.3.4 Softmax layer

In softmax layer, the view classification is attained and softmax function is employed in the output layer, which is included as a normalised 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 are equated as,

$$\text{Opt}_x \frac{e^{z_x}}{\sum_{x=1}^{C} e^{z_x}}$$

where output that is US image view of the softmax is denoted as $\text{opt}_x$, 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 with different cardiac views are used and 35% of the image is incorporated in the process of training where the remaining images are utilised in the testing phase. The image utilised 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 4 GB of RAM and a 500 GB hard disk capacity. The US images used in this experimentation are captured from the US video. The input US image is given in Fig. 3.
4.1 Analysis of pre-processing

The noise and other unwanted information in the image is removed and normalised by NL-means filter and body mass normalisation. The pre-processed image is converted to grey-scale that highlight the necessary information in the US image [28]. The pre-processed sub-coastal view, mid-esophageal view, apical four-chamber and apical two-chamber view are given in Fig. 4.

In Fig. 4, pre-processed and grey-scale image is given. Figure 4a depicts sub-coastal view, Fig. 4b depicts mid-esophageal view, Fig. 4c depicts apical four-chamber, and Fig. 4d depicts apical two-chamber view.

4.2 Analysis of classification

The R-DCNN and the existing techniques SVM [18], histogram features with BPNN [19], neuro-fuzzy system [20] and ML-boosting [21] are compared for the evaluation of the performance. The classification performance is investigated by the performance metrics namely accuracy, sensitivity, specificity [29], F1-Score and Matthews correlation coefficient (MCC).

4.2.1 Accuracy

Classification summarises 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 Fig. 5. The accuracy value is estimated as:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

In Fig. 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-DCNN achieves 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 (Table 3).

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
Fig. 4 Pre-processed US image. **a** Subcostal view. **b** Mid-esophageal view. **c** Apical four-chamber view. **d** Apical two-chamber view.
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|

Fig. 5  Comparison of accuracy

Table 3  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|

different algorithms is given in Table 4 and depicted in Fig. 6. The sensitivity value is estimated as:
In Fig. 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 signifies 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

\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\]
specificity supports the detection accuracy in the whole classification sample. The specificity for different algorithms and image count is given in Table 5 and illustrated in Fig. 7. The specificity value is estimated as

\[
\text{Specificity} = \frac{TN}{TN + FP}
\]

In Fig. 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

In Fig. 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-Score value 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 6 and illustrated in Fig. 9. The MCC value is estimated as:

| 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 system               | 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   |
In Fig. 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 cardiac is 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 need medical experts in the diagnosis of disease and the estimation of different view is also time-consuming. To solve this issue, computational techniques are initiated to classify the views. In this also, it faces issues like feature selection, training and classification. Considering these drawbacks, an effective rank-based deep convolutional neural network (R-DCNN) is proposed. The pre-processing is 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 optimisation and artificial intelligence approaches.

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